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

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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 angel and VC investment into eligible start-ups at the intensive margin, with larger and more experienced investors being more responsive. However, the tax incentive does not increase the likelihood of receiving angel and VC funding for eligible start-ups. We show that investors shift late-stage investment into eligible early-stage investment. The investor tax incentive also encourages firm entry in affected industries, but not the entry of investors.

JEL Codes:
Keywords: venture capital, angel investment, tax incentives, entrepreneurship

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1 Introduction

Venture capital (VC) and angel investment together constitute an important source of financing for start-ups around the world. To encourage and stimulate the growth of early-stage financing, countries implement various incentive schemes, including tax incentives. How do tax breaks for angel and VC investment affect financing for start-ups? Evidence on the effectiveness of investor-level benefits is still limited. In this study, we address this question by examining the impact of a tax incentive scheme for angel and VC investors in China, which has grown to become one of the largest markets for venture capital and has experienced a remarkable rise in innovation and entrepreneurial activity in the recent decades (Chen et al., 2021; Zhou, Zhang and Sha, 2021*a*).

We examine both firm-level and investor-level outcomes after the introduction of a generous new tax incentive for VC and angel investment in China. This tax incentive is available to angel investors and VCs investing in qualified technology start-ups at seed capital or start-up stage, once the equity investment is held for more than 2 years. Under the scheme, 70% of incorporated VCs' qualified investments can be used to offset their corporate income tax (CIT). For legal or individual partners in VC partnerships, 70% of the VCs' qualified investment allocated to them from the partnership can be used to offset their corporate or personal income tax, respectively. In addition, 70% of angel investors' qualified investments can be used to offset personal income taxes arising from disposals of equity in eligible start-ups. This policy was first piloted in eight locations in 2017 and rolled out nationwide in 2018.

Our estimation strategy involves three steps. First, we take a standard difference-in-differences (DID) approach to estimate the effects of the Chinese angel and VC tax incentive on the financing of eligible technology start-ups. We use funding-rounds data provided by Crunchbase during 2014-2019. To qualify for the scheme, the start-ups need to be young technology firms established within the last five years. Based on the "age" and "technology status" criteria, we select eligible start-ups to form the treatment group. We use non-technology start-ups also established within the last five years as the control group. While the 2017 tax incentive scheme imposes location restrictions on VC investors, it does not restrict the locations of the investees.[1] Thus, for identification, we compare the

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

funding rounds performance of treated firms with control firms before and after 2017. We examine how the tax incentive affects total capital raised, number of investors and average investment. The dataset and the DID setting in the first part of our paper are similar to those used by Edwards and Todtenhaupt (2020), who studied the impact of the capital gains tax exemption in the US on small firms' funding activities. Importantly, the Chinese tax code allows deduction against taxable income arising from not only capital gains from equity disposals but also from dividends.[2] The Chinese policy setup, therefore, allows us to evaluate a potentially more generous incentive scheme.

Second, we examine the impact of the policy on investors' strategy by exploiting its staggered introduction. The tax incentive was first offered to VCs registered in eight pilot locations in 2017 and then rolled out nationwide in 2018. The location restriction is only applicable to investors, that is, a VC investor located in the pilot city can invest outside that city and still qualify for the tax deduction. Therefore, all qualified start-ups across the nation are treated in 2017 (as we examine in the first step of our analysis), but the investors are treated in a staggered fashion based on their location. The timing difference allows us to isolate the short-run impact of the VC tax incentive on investors. We aggregate Crunchbase funding rounds data to VC investor level at the quarterly frequency, and compare VCs located in pilot regions with VCs elsewhere during 2016Q1-2017Q4 in investor-level DID estimations.

The third step in our analysis pins down extensive margin effects on firms, namely, how the tax incentive affects start-ups' probability to receive angel or VC funding as well as their entry decisions. To achieve this, we use the city-industry level business registration data during 2014-2019, combined with the funding information from an alternative dataset on Chinese VC activities (Zero2IPO). To shed light on the impact on firm entry, we use the distinction between "technology" and "non-technology" classification that determines eligibility to the tax breaks. We classify each 3-digit industry as "technology" or "non-technology", and compare the number of newly-incorporated independent firms before and after 2017 while controlling for industry and city-level economic conditions. We then scale the number of start-ups receiving angel/VC funding by the

[2] This applies to VC investors. Angel investors can only offset capital gains.

number of start-ups (both under five years of age) in a particular city-three-digit-industry pair to obtain the funding probability for start-ups. Using this ratio as the outcome variable, and comparing "technology" and "non-technology" industries, we examine whether the tax incentive scheme makes funding more likely for eligible start-ups. Using the business registration data, we also analyze whether the VC tax incentive induces more VC investors to enter, or more VC funds to be established.

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 scheme, relative to non-technology start-ups. The magnitude of the increase in total funding for eligible technology start-ups is significant, around 16-18%. We further show that this increase in total funding is mainly driven by an increased number of investors funding qualified start-ups in each funding round. These benchmark results are robust when we control for the potentially-confounding effects of the national high-tech zones (Tian and Xu, 2022), and the local government's provision of angel/VC tax incentives.

There are significant heterogeneities in responses by different types of investors. After the tax incentive was implemented, technology start-ups became more likely to attract funding from larger VCs. In contrast, technology start-ups became less likely to receive funding from smaller VCs. We also show that technology start-ups became more likely to attract more experienced angels and VCs after 2017. These findings are starkly different from the evidence provided by Denes et al. (2020) based on US surveys, which shows that more sophisticated angel investors view the US investor-level tax credit as unimportant. One possible explanation for this difference is that larger or more experienced investors are more likely to generate positive taxable income in any given year. Hence, the tax deduction should be more meaningful for them. Smaller and less experienced investors, by contrast, tend to be less successful in generating returns and for them, there is likely to be no immediate or little taxable income. Although unused tax deductions can be carried forward, this may take a long time to materialize for younger and smaller investors.[3] Larger and more experienced investors should also have better resources (e.g., tax experts) to comply with the tax code

[3]If a VC chooses to be taxed using the fund-by-fund method, unused deductions cannot be carried forward. Unused deductions can be carried forward up to 5 years if a VC chooses to be taxed using the "aggregation" method.

(i.e., preparing documents for obtaining eligibility). Another possible explanation for the difference between our findings and Denes et al. (2020) is that the Chinese tax incentive is substantially more generous than the US scheme for large investments (as the US scheme features a cap), since the ceiling of deduction tends to be much higher. As such, the Chinese tax incentive can be sufficiently attractive to change the behavior of large/more experienced investors. Our results thus suggest that the tax incentive benefits larger and more experienced investors, which in turn may crowd out smaller investors in the market.

One potential concern about implementing investor-level tax incentives to stimulate financing for start-ups, however, is that it may lower the required rate of return before tax and lead to poorer investment decisions. We conduct two exercises to shed light on this issue. First, we compare the exit probability of technology and non-technology start-ups in a DID setting. We do not find any relative decrease in the exit rate of start-ups in the treatment group after the reform. More direct evidence is obtained from a triple DID estimation, where we interact the DID term with a dummy indicating start-ups of the lowest quality based on the Crunchbase rank for each start-up.[4] In this triple DID analysis, we find that technology start-ups in the bottom quartile of Crunchbase ranks do not benefit more from the tax incentive. This is against the notion that investors take on lower-quality investment projects with tax incentives.

Second, using the investor-level quarterly data during 2016-2017, aggregated from Crunchbase, we find that in the first four quarters following the implementation of the tax incentive, VCs in pilot regions significantly increase investment into technology start-ups, relative to investors located in other regions. Meanwhile, there is a relative decline in non-eligible late-stage investment by these treated investors. This analysis strengthens our conclusion that the tax incentive stimulates investment into targeted start-ups, and such an effect is realized in a short period of time. The decline in late-stage investment by pilot investors also indicates possible substitution between qualified and non-qualified investment. Further analysis indicates that government-linked investors respond as much as non-government-linked investors to the tax incentive scheme.

[4]Crunchbase rank is a dynamic ranking indicator based on its own algorithms to score and rank start-ups. The Crunchbase rank algorithm takes various factors into account, including social connections, the level of community engagement, funding events, etc.

Third, we find a relative increase in the number of new independent corporations in qualified industries, compared with that in non-qualified industries since the implementation of the 2017 tax incentive. This suggests that the Chinese tax incentive is effective in encouraging more technology start-ups to be established. This result is different from the findings of Denes et al. (2020) 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, it can change the funding behavior of large investors and consequently, have a material impact on new business formation. Finally, we do not find any significant impact of the tax incentive on the formation of new investors or on the funding probability for technology start-ups. This indicates while the tax incentive induces more technology firms to be established, it does not increase the *ex post* likelihood for a typical startup to receive angel/VC funding.

We contribute to the literature on early-stage financing as follows. First, an emerging body of work analyzes the policy-induced changes in investors' behavior by leveraging investor-level data that was previously not widely available to researchers. Two recent prominent studies on US data examine the impact of tax incentives for early-stage investments in the US. Edwards and Todtenhaupt (2020) analyze how the exemption of capital gains tax affects the funding of start-ups, using the 2010 Small Business Jobs Act (SBJA) in the United States as a natural experiment. They find that the exemption of capital gains tax led to a 12% increase in capital raised by start-ups qualified for the scheme, based on the funding rounds data provided by Crunchbase. Denes et al. (2020) examine state-level angel investor tax credit using the US data and find that the tax credit leads to an increase in state-level angel investment. However, Denes et al. (2020) show that the US angel tax credit does not influence new company formation or local economic growth. They contribute this null impact to the fact that the US angel tax credit may have crowded out more professional and value-generating investors.

Consistent with these studies, we find that on average, the investor-level tax incentive is effective in stimulating financing for start-ups. We show that the deduction of investment against taxable income for VCs yields a substantial and positive response in our context, comparable to that found by Edwards and Todtenhaupt (2020) in the US. On the other hand, our results deviate from the findings of Denes et al. (2020) on firm-level outcomes, as we find that the increased VC and angel funding leads to a rise in entrepreneurship in eligible industries.

There are two possible explanations for the difference in terms of the policy effectiveness on firm entry between China and the US. First, the scale of the Chinese angel/VC incentive is likely larger than that in the US: it allows VCs to claim deductions against their taxable income, which does not solely depend on realized capital gains; it also allows for deductions with a potentially high ceiling and in a more timely manner—as soon as the invested equities are held for more than 2 years. By comparison, the 2010 US Small Business Jobs Act (SBJA) studied by Edwards and Todtenhaupt (2020) is only about realized capital gains from the sale or exchange of qualified stocks held for more than five years. The angel tax credit studied by Denes et al. (2020) can only offset the angel's state-level tax. The generosity of the tax incentive in China may incentivize even experienced and professional investors to increase funding for eligible start-ups. This in turn would have a potentially larger impact on firms' entry decisions. Second, the Chinese tax incentive targets both angels and VCs. Consequently, there should be limited crowd-out between these two types of early-stage investors. Overall, our results suggest that generous investor tax incentives can be an effective way to increase funding and promote start-up formation.

Our study also contributes to the literature on financing entrepreneurship in developing countries. China is becoming a powerhouse for innovation and entrepreneurship. Meanwhile, the country has been using various schemes to encourage financing for entrepreneurship. This includes a 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). Relative to these other policy tools, studies on the effectiveness of Chinese investor-level tax incentives on entrepreneurship are still limited, partly due to the lack of data availability (Chen, 2022). Existing studies show that Chinese VCs have a material impact on start-ups. For example, Guo and Jiang (2013) show that Chinese VCs not only choose to fund better-performing firms, but also add value to these firms post-investment. On the other hand, considerable institutional differences are shown to exist between China and the West when it comes to financing start-ups. For example, Cong et al. (2020) point out that early-stage financing remains more challenging in

China than in the United States, possibly due to weaker property rights protection and legal institutions. It has also been documented that government plays an important role in the Chinese VCPE markets (Li et al., 2016; Suchard, Humphery-Jenner and Cao, 2021; Wang and Wu, 2020). Our study adds to the understanding of the driving forces behind the phenomenal surge of the Chinese VCPE investment and also quantifies the effectiveness of its tax incentives in facilitating entrepreneurship activities.

In their survey of the venture capital research, Da Rin, Hellmann and Puri (2013) highlight the data challenges in the research of early-stage financing. In our study, we use a unique quasi-experiment from China to identify the effects of tax incentives on angel and VC investment. We join a new series of papers that establish the causal relationships between tax incentives, funding activities and firm outcomes with a clear quasi-experimental set-up in a high-growth developing country. 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 Business angels and venture capital in China

The Chinese venture capital and private equity (VCPE) market has been growing rapidly in recent years, and currently represents the second-largest market in the world by aggregate deal value and number of unicorns, after the United States. Note that unlike in more developed markets, the distinction between venture capital and private equity is blurry in China and the VCPE market primarily consists of early-stage and growth equity investors (Cong et al., 2020).[5] Figure 1 plots the number of deals and the volume of VC investments during 2012-2022. The phenomenal development of the Chinese VCPE industry is potentially driven by several factors: the fast-growing economy that brings an immense market demand and fuels entrepreneurship; the growing wealth

[5] The market share of late-stage/pre-IPO equity investment and buyouts is considerably smaller in China, compared with that in the US.

of corporations and individuals that are crucial for the supply of VC funds; the increasing supply of talents due to the expansion of the country's higher education; and last but not least important, the strong policy supports from the government to nurture the ecosystem of research and innovation as the country transits from "the world's factory" to a "high-tech innovator".

Despite the fast development, the Chinese VCPE market remains different from more mature markets, like the US, in various aspects. For example, Chinese VCPE investors faced considerable difficulty in exit (particularly through IPO) due to its IPO restriction until recently.[6] The Chinese VCPE market also features heavy government involvement, especially through the government guidance funds (GGFs).[7] The government guidance funds aim to use state money to guide private venture capital firms to invest in industries the government considers strategically important. On the other hand, the GGFs exhibit various weaknesses such as the inability to complete fundraising, investment inefficiency, interference with investee firms' decision-making, and poorer performance (Colonnelli, Li and Liu, 2022; Fei, 2018; Luong, Arnold and Murphy, 2021; Wei, Ang and Jia, 2022).

In comparison, 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 angel and VC tax incentive schemes

Table 1 illustrates the tax treatments for VC investors in China. A Chinese VC can take one of the two business organization forms: corporations or limited partnerships, which are subject to different tax codes.[8] Since 2006, however, the majority of VCs have taken the partnership form. The

[6] China starts to implement a registration-based IPO system in 2019 in the new STAR market.

[7] According to Zero2IPO, the total value of the government guidance funds was nearly 4.7 trillion yuan (670 billion USD) by the end of 2020.

[8] Chinese venture capital funds could be formed as partnerships only since 2007, following the passage of the Partnership Enterprise Law (PEL) in August 2006.

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 fund is generally subject to the 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).[9]

We examine a tax incentive provided for angel and VC 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 by way of 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 hence, benefit from the tax incentive as described above. For VCs taking the corporate form, 70% of the investment amount can offset their CIT liabilities.

A similar tax incentive was also granted to angel investors. Specifically, 70% of the investment amount can be offset for personal income tax purposes against the angel investor's taxable 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 deregistered 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 deregistration.

Importantly, to enjoy the tax benefit, there are criteria set upon both the investees and the investors. Table D1 in Appendix D lists the criteria in detail. For start-ups, they need to: 1) be a tax

[9] 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%.

resident in mainland China; 2) be no more than 5 years 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) non-listed in the year in which the investment is made or in the following 2 years; 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 the following year.

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

For angel investors qualifying for the tax incentive, they 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.

2.3 Earlier policies

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, by 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 was not applicable to individual investors or angel investors, and hence, the 2017 tax scheme also increases the number 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 D1 in Appendix D). 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.

The second confounding factor is the Chinese local government's involvement in the VCPE market. For example, local governments may offer special benefits, including preferential tax treatment, for VCPEs registered in their jurisdictions. The timing, scale and content of these special benefits vary across regions, which makes the comparison difficult. Nevertheless, the local tax incentives usually reduce investors' tax liability to the local governments, similar to the U.S. state-level angel tax credit. Therefore, while the presence of local tax incentives may reduce the effect of the 2017 scheme, such crowd-out effect should be rather limited.

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. 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. To analyze firm entry, we control for city-industry fixed effects in estimations. Therefore, our approach should have controlled for the impact of the high-tech zones, unless the start-up is located in a newly established high-tech zone during our sample period. In Table F1 of Appendix F, we provide the list of national high-tech zones established during 2014-2019 in China. As a robustness check, we exclude funding rounds or city-industries located in these high-tech zones from our empirical analysis. Generally speaking, our benchmark results are not affected by excluding these observations.

There are also several regulation changes that accompany the fast expansion of 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. On exit, the most significant reform came into effect in 2019 when China experiments with the registration-based IPO system in the newly established 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. Therefore, these regulation-related policy changes are unlikely to confound our findings.

3 Research design

3.1 Funding-round estimations

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 process of a certain start-up. We are also able to control for start-ups' characteristics (such as age) 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 not more than five years old. This feature of the tax incentive provides us with an opportunity to use the natural experiment approach, with the treatment group consisting of funding rounds for technology start-ups no more than five years old. Funding rounds for non-technology start-ups no more than five years old constitute the control group.

Alternatively, we could compare technology start-ups no more than five years old with the older ones. The advantage of this method is that the two groups of firms are more likely to experience the same industry trends. We report results based on this alternative DID estimation in Appendix X. We could also use the age threshold (60 months) in the regression discontinuity design to compare technology start-ups just below and just above the threshold. We report the RDD estimation results in Section 5.1.4. The main reason for us to use non-technology start-ups no more than five years old as the control group in the baseline estimations is as follows. We show that the investor-level tax incentive leads investors to reallocate funding from older firms to younger start-ups. In contrast, we find little substitution between financing for technology start-ups and non-technology ones. This reallocation pattern indicates that when we use older technology start-ups as the comparison group (either in the DID or the RDD estimations), there is likely to be an upward bias in the estimated treatment effect. We see patterns align with this prediction. Therefore, in our baseline funding-round estimations, we use non-technology start-ups as the control group.

In our baseline estimations, we exclude funding rounds made when a firm is more than 5 years old. Formally, we estimate the effect of the tax incentive on funding activities based on 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 logs), and $Ln(No.\ of\ investors)$ which is the number of investors per funding round (in logs). Dividing the total funding by the number of investors, we obtain a third outcome variable $Ln(Average\ investment)$ which is the average investment per investor per funding round (in logs). $Treated_i$ is a dummy that equals 1 if firm j belongs to the treatment group, and 0 otherwise. $Post_t$ is a dummy indicating years since 2017.

$X'_{i,j,t}$ is a set of firm-level and funding-round level characteristics that serve as control variables in estimations.[10] We use several control variables in our funding-rounds estimations. 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 after taking various factors(such as news, connections, funding data, etc) into account. The ranking captures comprehensive firm-level information that also can vary with the funding round, which would not be

[10]We report estimation results with and without control variables.

absorbed by firm-level fixed effects. Existing research (Edwards and Todtenhaupt, 2020; Hellmann and Puri, 2002) suggest that firm age influences funding activities. We thus include $Ln(Age)$ in estimations, which is the natural logarithm of firm age when a certain funding round occurs. Angel investors usually have unique investment preferences, especially for certain industries. Edwards and Todtenhaupt (2020) argue that industry preferences of angel investors may lead to the clustering of this type of investors in certain groups of start-ups. Therefore, in some estimations, we control for $Angel$ which is a dummy that equals 1 if the funding round involves an angel investor or an angel group, and 0 otherwise. In Equation 1, we also control for company-level fixed effects (ψ_i), funding-round fixed effects (δ_j), and time fixed effects (η_t). We cluster the standard errors over each start-up 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 treatment. We test this assumption using the event study methodology. Specifically, we estimate Equation 2:

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

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 company, funding-round, and year fixed effects in this dynamic estimation.

3.2 Investor-level estimations

In our investor-level analysis, we aggregate funding-round data from Crunchbase for each investor. We then leverage the fact that the tax incentive was only provided for VCs located in eleven pilot regions in 2017 for our second DID design. We regard these pilot-region investors as the treatment group, and investors in other regions as the control group. Since the tax incentive was rolled out nationwide in 2018, we use quarterly data from the first quarter of 2016 till the last quarter of 2017 for this analysis. Our DID specification is as follows:

$$Y_{s,t} = \alpha + \beta \times Treated_s \times Post_t + \delta \times X'_{s,t} + \eta_t + \delta_s + \epsilon_{s,t} \tag{3}$$

where $Y_{s,t}$ is the aggregated investment amount or the total number of deals (both in logs) for investor s in quarter t. $Post_t$ is an indicator that equals 1 since 2017, and 0 otherwise. We also conduct event study analysis analogous to Equation 2 for this quarterly data estimations.

3.3 Entry and funding probabilities

To examine the impact of the 2017 tax incentive on firm entry, we utilize business registration data for each city-3-digit industry pair during 2014-2018. Specifically, we estimate the following equation:

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

where $Ln(No.\ of\ new\ firms)_{i,j,t}$ is the number of newly established independent firms in city i, industry j and year t. City-industry pairs belonging to the high-tech industries are regarded as treated, while others form the control group. $Post_t$ equals 1 since 2017, and 0 otherwise. We control for city-industry and year-fixed effects. In some specifications, we also control for city GDP growth, GDP per capita, and population growth, which might all affect firm entry.

We use a similar set-up to examine the impact on the funding probability, based on the following equation:

$$\frac{No.\ of\ firms\ receiving\ funding_{ijt}}{No.\ of\ startups_{ijt}} = \beta \times Treated_{i,j} \times Post_t + \delta \times X'_{i,j,t} + \eta_{i,j} + \delta_t + \epsilon_{i,j,t} \tag{5}$$

where the outcome variable is the number of technology start-ups in city i and industry j that receive funding in year t, divided by the number of technology start-ups in that city-industry pair in year t.

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 due to the outbreak of COVID-19 in China in 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, the total amount of capital raised, and the number of investors. Crunchbase does not provide any breakdown of the aggregate investment amount, if a funding round involves multiple investors. In such cases, we divide the total amount of investment by the number of investors to obtain the average investment per investor.

We illustrate the steps to construct our funding-rounds dataset for the baseline estimations in Table 2. To construct the estimation sample, we follow Edwards and Todtenhaupt (2020) to implement the following selection procedures:

1. Exclude non-equity financing;

2. Exclude funding rounds without sufficient information on control variables;

3. Exclude firms with only one funding round, since we control for firm-level fixed effects;

4. Exclude funding rounds with irregular observations (for example, firms reporting negative firm age), likely due to reporting errors.

5. Select funding rounds that are made when the start-ups are no more than 5 years old. We use the date of the funding rounds and the start-up's establishment date to calculate the age of the start-up by the time of each funding round in Crunchbase.

An important feature of the Chinese tax incentive is that it is only available for VC and angel investors investing in technology start-ups. Specifically, there is a requirement for the annual R&D investment to be greater than 20% of total costs. The start-up also must meet the size requirement defined in terms of total assets, operating revenue and employment (see Table D1). Crunchbase does not provide detailed financial information, like R&D investment and total assets, at the firm level. It is also not feasible to match companies in Crunchbase with external data sources, since only firms' English names are provided. More generally, as these are private firms, financial information is difficult to obtain. One way to identify whether a start-up is a technology start-up, however, is to utilize its industry information. The Chinese government issues an official guideline for "high and new technology" industries. We list these industries and the corresponding 2-digit China Industry Classification (CIC) codes in Table A1 of Appendix A. While the tax incentive itself does not specify which technology industries are qualified industries, it is reasonable to assume that the officially acknowledged "high and new technology" industries are most likely to qualify. On the other hand, Crunchbase provides a list of activity labels for each target firm. Based on this information, we classify an activity in Crunchbase to belong to a qualified technology industry if it is mentioned by the official guidance. In Table A2 of Appendix A, we provide the list of Crunchbase activity labels that belong to the high-tech industries, and the corresponding 2-digit CIC industry codes. Table A3 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 mentioned in the official guidance. 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.[11]

In the final funding-rounds dataset for our benchmark estimations, we obtain 7,672 funding rounds for 3,378 start-ups during 2014-2019. Panel A of Table 3 illustrates the number of funding rounds, the average capital raised, the average number of investors, and the average investment per investor, per funding round year by year during our sample period. There was an increase in the number of funding rounds in 2015 and a drop in 2019. This is consistent with the pattern we observe in Figure 1. In terms of total capital raised per funding round, there appears to be an upward trend during 2014-2019. This trend of increasing funding is also reflected in the average

[11] In Table E3 of Appendix E, we report the estimation results when we relax this criterion.

capital raised per investor per funding round. By 2019, these two figures have become substantially larger than that in 2014.

Panel B provides the summary statistics for key variables in our baseline estimations.[12] We differentiate between the treatment and control groups, and report the mean, standard deviation and the t-test statistics for equal means for each variable. We observe that treated funding rounds tend to raise more capital and attract more investors on average. The average investment per investor for treated founding rounds also tends to be larger. Treated start-ups appear to be older when they receive funding, relative to start-ups in the control group. On average, start-ups in the control group have a lower rank in Crunchbase at the time of funding. On the other hand, the probability of having at least one angel investor is not statistically different between treated and control funding rounds.

4.2 Alternative data: Zero2IPO

We use an alternative dataset called Zero2IPO matched with the Chinese business register for our analysis of firm entry and probability to attract early-stage funding. Zero2IPO is the leading VC database in China which has better coverage of VC investment than alternative Chinese VC databases (such as CV Source) (Chen, 2022). While the Crunchbase dataset is superior in terms of the quality of coverage as we discuss below, Zero2IPO provides a 3-digit main industry code of each start-up receiving investment that we use in our analysis of entry and firms' probability to attract early-stage financing. In this analysis, we construct the ratio of start-ups receiving angel/VC investment to the total number of start-ups at the city-3-digit-industry level, which can be directly matched to the business register. Moreover, a firm in Crunchbase may report multiple industries without any ranking. It is difficult to assign a Crunchbase firm to a specific 3-digit CIC industry.

Another advantage of Zero2IPO is that we have information about the establishment date of each VC investor and each VC fund. This information is mostly missing for Chinese VCs in Crunchbase. We thus use Zero2IPO to examine whether the tax incentives induce more VC investors/funds to be established.

[12] Appendix B provides the variable definitions.

Despite these advantages, Crunchbase is clearly superior for our baseline and investor-level analyses. Figure C1 in Appendix C plots the number of funding rounds in Zero2IPO year by year during 2014-2019, and compares it to that based on Crunchbase. The number and the overall trend of funding rounds recorded in Zero2IPO is comparable to that in Crunchbase. However, the quality of coverage in Zero2IPO is poorer for the reasons below. We demonstrate major differences in Table C1 in Appendix C. First, we do not observe firm age for around 30% of firms receiving funding during the sample period in Zero2IPO, while only around 3% of target firms do not report age in Crunchbase. This is a concern for our funding rounds analysis, since we utilize age to select start-ups no greater than five years old. Second, while around 17% of funding rounds in Crunchbase do not disclose the amount of investment, this ratio is as high as 40% in Zero2IPO.[13] For these reasons, we use Crunchbase data for the funding-round analysis.

4.3 Data on firm entry

We use the nationwide business registration data for China during 2014-2018 to study the impact of VC tax incentives on firm entry.[14] In the business registration data, we observe whether a firm is registered as a sole proprietorship or a corporation. We also observe the location of registration, year of establishment and the 3-digit CIC industry code for the firm's main product. On the other hand, the business registration data only provides limited information on the firms' financial status, including registered capital and employment.

Using the business registration data, we construct the number of newly-incorporated firms for each city-3-digit-industry pair during 2014-2018. Based on the industry classification of the newly-incorporated firms, we are able to measure firm entry into high-tech and non-high-tech industries, respectively. Matching the Zero2IPO data with the business registration data, we are also able to calculate the ratio of start-ups receiving angel/VC funding to the total number of start-ups no more than 5 years old, at the city-industry level.

[13] The missing investment problem in Zero2IPO arises as some investors do not disclose any investment amount, while others disclose a rough figure ("several million", for example) which cannot be utilized for aggregation across investors.

[14] By the time of our research, we do not have the business registration data for 2019.

5 Results

5.1 Funding-rounds estimations based on Crunchbase

5.1.1 Graphical evidence

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. We start with the funding-rounds data, and investigate the parallel trend assumption in Figure 2, where we consider three outcome variables: total funding, the number of investors, and the average investment per investor (all in logs, for each funding round).

There, we plot the estimated coefficients based on the dynamic specification Equation 2. Figure 2 shows that for all three outcome variables, the parallel trend assumption largely holds as there was no significant divergence between the treatment and control group before 2017. In all three graphs, we observe a jump in the outcome variables for the treatment group since 2017, attributable to the introduction of the tax incentive. However, the dynamic treatment effect tends to be only significant for total capital raised and the number of investors per funding round. There is an increase, albeit insignificant, in average investment per funding round for the treatment group.

5.1.2 Baseline estimation results

Table 4 reports the DID estimation results based on Equation 1. In this table, the treatment group consists of funding rounds of young technology start-ups (no more than 5 years old when receiving a particular round of funding). We benchmark the funding outcomes of this group against those of control group firms, which consists of young start-ups (no more than 5 years old by the time of each funding round) that are not categorized as 'technology start-ups'. Column 1 shows that the treatment group enjoyed an 18% increase in total capital raised since 2017, relative to the control group. Next, we decompose the total capital raised into two factors: the number of investors per funding round per start-up (Column 2), and the average investment per investor during each funding round (Column 3). The aim is to understand whether the tax incentive induces investors to increase the number of firms they invest in, or simply induces them to increase the investment amount per firm. Relative to the control group, treated firms attract on average 9 percent more investors after the implementation of the tax incentive. Column 3 shows that average investment per investor also tends to increase, however, the point estimate in this regression is not statistically significant.

In Column 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. Column 6 shows a significant increase in average investment per investor, once we control for firm-level characteristics. In Appendix E1, we report estimation results analogous to Table 4 without controlling for funding-round fixed effects.[15] The results there are qualitatively similar to those in Table 4. Taken together, Table 4 shows a positive effect of the tax incentive on funding for eligible start-ups. This overall increase in funding for treated firms is driven by the rise in both the number of investors and the average investment amount per investor.

5.1.3 Robustness checks

Placebo test. In Table E2, we conduct a placebo test where we only include in the estimations funding rounds made when a firm is over 5 years old. We further divide these funding rounds to be two groups: those made when the firm is between 6-10 years old (columns 1-3), and those made when the firm is greater than 10 years old (columns 4-6). Based on this sample, we do not find any change in funding activities for a typical technology firm, relative to the non-technology firms. This placebo test lends further support to our claim that the 2017 tax incentive increases funding for eligible technology start-ups.

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

[15] We have a slightly larger sample for this exercise, since we exclude funding-rounds with unknown sequence numbers in Table 4.

industries are excluded from estimations for cleaner identification. In Appendix E3, 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 treatment effects are of the same signs based on this alternative larger sample, the magnitudes tend to be smaller.

The earlier tax incentive. In Table D2, 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 does not target start-ups and imposes strict requirements on firm status. 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, the number of investors, or the average investment amount per funding round between high-tech and non-high-tech start-ups in this DID estimations. This is consistent with our conjecture that the 2015 VC tax incentive scheme had limited impact on funding activities, due to its restrictiveness.

National high-tech zones. Next, we examine whether our baseline results are confounded by the establishment of national high-tech zones. Table F1 lists the name and establishment year of national high-tech zones during 2014-2019. Since we control for firm-level fixed effects when estimating Equation 1, the impact of the high-tech zones should be absorbed for firms located in high-tech zones established before 2014 (the start of 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 are established since 2014. Only 8.5%he of funding rounds are excluded. Based on the smaller sample, we continue to find a significant increase in total capital raised and the number of investors for treated funding rounds since 2017. We also end up with a null impact on the average investment per investor for the treated group, the same as our baseline results. Therefore, our benchmark results are not affected 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 VCPE investors. Local governments may offer various incentive schemes to attract the VCPE investors. For example, local governments may offer a one-time bonus for PEVC investments made into local firms. The form of the local investment incentives varies considerably across regions, which makes the comparison difficult. However, a usual format is for the local government to provide tax rebates for PEVC investors, up to a fixed ratio of the investors' local tax liability.[16] Importantly, these local tax incentives for PEVC investors generally do not limit to investment into high-tech start-ups. Still, it is possible that 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 VCPE tax incentives, the implementation and the end years. We find that around 16% of our funding rounds sample would be affected by the existence of local PEVC tax incentives. We then interact a dummy indicating the presence of local VCPE tax incentives with $Post \times Treated$. Table G1 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, there is little crowd-out between local tax incentives and the 2017 tax deduction benefit.

5.1.4 Alternative strategies

Regression discontinuity design. The 2017 tax incentive specifies an age limit for eligible start-ups: they need to be no greater than 5 years old at the time of investment. We employ a sharp regression discontinuity design (RDD) to examine funding activities just below and above this age threshold. We use the following regression specification:

$$Y_{ijt} = \alpha + \beta Below_{ijt} + f(t) + g(t) + \phi_i + \epsilon_{ijt} \tag{6}$$

where the running variable t measures the number of months relative to the age threshold (60

[16]Corporate and personal income taxes are shared between the central and local governments in China, with a ratio of 60:40.

months). $Below_{ijt}$ is a dummy variable that equals 1 if a funding round occurs when the start-up is no more 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 start-ups made during 2017-2019, if the start-up 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 3 the amount of total funding, number of investors, and average investment per investor, averaged across funding rounds in each bin. Figure 3 shows a clear drop in funding activities once the start-up passes the age threshold. In comparison, when we analyze non-technology start-ups during the same sample period (right-hand side panels in Figure 3), we do not observe such discontinuity. We report the RDD estimation results based on Equation 6 in Table 5. Consistent with Figure 3, the first three columns show a significant jump in total funding, number of investors, and average investment for technology start-ups below the age threshold. However, the RD estimates tend to be much larger than the baseline DID estimates, suggesting possible upward bias as we discussed.

In Figure E1, we report the RDD plot for all start-ups, and technology start-ups during 2014-2016. The age limit was initiated in the 2017 tax code, and 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 E4 further reinforce our conclusion.

Alternative difference-in-differences. We can also compare funding activities of technology start-ups below and above the age threshold, using the DID framework. The benefit of this alternative DID is that both the treatment and control groups are firms in the technology sector. Therefore, they are likely to be subject to similar industry trends. Specifically, in this exercise, we include technology start-ups no more than five years old in 2017 as the treatment group, and we keep these firms' funding rounds from 2014 until they pass the age threshold. We select technology start-ups already over the age limit in 2017 as the control group, and keep their funding rounds during 2014-2019. Table X reports results from this alternative DID estimation. Generally speaking, we continue to find an increase in funding for eligible technology start-ups.

5.1.5 Heterogeneity

Across funding rounds In Table 6, we examine whether the tax incentive induces more investment into early stage start-ups or those in later stage. We classify each funding round to be pre-A or non-pre-A, based on the sequence number reported by Crunchbase. We then interact an indicator for pre-A funding round with $Treated \times Post$, and include this interaction term in the DID estimation. Generally speaking, we tend to find a more significant increase for pre-A investment, especially in terms of total capital raised. There is also some weak evidence that the tax incentive also leads to more average investment per investor into early-stage start-ups. This result is intuitive–the earlier the investment is made, the more likely for any subsequent investment to benefit from the tax deduction.

Across investor types In this section, we differentiate between different investors and examine whether they respond differently to the 2017 tax incentive. First, we differentiate between angels, VCs and PEs. The classification is based on the investor type provided by Crunchbase for each investor. We first examine whether following the implementation of the angel/VC tax incentive, qualified start-ups are more likely to attract certain types of investors. In the first three columns of Table 7, the outcome variables are dummies indicating the presence of a certain type of investors (i.e., angels, VCs and PEs) per funding round. We find that the tax incentive increases the likelihood of qualified start-ups receiving funding from angels and VCs. The effect on the likelihood of receiving funding from a PE investor is positive but insignificant (column 3). In Columns 4-6 in Table 7, we focus on the number of a certain type of investor for each funding round. We find that technology start-ups attract more VC investors since 2017, relative to non-technology start-ups. In contrast, there is no significant change in the number of angel or PE investors for the treated funding rounds. Note that PE investors can also claim tax deductions for their investment, as long as they set up VC funds and make eligible investments.[17] However, the PE investors may not focus on early-stage investment and consequently, may be less sensitive to the tax incentive. Our finding is consistent with this conjecture.

Next, we consider heterogeneity across VC investors of different sizes and ages (Table 8). For this exercise, we only keep VCs in the estimations, but the results hold if we bring back PEs. We use the total number of investments by the time we collect the data to measure the size of each investor. We regard a VC with a number of investments above the sample median as being large. Investor age is calculated based on the establishment date for each investor, relative to the time of our data collection. A VC is considered to be old if its age is above the sample median. We then construct dummies indicating the presence of each size group of VC investors per funding round per firm. We report the Probit estimation results where we use the dummies as the dependent variable in columns 1-4 of Table 8. We find that after the tax incentive was implemented, the likelihood of treated start-ups receiving funding from larger or older VCs significantly increases, relative to the control group (column 1). Moreover, we observe a crowding out of small VC funding (column 2). We also observe that older VCs are both more likely to invest in treated firms while large and older investors are significantly more attracted to treated firms relative to control firms.

Columns 5-8 report the DID estimation results about whether technology start-ups attract more investors of a certain type since the implementation of the tax incentive. At this margin, we find that the treatment group tends to attract a larger number of larger and older VCs since the reform, relative to the control group. In contrast, there is no significant difference between the treatment and control groups in terms of attracting smaller or younger VCs.

In Table 9, we consider different types of angel investors. Specifically, we regard an angel investor as being more experienced if his/her investment number, by the time of our data collection, is above the sample median. Interestingly, we find that more experienced angel investors respond more to the tax incentive–since the reform, they are more likely to fund a technology start-up, relative to a non-technology one (columns 1 and 2). In comparison, the likelihood of having a less experienced angel investor in a certain funding round does not differ between the treatment and

[17] The VC fund needs to be officially registered.

control groups (columns 3 and 4). This finding is different from the survey evidence from Denes et al. (2020) showing that mature and experienced angel investors in the US do not consider the state-level angel tax credit to be of first-order importance for their investment decisions.

One possible explanation for the contrast between investors of different sizes or 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. On the other hand, given the generosity of the Chinese tax incentive, it should be sufficient to affect the behavior of large and experienced investors. Besides, anecdotes suggest that to apply for the tax break, both investors and start-ups need to provide evidence for their eligibility. It is possible that larger investors 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. Our analysis thus suggests that the tax incentive benefits larger and more experienced investors, which crowds out smaller investors.

5.1.6 Conditional funding probability

One interesting question is that conditional on receiving a fund, whether the tax incentive increases the chance of receiving subsequent funding for eligible start-ups. One exercise is to test whether the likelihood of receiving post-A funding increases since the reform, conditional on having received pre-A funding. Table 10 reports the Cox model estimation result. Specifically, we estimate the following model:

$$h(J|t,x) = \lambda(t) exp(\alpha_0 Post + \alpha_1 Treated + \beta Treated \times Post + \gamma z') \tag{7}$$

where $h(J|t,x)$ is the hazard rate of receiving the first post-A funding after t days since the receiving the last round of pre-A funding, conditional on a vector of variables, including the $Post$ dummy and the $Treated$ dummy as in the baseline estimations. $lambda(t)$ 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 rate of receiving post-A funding for 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 of receiving post-A funding for the treated group relative to the control group, conditional on having received pre-A funding during our sample period.

Table 10 shows that relative to the control group (non-tech start-ups no more than 5 years old), the treated group is significantly more likely to receive subsequent funding since 2017, conditional on receiving pre-A funding. This result is robust whether we use the full sample (columns 1 and 2), or a smaller sample of matched start-ups (columns 3 and 4). The estimated $exp(\beta)$ is around 1.3-1.4, indicating that the treated group has a 1.3-1.4 times higher probability of receiving post-A funding relative to the control group since the policy reform.

5.1.7 Quality of investment

Our analysis so far indicates that the tax incentive induces VCs and angel investors to invest in technology start-ups. A related question is whether the tax incentive lowers the required rate of return before tax, which can be reflected by a lower average quality of start-ups that receive funding. We examine this issue in this section.

One 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 exit since the reform. As a first test, we compare technology firms receiving funding in 2016 for the first time with those receiving funding in 2017 for the first time. Panel A of Table 11 tabulates the percentage of firms that exit by the sample period end, for the two groups separately. Out of the 717 technology start-ups that received first funding in 2016, around 5% exited by 20XX. This exit rate is statistically higher than that of the 558 technology start-ups that received first funding in 2017. And such difference in exit rate is mainly driven by the difference in the IPO rate. However, we obtain a similar pattern when we compare non-technology firms that received first funding in 2016 with non-technology firms that received first funding in 2017 (Panel B of Table 11). Therefore, the decline in exit rate in the later-funded group is likely to be driven by the common trend.

To further analyze this issue, we construct a dummy $Exit$ that equals 1 if a startup is known to be either acquired or went through an IPO, and 0 otherwise. Table 12 reports the Cox model estimation results where we use $Exit$ as the outcome variable. We first consider start-ups that received first funding after January 2017 in columns 1-4. 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). The first columns show that relative to non-tech start-ups, there is no significant difference in the likelihood of exit between treated and control groups. In columns 5-8, we repeat the Cox model estimation where we consider start-ups that received at least one funding after January 2017. We fail to detect significant difference in exit likelihood between the two groups, using this larger sample.

Alternatively, we use the variable $Rank$ in Crunchbase to measure the quality of the start-ups. In Table 13, we construct a dummy variable that equals 1 if a start-up's $Rank$ fall into the bottom quartile of the full sample. We then interact this dummy with $Post \times Treated$ in a triple DID estimation. We find that the bottom-ranked technology start-ups do not experience a significantly larger flow of funding, or increased number of investors, or average funding per investor, than technology start-ups of better ranks. Taken evidence from this section together, we show that the 2017 tax incentive did not lead investors to lower the quality of investment.

5.2 Investor-level estimations

5.2.1 Baseline estimations

In this section, we aggregate Crunchbase funding-rounds data to each investor, and examine the short-run impact of the 2017 tax incentive taking advantage of its staggered nature. Note that the tax incentive for VCs was first applicable to only investors located in eleven pilot locations in 2017. It was then rolled out nationwide in 2018. This difference in timing does not affect estimations based on funding-rounds data, since the VC tax incentive does not restrict the location of the start-ups. However, once we aggregate to the investor level, we can utilize this timing difference to examine whether investors located in pilot cities react quickly to the tax incentive, relative to investors elsewhere. For angel investors, on the other hand, the 2017 tax incentive set a restriction on their investment location, but not on the angels. For a clean identification, we exclude angel investors from this part of analysis.

Specifically, we aggregate the funding-rounds data for each investor, and then calculate the number of investments and the total investment amount for each investor during each quarter of 2016-2017. For funding rounds with multiple investors, we use the average investment amount (i.e. total capital raised divided by the number of investors) as the approximate amount of investment for each investor. Then we aggregate the investment amount for each investor during each quarter. We use this quarterly data for a standard difference-in-differences analysis. In this exercise, investors located in pilot regions are the treatment group and investors elsewhere are the control group. We report estimation results in Table 14.

Panel A of Table 14 reports the short-run impact of the 2017 tax incentive on the number of investments per investor. In column 1, we find that relative to the control group, investors located in pilot regions significantly increase the number of investments into qualified high-tech start-ups by 30%he within a year after the introduction of the scheme. In column 2, we find no significant difference between treated and control groups in terms of the number of investments into non-high-tech start-ups. In column 3, we find that investors in pilot regions cut the number of late-stage investments by around 49% relative to the control group. This suggests a possible substitution between qualified and nonqualified investments. Panel B shows the analogous analysis using the amount of investment (in logs) as the dependent variable. We obtain similar patterns as in Panel A. The difference is that we observe a significantly positive effect on treated VCs' investment amount into non-technology start-ups (column 2, Panel B). It is possible that investors utilize the tax savings to invest in non-high-tech start-ups, causing positive spillovers. However, the estimated treatment effect in this column is less than half of that in column 1, Panel B.

In Table 15, we report the short-run impact of the tax incentive on the likelihood of making a certain type of investment at the investor level. Specifically, in column 1, we construct a dummy that equals 1 if an investor makes at least one investment into technology start-ups in a certain quarter. We show that relative to the control group, investors in pilot regions 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 in a certain quarter. We continue to find a relative increase in this margin for treated start-ups, again suggesting possible spillover effects. In column 3, we construct a third dummy that equals 1 if an investor makes at least one late-stage investment in a certain quarter. There, we observe a significant decline in the late-stage investment probability by treated investors, which indicates a substitution between early-stage and late-stage investments.

5.2.2 Investors with government background

One feature of the Chinese VCPE market is the heavy involvement of the government. We identify investors with government backgrounds using the following method. First, we search manually in several online platforms [18] about the ultimate controlling shareholder of investors listed in Crunchbase. If the ultimate controlling shareholder of an investor is labeled as "Government", "State Council", "Ministry of Finance", "State-owned Assets Supervision and Administration Commissions (SASACs)", this investor is defined as one with government backgrounds. Out of the 2,115 investors in Crunchbase, we manage to identify the ultimate controlling shareholders for 1,888 investors. Among these, 297 investors (around 15.7%) are ultimately controlled by the government.

In Table H1, Appendix H, we provide the summary statistics for investors with and without government background, based on data from Zero2IPO [19]. There, we find that government-linked investors tend to be larger, reflected by a larger capital under management and a larger number of investments. Government-controlled investors also manage a larger number of funds. There is also some evidence that government-controlled investors are more successful in generating exits, although the difference is not statistically significant. This finding is consistent with existing studies which show that politically connected investors may have an advantage in facilitating exits (Cumming, Grilli and Murtinu, 2017; Wang and Wu, 2020).

It remains an open question whether government-controlled investors respond to the VC investment incentives differently. If these investors are less orientated towards profit maximizing,

[18] They are Qcc.com, WIND database and Zero2IPO database.

[19] Crunchbase only provides the number of investors' historical investments, exits and investors' age. In addition to these details, Zero2IPO also reports the capital volume and the number of funds managed by investors. Also, Zero2IPO has better coverage of investors' age than Crunchbase.

we may find them to respond less. In Table H2 of the Appendix H, we conduct a triple DID estimation based on the quarterly data, where a dummy indicating government-controlled investors is interacted with $Post \times Treated$ and added to Equation 5. There, we find no difference between government-controlled investors and others, as the estimated coefficient on the triple interaction term is statistically insignificant.

5.3 The impact of the tax incentive on firm and investor entry

Does the angel/VC tax incentive lead to 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-3-digit-industry pair. There are 545,590 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.

Table 16 reports the results. In columns 1-3, 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 control for city-industry-year fixed effects and year-fixed effects. In column 3, we further include city-year fixed effects, to control for city-level macroeconomic conditions. In all three columns, we find that the number of new firms in high-tech industries has increased by around 8% since 2017, compared with that in non-high-tech industries. In column 4, 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. In Table F3, we re-estimate Table 16 while excluding cities with newly established national high-tech zones. This barely affects the pattern we obtain in Table 16.

We also examine whether due to the tax incentive, more VCs or VC funds are established since 2017. We obtain the list of VCs and VC funds, as well as their establishment dates, from Zero2IPO. We then calculate the number of VCs (or VC funds) established in a particular city in a particular quarter during 2016Q1-2017Q4. Our analysis here hinges on the assumption that the VC tax incentive was first introduced in eight pilot regions in 2017, and then rolled out to other locations one year later. In the first column of Table 17, we examine whether more VCs were established since 2017Q1 in pilot regions. We use the number of newly established VCs in a city in a certain quarter (in logs) as the dependent variable in the DID estimations. There, the estimated treatment effect is small in absolute magnitude and also statistically insignificant. In column 2, we use the number of VC funds in a city in a certain quarter (in logs) as the dependent variable. Again, we obtain a small and insignificant treatment impact. Based on these results, we conclude that the tax incentive does not induce more VCs or VC funds to be established.

5.4 Probability of receiving VC funding

One related issue is whether the 2017 tax incentive affects the probability of qualified start-ups receiving angel/VC funding *ex post*. We investigate this issue in this section.

Specifically, for each city-industry pair, we use the number of start-ups no more than 5 years old and receiving angel/VC funding in year t as the numerator. We calculate the numerator based on Zero2IPO, since we obtain the 3-digit industry code for the start-ups' main products in that database. In contrast, Crunchbase does not identify the firm's main industry, which makes it problematic to match with the city-industry-level business registration data. For the denominator, we use the accumulated number of newly established independent corporations in the same city-industry pair from year $t-4$ to year t, based on the business registration data. We then use the ratio as the outcome variable in columns 1-3 of Table 18. There, we do not observe a significant change in the probability of receiving angel/VC funding for treated city-industry pairs, relative to the control group. The estimated treatment effect is all negative with very large standard errors.

In columns 4-6, we instead use the number of start-ups no more than 5 years old and receiving angel/VC funding for the first time in year t as the numerator. We scale this alternative numerator with the same denominator as in the previous three columns. Again, the estimated coefficients in all columns are negative but statistically insignificant. These results indicate that while more technology start-ups receive VC funding since 2017, it is not easier to obtain angel/VC funding *ex* *post* possibly as the tax incentive also induces more start-ups to be established.

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 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.

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 in turn affects the venture capital market structure.

On the other hand, we show that when tax incentive is 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. If new firms are associated with new jobs and new ideas, the tax incentive may have a positive impact on employment and innovation.

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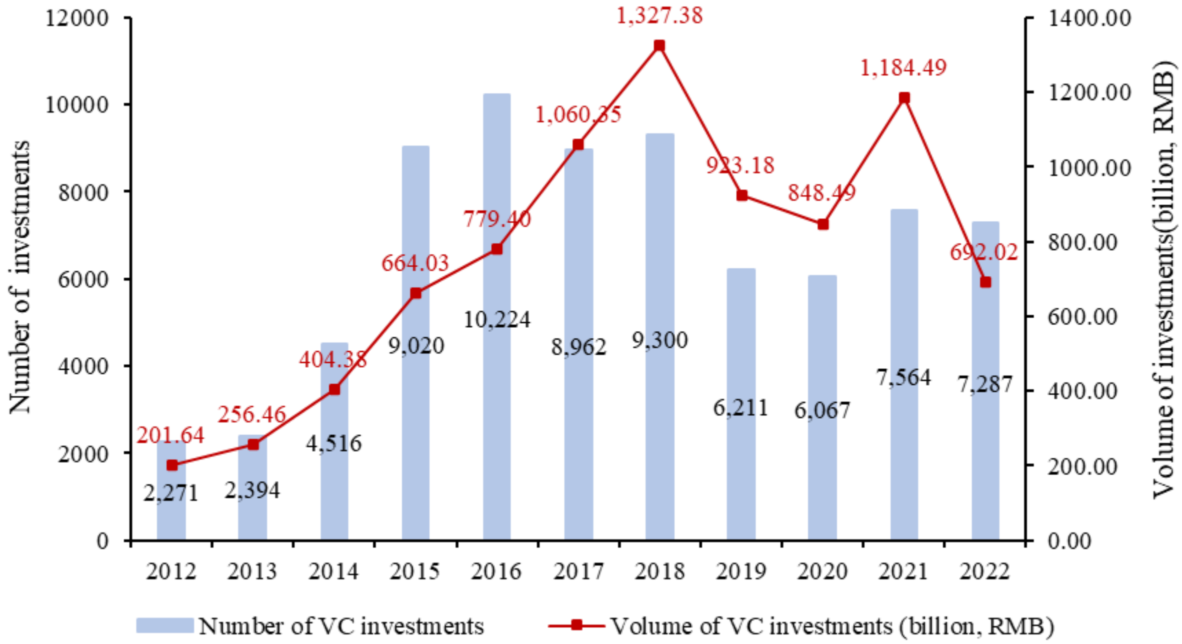
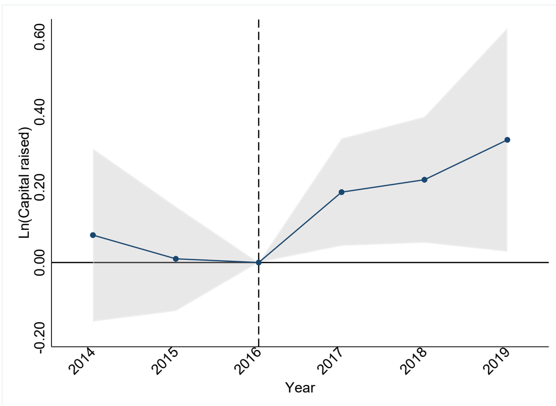
Zhou, Lu Jolly, Xinyu Zhang, and Yezhou Sha. 2021*b*. "The role of angel investment for technology-based SMEs: Evidence from China." *Pacific-Basin Finance Journal*, 67: 101540.

Figure 1: Number and volume of VC investments in China

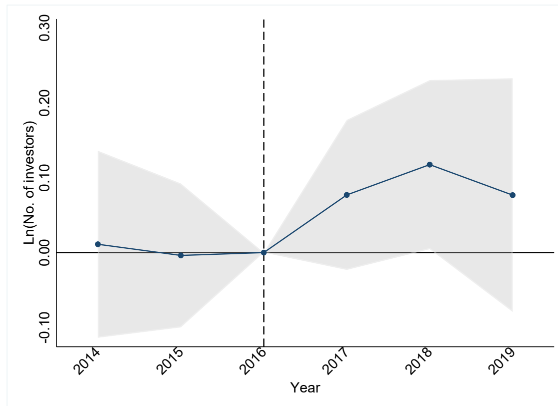


Note: This figure displays the trend of VC development in China from 2012-2022. The blue bar displays the number of VC investments. The red line displays the volume of VC investments (in billion, RMB).

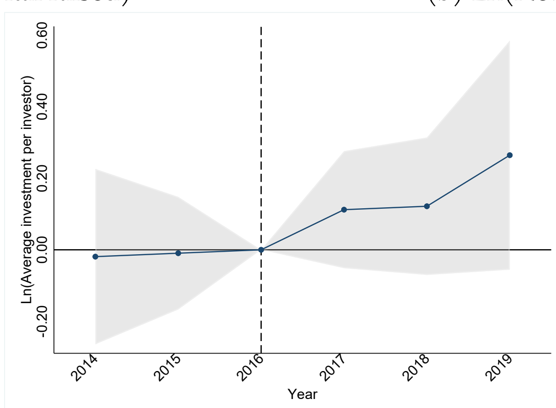
Figure 2: Dynamic effects of the investor tax incentive: funding rounds estimations



(a) Ln(Capital raised)



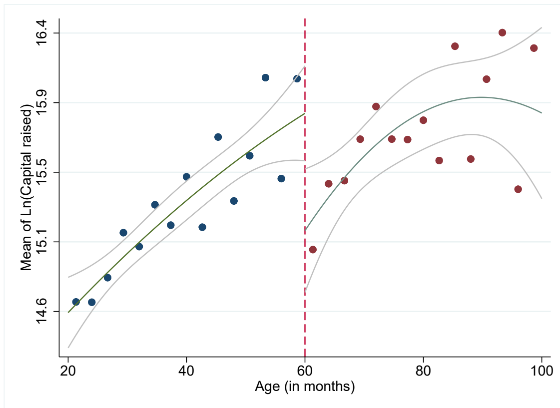
(b) Ln(No. of investors)



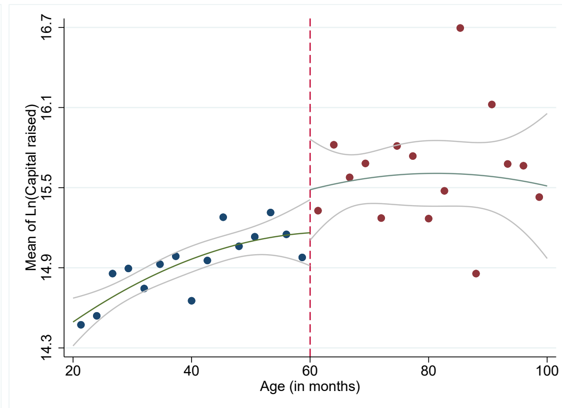
(c) Ln(Average investment per investor)

Note: These figures plot the dynamic effects of the tax-incentive policy on capital raised, the number of investors and the average funding amount. We set one year before the policy (year=2016) as the benchmark. We perform dynamic DID estimations by equation2. 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.

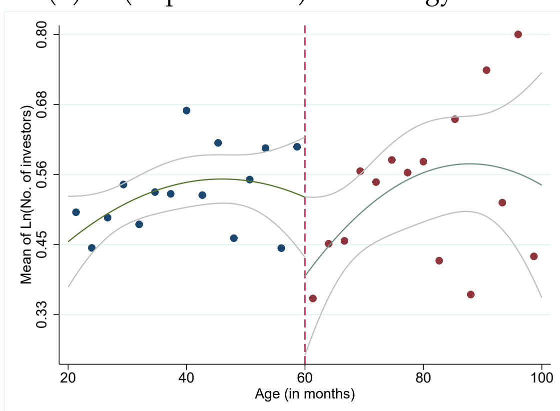
Figure 3: Regression discontinuity design: technology and non-technology firms during 2017-2019



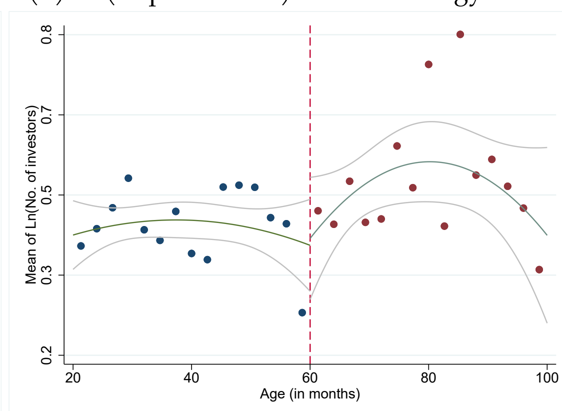
(a) Ln(Capital raised): technology firms



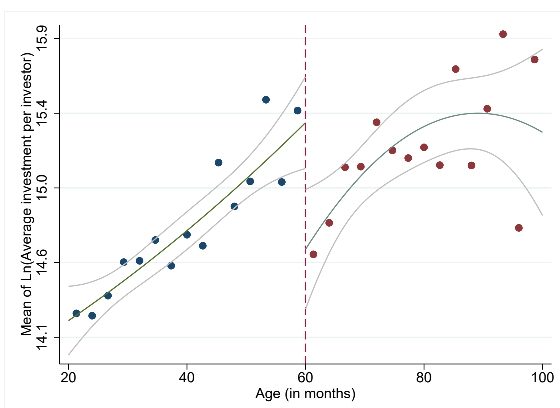
(b) Ln(Capital raised):non-technology firms



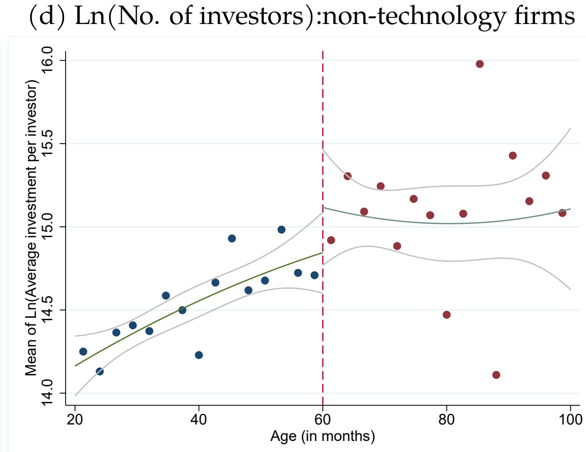
(c) Ln(No. of investors):technology firms



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



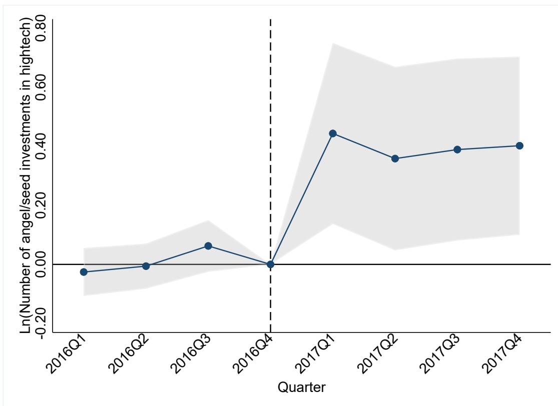
(e) Ln(Average investment):technology firms



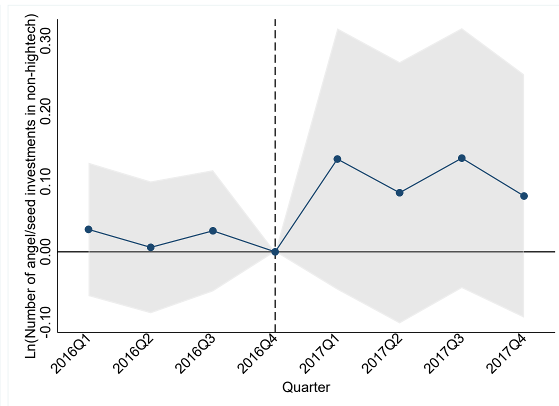
(f) Ln(Average investment):non-technology firms

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), (c), and (e) consists of funding rounds for technology firms from 2017-2019. The sample for panels (b), (d), and (f) consists of funding rounds of non-technology firms from 2017-2019.

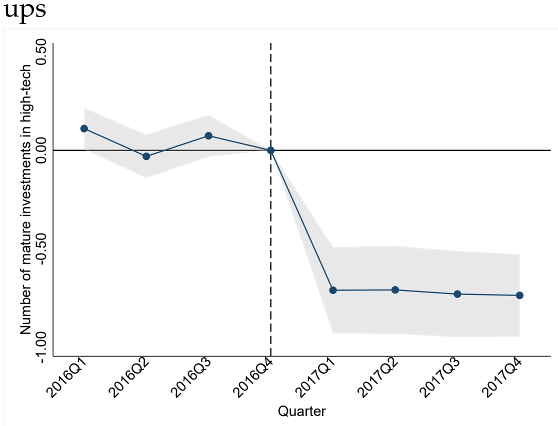
Figure 4: Investor-level evidence based on quarterly data: number of investments



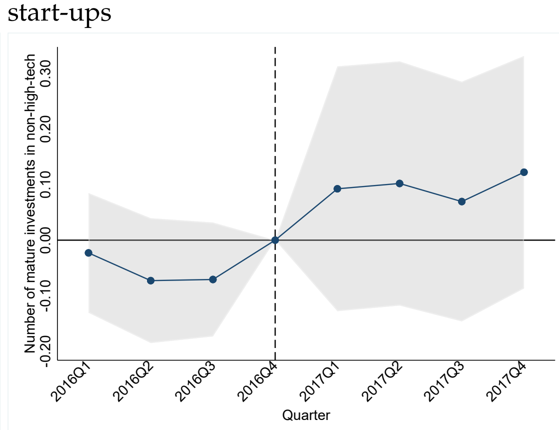
(a) Angel/seed investments in high-tech start-ups



(b) Angel/seed investments in non-high-tech start-ups



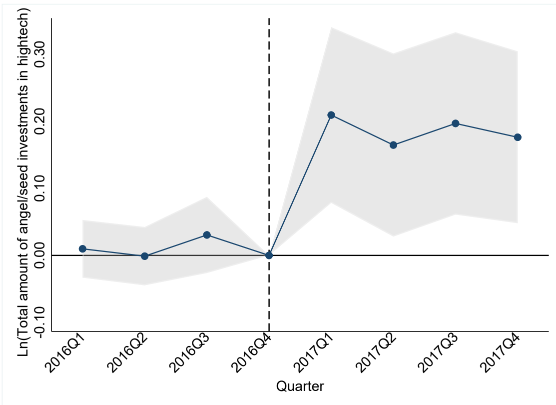
(c) Mature investments in high-tech



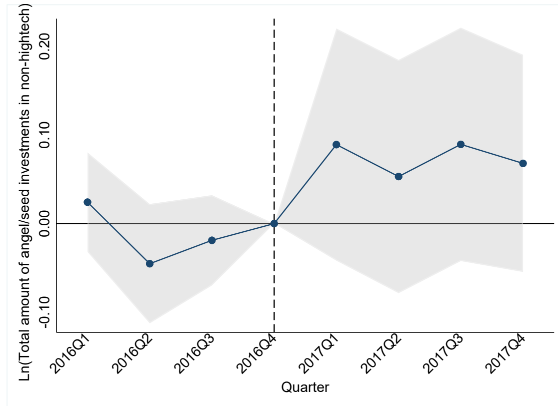
(d) Mature investments in non-high-tech

Note: These figures plot the dynamic effects of the tax incentive on the number of different types of investments (in logs). The sample construction is the same as that in Table 14, and the sample period is from 2016 to 2017. The treated group consists of VC investors who received tax incentives in 2017. The control group consists of investors who were not affected by this policy in 2017. Each dot displays the point estimate and the gray shaded area represents the 95% confidence interval. We control for investor, relative quarter and province-year fixed effects in dynamic DID estimations. Standard errors are robust and clustered at the firm level.

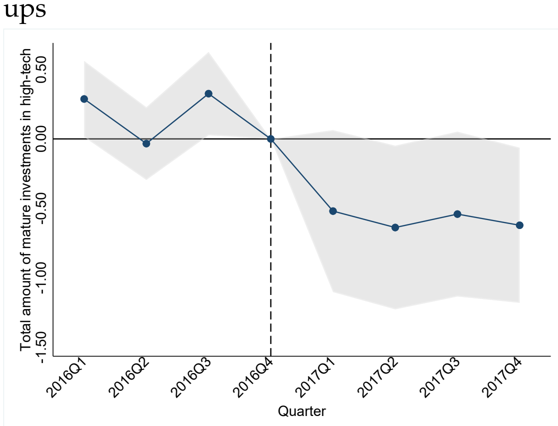
Figure 5: Investor-level evidence based on quarterly data: the amount of investment



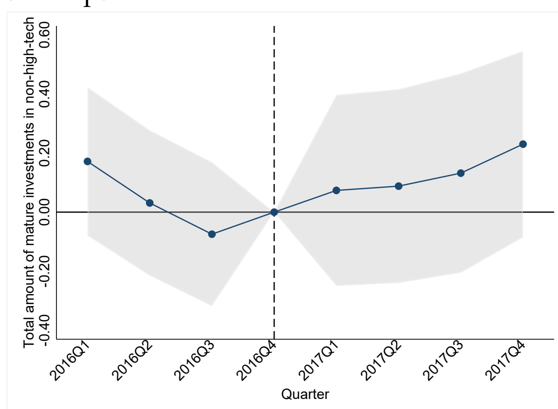
(a) Angel/seed investments in high-tech start-ups



(b) Angel/seed investments in non-high-tech start-ups



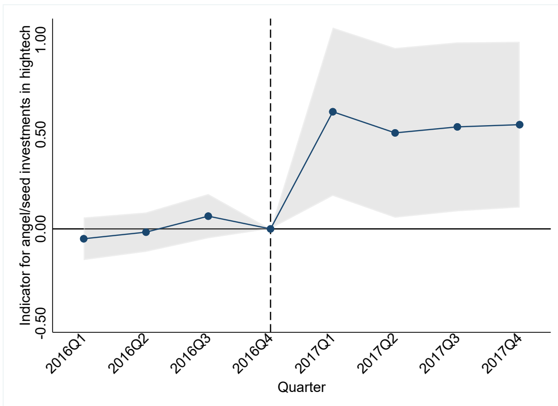
(c) Mature investments in high-tech



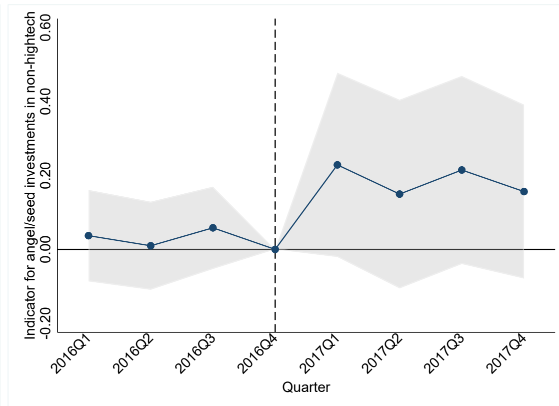
(d) Mature investments in non-high-tech

Note: These figures plot the dynamic effects of the tax incentive on the amount of different types of investments (in logs). The sample construction is the same as that in Table 14, and the sample period is from 2016 to 2017. The treated group consists of VC investors who received tax incentives in 2017. The control group consists of VC investors who were not affected by this policy in 2017. Each dot displays the point estimate and the gray shaded area represents the 95% confidence interval. We control for investor-level, relative quarter-level and province-year fixed effects in dynamic DID estimations. Standard errors are robust and clustered at the firm level.

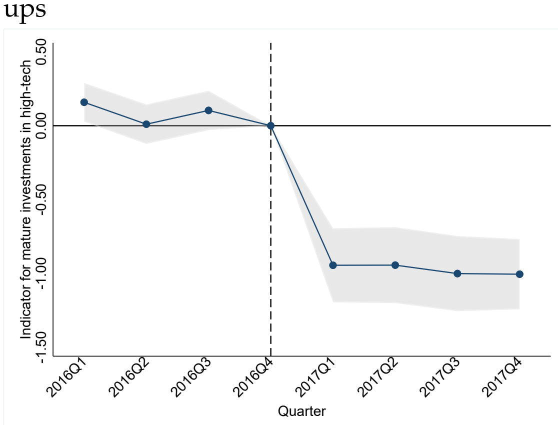
Figure 6: Investor-level evidence based on quarterly data: probability of investment



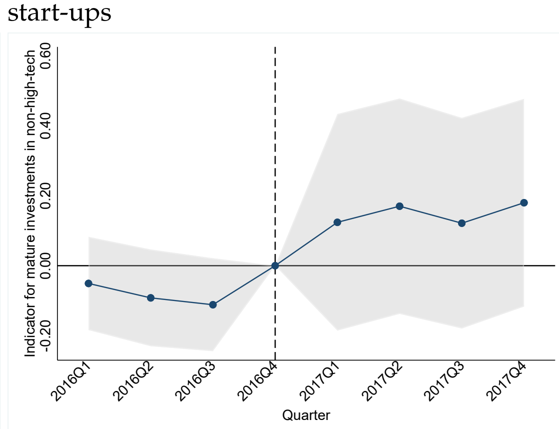
(a) Angel/seed investments in high-tech start-ups



(b) Angel/seed investments in non-high-tech start-ups



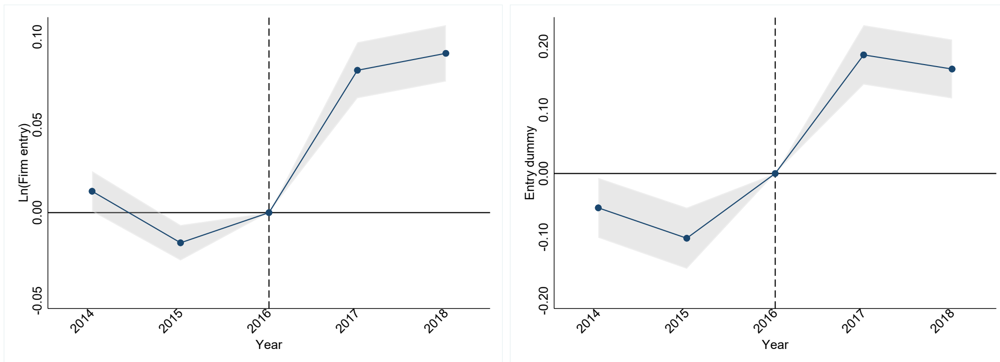
(c) Mature investments in high-tech



(d) Mature investments in non-high-tech

Note: These figures plot the dynamic effects of the tax incentive on investors' probability to conduct a certain type of investment. The sample construction is the same as that in Table 14, and the sample period is from 2016 to 2017. The treated group consists of VC investors who received tax incentives in 2017. The control group consists of investors who were not affected by this policy in 2017. Each dot displays the point estimate and the gray shaded area represents the 95% confidence interval. We control for investor,time and province-year fixed effects in dynamic DID estimations. Standard errors are robust and clustered at the firm level.

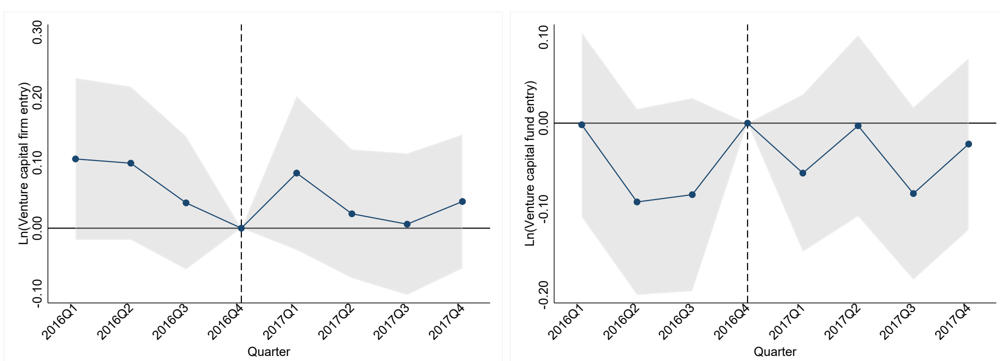
Figure 7: Investor tax incentive and the birth of new corporations



(a) Ln(Newly registered corporations) (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.

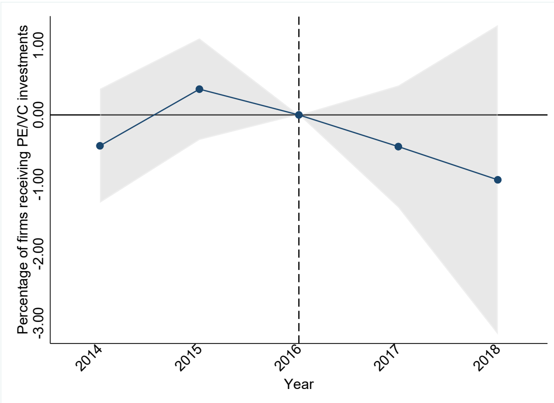
Figure 8: Investor tax incentive and the birth of VC firms and VC funds



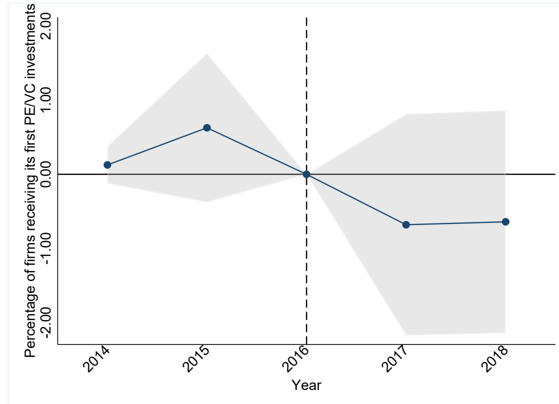
(a) Ln(VC firm entry) (2016Q1-2017Q4) (b) Ln(VC fund entry) (2016Q1-2017Q4)

Note: These figures plot the dynamic effects of the 2017 tax incentive on the birth of VC enterprises and VC funds. The dependent variable is the natural logarithm of the number of newly established VC firms or VC funds plus one within a city-quarter. 2017Q1 is regarded as the starting point of the policy. We set one quarter before the policy (2016Q4) as the benchmark. Each dot displays the point estimate and the gray shaded area represents the 95% confidence intervals.

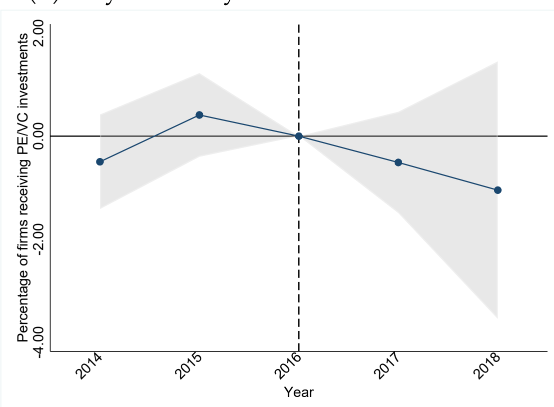
Figure 9: Investor tax incentive and the probability of receiving angel/VC investments



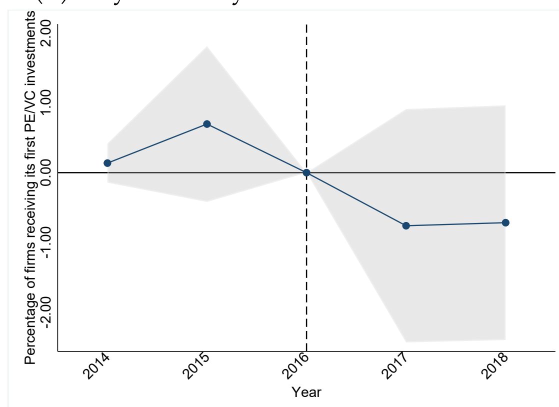
(a) City×Industry FE+Year FE+no controls



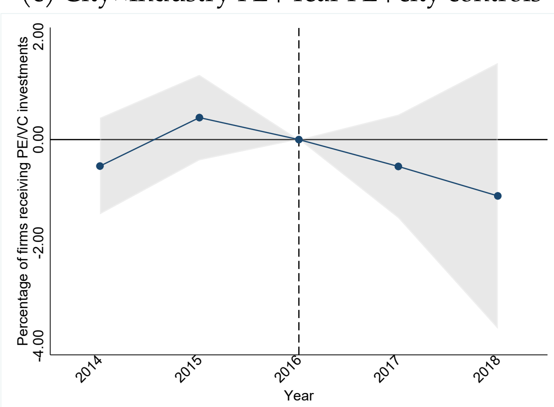
(b) City×Industry FE+Year FE+no controls



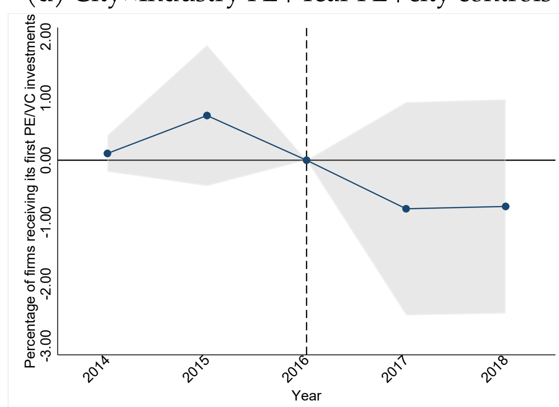
(c) City×Industry FE+Year FE+city controls



(d) City×Industry FE+Year FE+city controls



(e) City×Industry FE+Year FE+City×Year FE



(f) City×Industry FE+Year FE+City×Year FE

Note: These figures plot the dynamic effects of the 2017 tax incentive on the probability of a technology start-up receiving angel/VC funding. The dependent variable in figures (a),(c) and (e) is the number of technology firms no more than 5 years old and receiving PE/VC investments in year t, divided by the total number of technology start-ups no more than 5 years old, in city i, industry j and year t. The dependent variable in figure (b), (d) and (f) is the number of technology firms no more than 5 years old and receiving PE/VC investments in year t for the first time, divided by the total number of technology start-ups no more than 5 years old, in city i, industry j and year t. Each dot displays the point estimate and the gray area represents the 95% confidence intervals. In Panel a and b, we control for city-industry and year fixed effects. In Panel c and d, we control for GDP per capita, GDP growth, population, city-industry and year fixed effects. In Panels e and f, we control for city-industry fixed effects and city-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: 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

Notes: This table presents the sample selection process. We list how to get the benchmark regression sample and the number of observations in each step. *: The final sample size of each regression depends on the number of dependent variables.

Table 3: Summary statistics

Panel A: Summary statistics of key variables by year

Year	No. of funding rounds	Capital raised per round (USD) Mean	Capital raised per round (USD) Median	Number of investors Mean	Number of investors Median	Average investment per investor(USD) Mean	Average investment per investor(USD) Median
2014	801	10,338,338	1,612,374	1.53	1	5,587,441	823,431.5
2015	1440	7,884,458	1,543,501	1.73	1	3,873,596	783,484
2016	1586	15,979,686	1,523,087	1.88	1	6,516,126	1,346,992
2017	1425	13,167,746	2,174,249	1.95	1	7,025,323	1,495,249
2018	1348	34,398,608	3,078,699	2.18	2	10,214,510	2,549,841.3
2019	859	38,343,820	4,273,199	2.05	2	17,543,758	2,960,449

Panel B: Treated group v.s. Control group: two-sample t test with equal mean

	Treated group			Control group				
Variables	Obs.	Mean	S.D.	Obs.	Mean	S.D.	Mean Difference	T-Value
Ln (Capital raised)	2671	14.788	1.638	3551	14.660	1.56	0.128	3.136***
Ln (No. of Investors)	2998	0.483	0.568	3799	0.452	0.537	0.031	2.280**
Ln (Average investment)	2457	14.315	1.485	3231	14.248	1.469	0.066	1.677*
Ln (Age)	3267	0.881	0.548	4192	0.825	0.564	0.057	4.348***
Ln (Rank)	3267	7.795	0.53	4192	7.842	0.469	-0.047	-4.047***
Angel dummy	3267	0.038	0.19	4192	0.036	0.186	0.002	0.426

Panel C: Treated group v.s. Control group: non-parametric equality-of-medians test

	Treated group			Control group				
Variables	Obs.	Median	S.D.	Obs.	Median	S.D.	Median Difference	Pearson χ^2
Ln (Capital raised)	2671	14.296	1.638	3551	14.295	1.560	0.001	0.126
Ln (No. of Investors)	2998	0.000	0.568	3799	0.000	0.537	0.000	0.723
Ln (Average investment)	2457	14.228	1.485	3231	14.218	1.469	0.010	3.562*
Ln (Age)	3267	1.099	0.548	4192	0.693	0.564	0.406	6.110**
Ln (Rank)	3267	7.917	0.53	4192	7.940	0.469	-0.023	1.742
Angel dummy	3267	0.000	0.19	4192	0.000	0.186	0.000	0.181

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. Panel B reports summary statistics for the treated (funding rounds by technology start-ups no more than 5 years old) and control group (funding rounds by non-technology start-ups 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. Panel C reports the median and the standard deviations of each variable for treated and control groups, separately. The last two columns in Panel C present the difference in medians between the treated and control groups, and the corresponding Pearson χ^2 in non-parametric tests.

Table 4: Baseline results: evidence based on Crunchbase

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Average investment per investor)	(4) Ln(Capital raised)	(5) Ln(No. of investors)	(6) Ln(Average investment per investor)
Post × Treated	0.182***	0.093**	0.114	0.195***	0.091**	0.128*
	(0.062)	(0.041)	(0.070)	(0.063)	(0.041)	(0.071)
Ln (Age)				0.286***	0.098**	0.170**
				(0.071)	(0.045)	(0.080)
Ln (Rank)				0.043	0.018	0.012
				(0.033)	(0.020)	(0.036)
Angel dummy				0.170**	0.383***	-0.237***
				(0.078)	(0.044)	(0.083)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,458	5,980	4,783	5,368	5,909	4,717
R-squared	0.878	0.537	0.843	0.879	0.549	0.845

Notes: This table reports the effect of the investor-level tax incentive on the total amount of capital raised per funding round (columns (1) and (4)), the number of investors (columns (2) and (5)), and average investment amount per investor per round (columns (3) and (6)). The treated group consists of funding rounds made by technology start-ups that are no more than 5 years old. The control group consists of funding rounds made by non-technology start-ups no more than 5 years old. We restrict the sample to funding rounds completed during 2014-2019. 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: Regression discontinuity design estimations (updated)

	(1)	(2)	(3)	(4)	(5)	(6)
	Technology firms: 2017-2019			Non-technology firms: 2017-2019		
Dep. Var.:	Ln(Capital raised)	Ln(No. of Investors)	Ln(Average investment per investor)	Ln(Capital raised)	Ln(No. of Investors)	Ln(Average investment per investor)
$Below_{ijt}$	0.976***	0.313**	0.687*	-0.805**	-0.024	-0.439
	(0.357)	(0.124)	(0.364)	(0.406)	(0.094)	(0.372)
Bandwidth	24.558	21.937	18.387	18.891	27.733	17.118
Order of polynomial	2	2	2	2	2	2
N(effective)	1029	1025	701	935	1734	790

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)-(3) consists of funding rounds for all technology firms between 2017 and 2019. The sample for columns (4)-(6) 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 6: Heterogeneity across different funding rounds

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Average investment per investor)	(4) Ln(Capital raised)	(5) Ln(No. of investors)	(6) Ln(Average investment per investor)
Post × Treated	0.157**	0.098**	0.096	0.173***	0.095**	0.113
	(0.062)	(0.041)	(0.070)	(0.063)	(0.041)	(0.071)
Post × Treated×Pre-A	0.237**	-0.053	0.217*	0.215**	-0.047	0.174
	(0.093)	(0.057)	(0.117)	(0.092)	(0.056)	(0.117)
Ln (Age)				0.286***	0.099**	0.170**
				(0.071)	(0.045)	(0.080)
Ln (Rank)				0.040	0.018	0.011
				(0.033)	(0.020)	(0.036)
Angel dummy				0.170**	0.383***	-0.238***
				(0.078)	(0.044)	(0.083)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,458	5,980	4,783	5,368	5,909	4,717
R-squared	0.878	0.538	0.844	0.880	0.540	0.845

Notes: In this table, we examine the heterogeneity effects of the tax incentive across pre-A funding rounds and non-pre-A funding rounds. We construct a dummy indicate whether a funding round is labeled as "Angel" or "Seed" or "Pre-seed" in Crunchbase.The empirical samples used in this table are consistent with the samples used in Table 4. Standard errors are clustered at the firm level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

Table 7: Heterogeneity across investor types: angels, VCs and PEs (updated)

	Probit			Ln(No. of investors)		
Dep. Var.	(1) Angel	(2) VC	(3) PE	(4) Angel	(5) VC	(6) PE
Post × Treated	0.254**	0.118*	0.046	-0.002	0.079**	-0.037
	(0.115)	(0.062)	(0.069)	(0.008)	(0.033)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE				Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,294	7,297	7,287	5,909	5,909	5,909
R-squared	0.028	0.020	0.019	0.531	0.581	0.541

Notes: In this table, we examine the effects of the tax incentive on different types of investors using funding rounds data during 2014-2019. The treated group consists of funding rounds by technology start-ups that are no more than 5 years old. The control group consists of funding rounds by non-technology start-ups no more than 5 years old. In columns 1-3, we report Probit estimation results where the dependent variable is a dummy indicating the presence of a certain type of investor. We control for funding-round and year fixed effects in probit estimations. In Columns 4-6, the dependent variable is the number of a certain type of investor (in logs) for each funding round. We further include firm fixed effects in columns 4-6. Standard errors are clustered at the firm level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

Table 8: Heterogeneity across VC investors(updated)

	Probit				Ln(No. of investors)			
Dep. Var.	(1) Large	(2) Small	(3) Old	(4) Young	(5) Large	(6) Small	(7) Old	(8) Young
Post × Treated	0.143**	-0.167	0.149**	0.128*	0.088***	-0.004	0.079***	0.006
	(0.062)	(0.129)	(0.063)	(0.074)	(0.033)	(0.008)	(0.028)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE					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	7,297	7,282	7,297	7,287	5,909	5,909	5,909	5,909
R-squared	0.023	0.021	0.034	0.041	0.584	0.479	0.604	0.555

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 start-ups that are no more than 5 years old. The control group consists of funding rounds by non-technology start-ups no more than 5 years old. In Columns 1-4, we report Probit estimation results where the dependent variable is a dummy indicating the presence of a certain type of investor. In Columns 5-8, the dependent variable is the number of a certain type of investor (in logs) 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 9: Heterogeneity across different angel investors(updated)

	Pr(At least 1 experienced angel)		Pr(At least 1 inexperienced angel)	
Dep. Var.:	(1)	(2)	(3)	(4)
Post × Treated	0.280**	0.270**	-0.075	-0.059
	(0.122)	(0.122)	(0.236)	(0.229)
Controls	No	Yes	No	Yes
Funding-round FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	7,294	7,294	6,897	6,897
R-squared	0.024	0.027	0.055	0.058

Notes: In this table, we examine the effects of the tax incentive on more or less experienced angel investors, using funding rounds data during 2014-2019. The treated group consists of funding rounds by technology start-ups that are no more than 5 years old. The control group consists of funding rounds by non-technology start-ups no more than 5 years old. The estimation results are based on a Probit model where the dependent variable is a dummy indicating the presence of a certain type of investor. Investors whose number of historical investments is above the sample median are defined as being more experienced. In columns 1 and 3, we do not include any control variables. While in columns 2 and 4, we include $Ln(Age)$ and $Ln(Rank)$. Standard errors are clustered at the firm level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

Table 10: Cox model for the hazard rate of receiving subsequent investment

	(1)	(2)	(3)	(4)
	Full sample		Matched sample	
Post × Treated	0.358***	0.322***	0.311***	0.290***
	(0.093)	(0.096)	(0.100)	(0.100)
Treated	0.050	0.089	0.079	0.105
	(0.070)	(0.072)	(0.075)	(0.075)
Post	-0.621***	-0.561***	-0.577***	-0.528***
	(0.064)	(0.067)	(0.072)	(0.072)
Ln(Rank)		0.077		0.081*
		(0.048)		(0.049)
Ln(Age)		-0.112***		-0.111***
		(0.018)		(0.019)
exp(coefficient)	1.430	1.380	1.338	1.311
Observations	8,351	7,713	6,992	6,992
# of treated firms	2,226	2,072	2,072	2,072
# of control firms	3,609	3,306	2,072	2,072
χ^2	131.56	159.81	98.15	135.29

Notes:This table shows the semi-parametric estimates of the Cox model for the hazard rate of receiving subsequent investment. We keep the firms that received pre-A funding between 2014 and 2019 to construct a sample for survival analysis using the Cox model. The start date for survival analysis is the day when the firm received last pre-A funding, and the end date is the day when the firm received first non-pre-A funding (if applicable), or the end of the sample period(December 31, 2019). Treated is a dummy indicating whether it is a technology firm. Post is a dummy for the period after January 1, 2017. We control for the age and rank of the company at the time of receiving its last pre-A funding. Samples in columns (1) and (2) includes all companies that received pre-A funding between 2014 and 2019. In columns (3) and (4), we conduct a propensity score matching based on the age and rank at the beginning of the sample period for technology firms and non-technology firms.

Table 11: Exit rate for high-tech and non-high-tech start-ups

Panel A: High-tech firms

	2016 high-tech firms		2017 high-tech firms			
	Mean	S.D.	Mean	S.D.	Mean differences	p-value
Exit dummy	0.049	0.216	0.016	0.126	0.033***	0.002
Acquired dummy	0.015	0.123	0.009	0.094	0.006	0.31
IPO dummy	0.033	0.18	0.009	0.094	0.024***	0.004

Panel B: Non-high-tech firms

	2016 non-high-tech firms		2017 non-high-tech firms			
	Mean	S.D.	Mean	S.D.	Mean differences	p-value
Exit dummy	0.054	0.225	0.029	0.168	0.025**	0.016
Acquired dummy	0.02	0.141	0.016	0.125	0.004	0.519
IPO dummy	0.034	0.182	0.015	0.12	0.019**	0.013

Notes: In this table, we compare firms receiving funding for the first time in 2016 with those receiving funding for the first time in 2017. Panel A compares high-tech firms receiving first funding in either 2016 or 2017. Panel B compares non-high-tech firms receiving first funding in either 2016 or 2017. "Exit dummy" indicates whether a firm had an IPO or was acquired by 2021. "Acquired dummy" indicates whether a firm was acquired by 2021. "IPO dummy" indicates whether a firm had an IPO by 2021.

Table 12: Impact of the tax incentive on exit

	(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	0.037	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(coefficient)	0.978	1.042	1.038	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 shows the semi-parametric estimates of the Cox model for the hazard rate of exit. In columns (1)-(4), we restrict the sample to be firms that received their first funding after January 2017 and were no more than 5 years when receiving the funding. The start date for the survival analysis is the day when the firm received its first funding, and the end date is the day when the firm had an exit (IPO or being acquired), or the end of the sample period (December 31, 2021). In columns (5)-(8), we restrict the sample to be firms that received at least one funding after January 2017 and were no more than 5 years when receiving the funding. The start date for survival analysis is the day when the firm was established, and the end date is the day when the firm had a successful exit, 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 propensity score matching between the high-tech and non-high-tech start-ups based on the age and the Crunchbase rank on the start date.

Table 13: Quality of investment(updated)

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Average investment)
Post × Treated × Bottom rank	0.278	0.148	0.222
	(0.321)	(0.150)	(0.200)
Post × Treated	0.192***	0.086**	0.126*
	(0.063)	(0.041)	(0.071)
Ln(Age)	0.285***	0.098**	0.169**
	(0.071)	(0.045)	(0.080)
Angel dummy	0.167**	0.383***	-0.238***
	(0.078)	(0.044)	(0.083)
Firm FE	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,368	5,909	4,717
R-squared	0.879	0.549	0.845

Notes: In this table, we examine the effects of the 2017 tax incentive on firms with different Crunchbase ranks. We construct a dummy variable that equals 1 if a start-up's rank falls into the bottom 25%. The treated group consists of funding rounds by technology start-ups that are no more than 5 years old. The control group consists of non-technology start-ups 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 14: Effects of the tax incentive on investor-level performance: Intensive margin(updated)

Panel A: Effects on number of investments

	(1)	(2)	(3)	(4)
Dep. Var.:	Early-stage investments		Mature investments	
Ln(Number of investments)	High-tech start ups	Non-high-tech start ups	High-tech firms	Non-high-tech firms
Investors received tax incentives in 2017×Post	0.399***	0.079	-0.772***	0.150
	(0.152)	(0.079)	(0.098)	(0.102)
Province × Year FE	Yes	Yes	Yes	Yes
Relative Quarter FE	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
Number of investors	1428	1428	1428	1428
Observations	4,864	4,864	4,864	4,864
R-squared	0.370	0.380	0.520	0.473

Panel B: Effects on amount of investments

	(1)	(2)	(3)	(4)
Dep. Var.:	Early-stage investments		Mature investments	
Ln(Amount of investments)	High-tech start ups	Non-high-tech start ups	High-tech firms	Non-high-tech firms
Investors received tax incentives in 2017×Post	0.175***	0.083	-0.746***	0.144
	(0.062)	(0.060)	(0.262)	(0.147)
Province × Year FE	Yes	Yes	Yes	Yes
Relative Quarter FE	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
Number of investors	1428	1428	1428	1428
Observations	4,864	4,864	4,864	4,864
R-squared	0.325	0.325	0.540	0.453

Notes: In this table, we examine the effects of the 2017 tax incentive on investor-level outcomes. We regard VC investors located in the pilot regions as the treated group. VC investors located in other regions belong to the control group. Estimations are based on quarterly investor-level data from 2016Q1-2017Q4. Standard errors are clustered at the firm-level and are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 15: Effects of the tax incentive on investor-level performance: Extensive margin (updated)

	(1)	(2)	(3)	(4)
Dep. Var.:	Early-stage investments		Mature investments	
Ln(Number of investments)	High-tech start ups	Non-high-tech start ups	High-tech firms	Non-high-tech firms
Investors received tax incentives in 2017×Post	0.563**	0.150	-1.063***	0.225
	(0.223)	(0.110)	(0.110)	(0.144)
Province × Year FE	Yes	Yes	Yes	Yes
Relative quarter FE	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
Number of investors	1428	1428	1428	1428
Observations	4,864	4,864	4,864	4,864
R-squared	0.367	0.378	0.426	0.434

Notes: In this table, we examine the effects of the 2017 tax incentive on investor-level outcomes at extensive margin. The dependent variable is a dummy that equals 1 if a VC investor makes at least one investment into a certain type in quarter t, and 0 otherwise. We regard VC investors located in the pilot regions as the treated group. VC investors located in other regions belong to the control group. Estimations are based on quarterly investor-level data from 2016Q1-2017Q4. Standard errors are clustered at the firm level and are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 16: Impact of the investor-level tax incentive on birth of independent companies

	(1)	(2)	(3)	(4)
Dep. Var.:	Ln(No. of new firms)			I(At least 1 new firm)
Hightech × Post	0.084***	0.087***	0.084***	0.229***
	(0.007)	(0.008)	(0.007)	(0.015)
Hightech				-0.364***
				(0.010)
Ln(GDP per capita)t-1		-0.038***		
		(0.013)		(0.006)
(GDP growth rate)t-1		0.123***		-0.058
		(0.023)		(0.050)
Ln(Population)t-1		-0.321***		0.310***
		(0.040)		(0.004)
City×Industry FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes
City × Year FE			Yes	
Observations	545,590	483,234	545,575	483,431
R-squared	0.846	0.846	0.854	0.028

Notes: This table reports the effects of the tax incentive on birth of independent companies based on business registration data during 2014-2018. The dependent variable in columns 1-3 is the number of newly established independent firms in city i, industry j and year t (plus 1, in logs). The dependent variable in column 4 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. $Hightech$ is a dummy that equals 1 if a city-industry pair belongs to the "new and high-tech" industry. $Post$ equals 1 since 2017. Standard errors are clustered at the city-industry level and are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 17: Impact of the investor-level tax incentive on birth of VCs and VC funds

	(1)	(2)
Dep. Var.:	Ln(VC firm entry)	Ln(VC fund entry)
Pilot city×Post2017	-0.023	0.002
	(0.026)	(0.038)
City FE	Yes	Yes
Relative quarter FE	Yes	Yes
Observations	2,696	2,696
R-squared	0.866	0.826

Notes: This table examines the impact of the 2017 tax incentive on the birth of venture capital firms and venture capital funds. We aggregate the number of newly established VC firms or VC funds for each city-quarter pair based on Zero2IPO. The dependent variable is the number of newly established VC firms or VC funds (plus 1, and in logs). The sample period is from 2016Q1 to 2017Q4. $Post$ equals 1 since 2017Q1. $Pilotcity$ is a dummy indicating whether a city belongs to the 8 pilot areas. Standard errors are clustered at the city level and are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 18: Impact of the tax incentive on funding probability

Dep. Var.:	(1) Percentage of start-ups receiving funding in year t	(2)	(3)	(4) Percentage of start-ups receiving first funding in year t	(5)	(6)
Hightech × Post	-0.706	-0.787	-0.731	-0.905	-1.009	-0.930
	(0.806)	(0.900)	(0.830)	(0.921)	(1.027)	(0.942)
Ln(GDP per capita)t-1		-0.392			-0.523	
		(0.345)			(0.381)	
(GDP growth rate)t-1		-0.291			-0.462	
		(0.179)			(0.293)	
Ln(Population)t-1		0.245			0.327	
		(0.382)			(0.531)	
City × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City × Year FE			Yes			Yes
Observations	484,063	431,654	484,049	484,063	431,654	484,049
R-squared	0.742	0.742	0.744	0.562	0.562	0.567

Notes: This table reports the impact of the 2017 tax incentive on the probability of receiving funding for start-ups (no more than 5 years old at the time of funding). We first calculate the number of start-ups receiving (first) funding for each city-industry pair during 2014-2018 based on Zero2IPO. Next, we calculate the number of newly established firms from year t-4 to year t for each city-industry pair based on the business registration data. The dependent variable is the ratio between the two variables. $Hightech$ is a dummy that equals 1 if a city-industry pair belongs to the "new and high-tech" industry. $Post$ equals 1 since 2017. 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 Industry classification for high-tech and non-high-tech

Table A1: High-tech industry and 2-digit CIC code

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 2-digit CIC code for high-tech industries that meet the official guidance. The industry classification standard is GB/T 4754-2017.

Table A2: Activity label (in Crunchbase) and CIC code of high-tech firms

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 label of treated group reported in Crunchbase. The corresponding 2-digit CIC codes are reported in the square brackets.

Table A3: Activity label (in Crunchbase) of non-high-tech firms

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.

B Variable definition

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 involved in a funding round.	Crunchbase
Ln(Average investment)	The natural logarithm of the average amount of funding per investor in a funding round.	Crunchbase
Ln(Age)	The natural logarithm of difference between the announcement date of the funding round and the founding date of the start-ups in years.	Crunchbase
Angel dummy	A dummy variable equals one if the funding round involved an angel investor, zero otherwise	Crunchbase
Ln(Rank)	The natural logarithm of Crunchbase rank of funding round divided by 100. Crunchbase rank is a dynamic and comprehensive ranking using Crunchbase's intelligent algorithms to score and rank entities. The Crunchbase rank algorithm takes many factors into account, including the social connections, the level of community engagement, funding events etc. It measures the prominence of an entity.	Crunchbase
Exit dummy	A dummy variable equals one if the company was acquired or had a successful IPO in that year, and zero before investors exit, zero otherwise.	Crunchbase
Acquired dummy	A dummy variable equals one if the company was acquired in that year, and zero before investors exit.	Crunchbase
IPO dummy	A dummy variable equals one if the company had a successful IPO in that year, and zero before investors exit, zero otherwise.	Crunchbase
Top Rank	An indicator equals one if a firm ranking at the top 25% in Crunchbase, zero otherwise.	Crunchbase
Treated	A dummy variable equals one if more than 50% of a firm's activity labels reported by Crunchbase are high-tech industry, zero otherwise.	Crunchbase

Post	A dummy variable equals one since the year(quarter) after 2017 (2017Q1).	
Investors received tax incentives in 2017	An indicator variable equals if the investor located in Beijing city, Tianjin city, Hebei province, Guangdong province, Anhui province, Sichuan province, Wuhan city, Xian city, and Shenyang city, otherwise zero.	Zero2IPO
Ln (Number of investors)	The natural logarithm of the number of investments in different categories.	Zero2IPO
Ln (Investment amount)	The natural logarithm of the total amount of investments in different categories.	Zero2IPO
Ln (Firm entry)	The natural logarithm of number of newly established incorporated firms plus one within a city-industry-year pair.	Industrial and Commercial Registration database
Entry dummy	A dummy variable equals one if there are new firm entries in a city-industry-year pair, otherwise zero.	Industrial and Commercial Registration database
Percentage of firms less than 5 years old and receiving PE/VC investments in year t	The number of firms less than 5 years old and receiving any PE/VC investments in year t divided by the number of firms less than 5 years old in year t.	Crunchbase; Industrial and Commercial Registration database
Percentage of firms less than 5 years old and receiving their first PE/VC investments in year t	The number of firms less than 5 years old and receiving the first PE/VC investments in year t divided by the number of firms less than 5 years old in year t	Crunchbase; Industrial and Commercial Registration database
Pilot city	A dummy indicating whether the city is eligible for the tax incentive.	
Ln (VC firm entry)	The natural logarithm of the number of newly established VC firm plus one within a city-quarter pair.	Zero2IPO
Ln (VC fund entry)	The natural logarithm of the number of newly established VC fund plus one within a city-quarter pair.	Zero2IPO

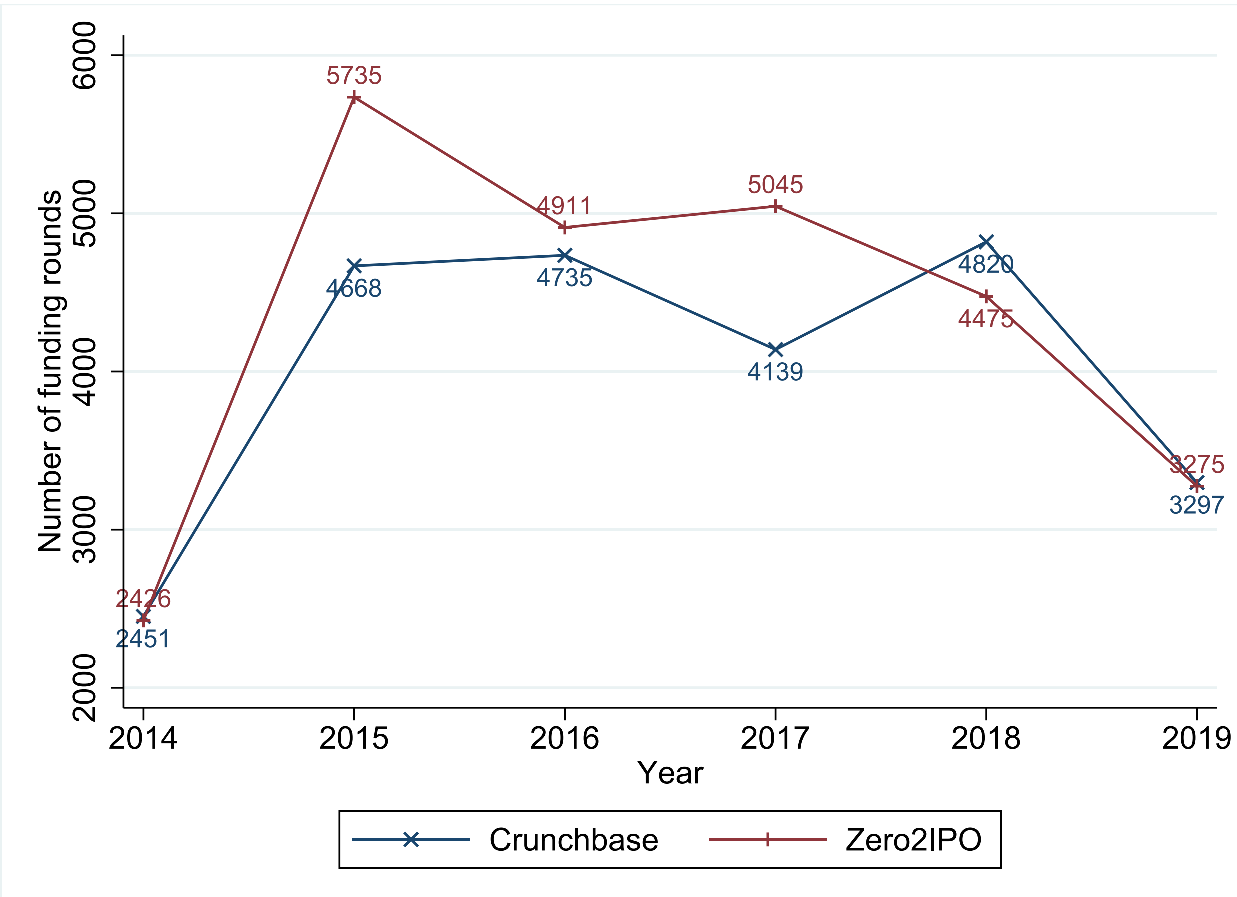
C Comparison between Crunchbase and Zero2IPO

Table C1: 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. 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 convert Zero2IPO data into funding round level and compare funding rounds between Crunchbase and Zero2IPO under different selection criterias.

Figure C1: Funding rounds coverage



Note: This figure compares the number of funding rounds for all companies reported in Crunchbase and Zero2IPO from 2014-2019. Zero2IPO does not directly report the number of funding rounds for companies, but rather reports investment events at the investor level. Therefore, we manually aggregated investment events into funding-rounds level for each company to obtain the funding round data. This table covers funding rounds for companies across all ages and industries.

D Policy comparison

Table D1: Comparison with confounding tax intensive in 2015

		Tax deduction for VC's investment in unlisted high-tech SME	Tax deduction for angel and VC's investment in high-tech start-ups
Implementation time		2008.01.01(for corporations)	2017.01.01 (for pilot regions)
		2015.10.01 (for partnerships)	2018.01.01 (nationwide)
Is it applicable to VC?		Yes	Yes
Is it applicable to Angel investors?		No	Yes
Tax incentives		70% of the investment amount can be offset against the taxable income amount allocated to them from the partnership or the taxable income of VC enterprise.	For VC, 70% of the investment amount can be offset against the taxable income amount allocated to them from the partnership or the taxable income of VC enterprise. For angels, 70% of the investment amount could be offset against the personal taxable gains from disposals of the investment.
Investment holding period		Two years	Two years
Investment targets	Registration place	Mainland China	Mainland China
	Degree of innovation	Officially identified as high-tech enterprise	R&D expenses account for no less than 20% of total costs and expenses in which the investment is made and the following tax year.
	Development stage	Non-listed in the year in which the investment is made or in the following 2 years.	1. No more than 5 years old at the time of investment; 2. Non-listed in the year in which the investment is made or in the following 2 years.
	Employment	No more than 500 employees	No more than 200 employees, at least 30% of whom must have a university degree.
	Operating conditions	Annual revenue and total asset are not greater than RMB 200 million at the time of investment	Annual revenue and total asset are not greater than RMB 50 million * at the time of investment.

Notes:This table displays the comparison of tax deduction for VCs in 2015 and tax deduction for VCs and angels in 2017. *: In 2017, total assets and annual sales revenue for start-ups did not exceed 30 million yuan when receiving investments. By 2018, this standard was amended to 50 million yuan.

Table D2: Placebo estimations

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Average investment)
Post×Treated	-0.062	0.055	-0.108
	(0.098)	(0.054)	(0.111)
Ln(Age)	0.418***	0.046	0.447***
	(0.090)	(0.055)	(0.101)
Ln(Rank)	0.063	-0.001	0.035
	(0.049)	(0.028)	(0.056)
Angel dummy	0.179*	0.392***	-0.259**
	(0.099)	(0.059)	(0.112)
Firm FE	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	2,828	2,910	2,426
R-squared	0.864	0.562	0.835

Notes: In this table, we examine the effects of tax incentive in 2015 on on total funding raised, number of investors and average investment per investor. We restrict the sample to be funding rounds completed during 2012-2016. The treated group consists of funding rounds made by technology start-ups that are no more than 5 years old . The control group consists of funding rounds made by non-technology start-ups 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.

E Robustness checks for the funding-rounds estimations

Table E1: Baseline results without controlling for funding-round fixed effects

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Average investment per investor)	(4) Ln(Capital raised)	(5) Ln(No. of investors)	(6) Ln(Average investment per investor)
Post × Treated	0.192***	0.098**	0.131*	0.205***	0.096**	0.143*
	(0.070)	(0.040)	(0.076)	(0.070)	(0.040)	(0.076)
Ln (Age)				0.762***	0.132***	0.648***
				(0.083)	(0.043)	(0.090)
Ln (Rank)				0.068*	0.026	0.027
				(0.037)	(0.020)	(0.041)
Angel dummy				0.116	0.399***	-0.296***
				(0.083)	(0.045)	(0.087)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Funding-round FE	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,634	6,231	4,939	5,542	6,157	4,872
R-squared	0.832	0.520	0.799	0.839	0.533	0.806

Notes: In this table, we keep funding rounds labeled as ”unknown” and ”private equity” in the estimation sample. We re-conduct the baseline estimations in Table 4 using this larger sample and do not control for funding-round fixed effects.

Table E2: Placebo tests based on firms greater than 5 years old (updated)

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm age from 6 to 10			Firm age greater than 10		
Dep. Var.:	Ln(Capital raised)	Ln(No. of investors)	Ln(Average investment)	Ln(Capital raised)	Ln(No. of investors)	Ln(Average investment)
Post×Treated	0.168	0.144	0.102	0.056	-0.069	0.170
	(0.138)	(0.142)	(0.200)	(0.157)	(0.151)	(0.215)
Ln(Age)	1.025	0.081	0.645	0.097	-1.101	1.954
	(0.724)	(0.878)	(1.015)	(1.271)	(0.914)	(1.493)
Ln(Rank)	-0.102	0.027	-0.122	-0.240***	-0.063	-0.189**
	(0.063)	(0.067)	(0.098)	(0.086)	(0.079)	(0.090)
Angel dummy	-0.263	-0.624**	0.312	0.316**	0.499**	-0.163
	(0.367)	(0.283)	(0.339)	(0.127)	(0.205)	(0.230)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	526	625	502	495	533	439
R-squared	0.948	0.608	0.908	0.928	0.578	0.870

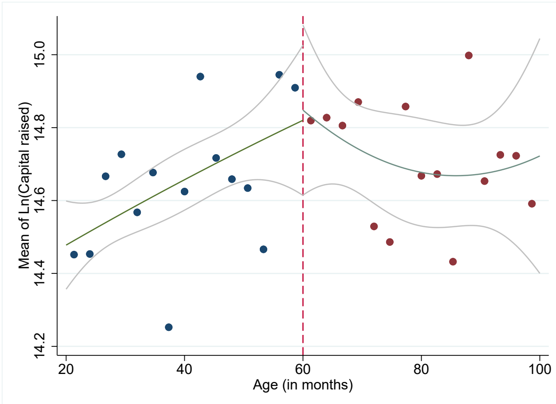
Notes: This table reports the placebo results using funding rounds from companies that are older than five years when the funding round occurred. In columns (1)-(3), the regression sample consists of funding rounds made by companies that were 6-10 years old. In columns (4)-(6), the regression sample consists of funding rounds from companies that were greater than 10 years old. The treated group, control group and sample period are the same as specified in Table **??**. Standard errors are clustered at the firm-level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

Table E3: Benchmark results based on a broader treatment group (updated)

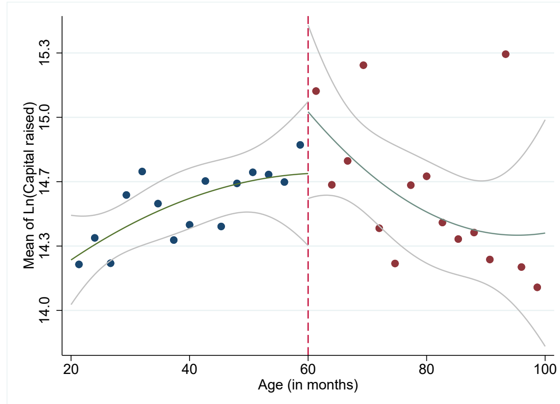
	(1)	(2)	(3)
Dep. Var.:	Ln(Capital raised)	Ln(No. of investors)	Ln(Average investment)
Post×Treated	0.122**	0.037	0.087
	(0.051)	(0.034)	(0.059)
Ln(Age)	0.256***	0.125***	0.122*
	(0.057)	(0.035)	(0.064)
Ln(Rank)	0.002	-0.007	0.004
	(0.027)	(0.016)	(0.029)
Angel dummy	0.057	0.352***	-0.305***
	(0.066)	(0.040)	(0.067)
Firm FE	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	8,425	9,238	7,432
R-squared	0.876	0.546	0.844

Notes: In this table, we examine the tax-incentive policy effects on total fund raised, number of investors and average funding amount based on a broader treated group. The treated group consists of firms have at least one high-tech industry in the industry descriptions reported by Crunchbase. The control group is the same as specified in Table **??**. Standard errors are clustered at the firm-level and are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

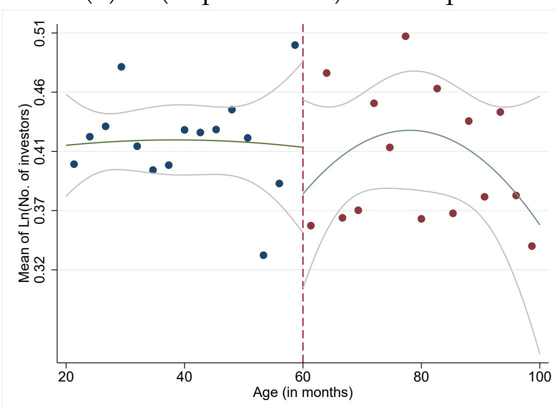
Figure E1: RDD figures: placebo tests



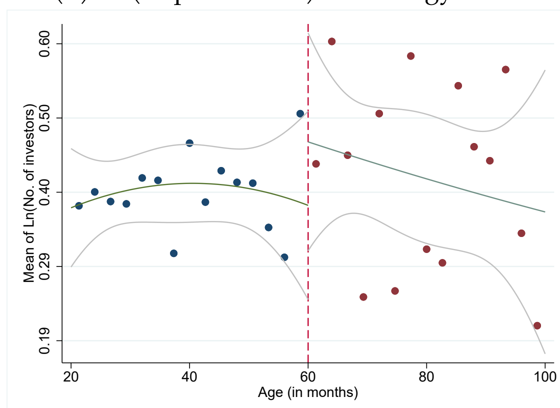
(a) Ln(Capital raised):full sample



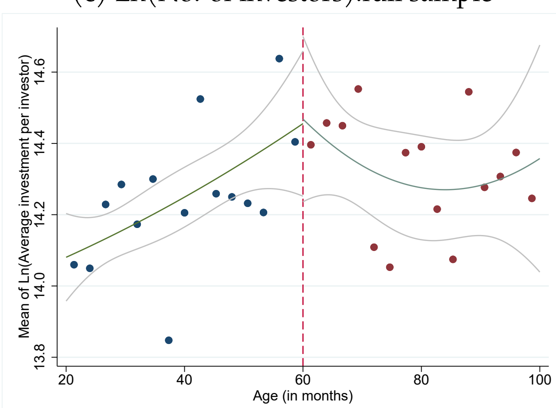
(b) Ln(Capital raised):technology firms



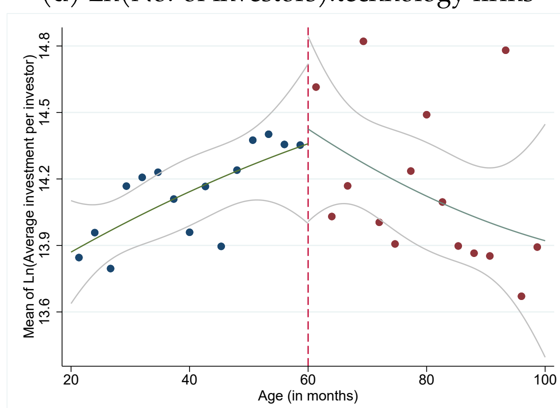
(c) Ln(No. of investors):full sample



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



(e) Ln(Average investment):full sample



(f) Ln(Average investment):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 cut-off. 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), (c), and (e) consists of funding rounds for all firms from 2014-2016. The sample for panels (b), (d), and (f) consists of funding rounds for technology firms from 2014-2016.

Table E4: RDD results: placebo tests (updated)

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample: 2014-2016			Technology firms: 2014-2016		
Dep. Var.:	Ln(Capital raised)	Ln(No. of Investors)	Ln(Avearge investment)	Ln(Capital raised)	Ln(No. of Investors)	Ln(Avearge investment)
$Below_{ijt}$	0.303	0.033	0.311	0.319	-0.051	0.393
	(0.204)	(0.053)	(0.216)	(0.368)	(0.117)	(0.338)
Bandwidth	27.120	41.754	24.319	29.132	35.699	33.237
Order of polynomial	2	2	2	2	2	2
N(effective)	2627	4669	2065	773	961	803

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)-(3) consists of funding rounds from all firms (including technology firms and non-technology firms) between 2014 and 2016. The sample for columns (4)-(6) 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.

F Control for effects of national high-tech zones

Table F1: List of National certified high-tech zone 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 certified since 2014. $Yearcertified$ shows the time when the zone was approved by the central government to become a national high-tech zone.

Table F2: Benchmark results after excluding funding round in high-tech zones (updated)

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Average investment)
Post×Treated	0.205***	0.087**	0.135*
	(0.067)	(0.043)	(0.075)
Ln(Age)	0.290***	0.099**	0.177**
	(0.075)	(0.048)	(0.083)
Ln(Rank)	0.043	0.027	-0.004
	(0.035)	(0.021)	(0.038)
Angel dummy	0.183**	0.390***	-0.241***
	(0.080)	(0.047)	(0.082)
Firm FE	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4,895	5,377	4,282
R-squared	0.880	0.545	0.847

Notes: In this table, we re-examine the effects of the investor-level tax incentives after excluding funding rounds that occurred in high-tech zones from the benchmark sample (i.e. sample in columns 4-6 of Table**??**). The location of high-tech zone certified since 2014 is listed in TableF1. Standard errors are clustered at the firm-level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

Table F3: Impact on birth of independent companies after controlling for high-zone policy effects

	(1)	(2)	(3)	(4)
Dep. Var.:		Ln(No. of new firms)		I(At least 1 new firm)
Hightech×Post	0.083***	0.087***	0.084***	0.219***
	(0.008)	(0.009)	(0.008)	(0.016)
Hightech				-0.356***
				(0.011)
Ln(GDP per capita)		-0.046***		0.222***
		(0.014)		(0.006)
(GDP growth rate)		0.149***		-0.066
		(0.024)		(0.053)
Ln(Population)		-0.688***		0.299***
		(0.059)		(0.005)
City×Industry FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes
City×Year FE			Yes	
Observations	474,225	411,869	474,210	412,066
R-squared	0.846	0.846	0.855	0.03

Notes: This table examines the impacts of tax incentive on birth of new independent incorporated firms after controlling for the high-tech zone policy effects. Starting from the sample used in Table16, we further exclude cities with national-certified high-tech zones listed in TableF1 and re-examine the impacts of investor-level tax incentives on independent firm entry. Standard errors are clustered at the city-industry level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

G Interaction with local tax incentives

Table G1: The role of local tax benefits (updated)

Dep. Var.:	(1) Ln (Capital raised)	(2) Ln (No. of investors)	(3) Ln (Average investment)
Post × Treated	0.186***	0.093**	0.104
	(0.068)	(0.044)	(0.077)
Post × Treated×	0.050	-0.013	0.134
Local tax benefit	(0.121)	(0.064)	(0.128)
Ln(Age)	0.287***	0.098**	0.170**
	(0.072)	(0.045)	(0.080)
Ln(Rank)	0.043	0.018	0.011
	(0.033)	(0.020)	(0.036)
Angel dummy	0.169**	0.383***	-0.239***
	(0.078)	(0.044)	(0.083)
Firm FE	Yes	Yes	Yes
Funding round FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,368	5,909	4,717
% of obs. to receive the local tax benefit	16.37%	16.48%	16.45%

Notes:This table presents the heterogeneity of benchmark results when firms located in a city with a local tax benefit for start-ups. Here, the local tax benefit refers to a series of tax incentives implemented by local governments to encourage venture capital firms to invest in local start-ups, including tax refunds, tax rewards etc. These local tax benefits require both startups and venture capitalists to be registered in the same city. $Localtaxbenefit$ is a dummy variable that equals one when the local tax benefit comes into force; otherwise zero. In columns 1-3, we examine the effects on total funding raised, number of investors and average investment per investor, separately. Sample and empirical strategy are the same as those in columns (4)-(6) of Table **??**. Standard errors are clustered at the firm-level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

H Government-backed investor v.s. Non-government-backed investor

Table H1: Summary statistics by the end of 2020

	Government-backed investor		Non-government-backed investor		Mean difference	T-value
	Mean	# of investors	Mean	# of investors		
Capital volume (Million, CNY)	53,111.670	115	4,851.113	388	48,260.560***	4.387
Number of historical investments	60.661	192	42.413	731	18.248*	1.749
Number of exits	18.764	123	13.185	372	5.579	1.437
Number of funds	18.133	158	14.881	687	3.252	1.065
Age	12.560	200	8.090	837	4.470***	10.563

Notes: This table reports the summary statistics for government-backed VCs and non-government-backed VCs. All these data come from Zero2IPO database at the end of 2020. The last two columns report the difference in means between the government-backed investors and non-government-backed investors and their T-values for the equal-mean tests.

Table H2: Heterogeneous effects of tax incentives on investor-level performance: government-backed investor and non-government-backed investor

	(1)	(2)	(3)
	Early-stage investments in high-tech start ups		
Dep. Var.:	Ln(Number of investment)	Ln(Investment amount)	1(At least one investment)
Investors received tax incentives	0.038	0.018	0.055
in 2017×Post×Government-backed	(0.028)	(0.015)	(0.038)
Investors received tax incentives	0.280***	0.260***	0.383***
in 2017×Post	(0.072)	(0.079)	(0.110)
Province×Year FE	Yes	Yes	Yes
Relative Quarter FE	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes
Number of government-backed investors	147	147	147
Number of non-government-backed investors	799	799	799
Observations	3,475	3,475	3,475

Notes: This table reports the heterogeneous effects of tax incentives on investor-level performance across government-backed investors and non-government-backed investors.*Government-backed* is a dummy that equals 1 if the investor is government-backed, and 0 otherwise. We interact *Government-backed* with *Investors received tax incentives in 2017×* $Post$, and perform a triple DID estimation using the sample in Table 14. In this table, we focus on early-stage investments in technology start-ups. The dependent variables in columns 1-3 are the amount of investments, the number of investments and a dummy indicating at least one investment within a city-quarter pair.

I DID estimation based on high-tech firms

Table J1: Standard DID estimation based on high-tech firms

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Average investment per investor)	(4) Ln(Capital raised)	(5) Ln(No. of investors)	(6) Ln(Average investment per investor)
Post×Below5	0.169**	0.134**	0.040	0.173**	0.143***	0.039
	(0.073)	(0.055)	(0.088)	(0.073)	(0.055)	(0.088)
Ln(Rank)				-0.050	0.002	-0.049
				(0.043)	(0.028)	(0.046)
Angel dummy				0.194*	0.438***	-0.126
				(0.113)	(0.066)	(0.112)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,019	3,430	2,723	3,019	3,430	2,723
R-squared	0.892	0.544	0.857	0.893	0.553	0.858

Notes: In this table, we conduct standard DID estimations using funding rounds data from high-tech firms. $Below5$ is a dummy variable that equals 1 if the funding round made by high-tech firms that were no greater than five years old in 2017, otherwise equals 0 if the funding round made by high-tech firms that were older than five years old in 2017. For firms that were below 5 years old in 2017, we only keep funding rounds that occurred before firms reached the age of five. We restrict the sample to funding rounds completed during 2014-2019. Standard errors are clustered at the firm level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.