Too Young to Benefit: How Tax Incentives Crowd Out the Youngest Startups

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Abstract

Can tax incentives effectively channel venture capital to the young startups that need it most? We examine China's 2018 tax policy, which offers a 70% deduction for investments in startups under 60 months old but requires a 24-month minimum holding period. Using 71,844 venture capital deals from 2015-2022, we uncover unintended consequences: investments bunch significantly below the 60-month threshold (132% excess mass) but crowd out the youngest startups (0-24 months). We build a structural model that reveals this reallocation arises from the holding period interacting with age-varying survival probabilities. Counterfactual simulations quantify this mechanism, with the holding period alone reducing investment in the youngest firms by 5.15%. This distortion yields substantial real effects. Using difference-in-differences estimation, we show the policy increases innovation and human capital investment overall, but crowded-out young startups lag significantly behind older yet still-eligible counterparts. This study first documents intra-group crowding out in tax incentives, highlighting how holding periods and endogenous risks systematically distort allocation, deviating from policy intent.

Keywords: Tax Distortions, Venture Capital, Startup Financing, Bunching Estimator

JEL Classification: G24, G23, H25, O31

1 Introduction

Young firms drive innovation, job creation, and economic growth (Adelino et al., 2017; Akcigit and Kerr, 2018; Ma et al., 2022). Early-stage firms, however, face severe financial constraints(Da Rin et al., 2006). Governments worldwide have introduced tax incentives to stimulate venture capital (VC) investment in such firms. As economies increasingly compete through innovation, whether these policies successfully channel capital to their intended beneficiaries has become a critical question for policymakers and economists (Denes et al., 2023; Chen and Hshieh, 2024).

This paper examines a Chinese tax incentive implemented in 2018 (Circular No. 55 [2018]) to support high-tech startups. The policy offers investors a 70% tax deduction for investments in startups younger than 60 months. We document a striking finding: following implementation, the youngest firms—those aged 0-24 months and the policy's intended core beneficiaries—experienced significant crowding-out, while investment shifted toward more mature firms approaching the 60-month threshold. Three questions motivate our analysis: What mechanism drives this distortion? Which policy design features harm the firms most in need of support? What are the real consequences for firm development?

This policy differs fundamentally from broad-based capital gains tax cuts(Edwards and Todtenhaupt, 2020; Aguiar et al., 2024) by screening investment targets based on firm age—an exogenous, non-manipulable characteristic. More critically, it combines the 60-month age threshold with a 24-month minimum holding period. This design creates an implicit survival constraint: tax benefits can only be realized if the invested startup survives until the holding period ends. Since startup survival probability increases significantly with age,[1] the effective value of the tax deduction varies systematically across firms of different ages, fundamentally altering the incentive structure within the eligible pool.

Reliance on minimum holding periods is not unique to China but represents a common feature of such policies globally. The U.S. Qualified Small Business Stock (QSBS) program requires a 5-year holding period; the Australian Venture Capital Limited Partnership (VCLP) scheme mandates 12 months; the Canadian Labour-Sponsored Venture Capital Corporation (LSVCC) requires 8 years. Policymakers employ this tool to screen for patient capital and filter out short-term speculation, yet the economic consequences of the embedded survival constraint mechanism have been largely overlooked.

This oversight occurs primarily because the survival constraint is difficult to cleanly identify in most settings. Mainstream incentive schemes—including the QSBS, VCLP, and LSVCC—lack explicit hard age limits, relying instead on multidimensional eligibil-

[1]Survival probabilities derive from National Enterprise Credit Information Publicity System (NECIPS) database, tracking firms from founding to closure. We calculate P(survival | age = a, holding = 24 months). Figure 6 displays distribution of 24-Month survival rate.

ity criteria such as total asset caps, employee size, and industry classification.[2] Firms can strategically adjust these characteristics within certain ranges, making it difficult to separate the survival constraint effect from endogenous firm selection behavior such as adjusting capital structure or optimizing funding timing(Chen et al., 2021; Ewens et al., 2024). The Chinese policy, in contrast, provides a unique identification opportunity. Its hard 60-month age cutoff creates a sharp discontinuity, allowing behavioral changes around this threshold to be attributed to the tax incentive effect rather than endogenous firm adjustments. This institutional feature, combined with a moderate 24-month holding period, enables clean isolation of the survival constraint mechanism and, for the first time, quantification of how it systematically distorts capital allocation.

Our empirical analysis leverages a comprehensive dataset. From CVSource and PEdata, we obtain 71,844 VC transactions spanning 2015-2022, covering 20,492 startups and 22,155 investors across the 2018 policy implementation. We construct precise age measures by manually matching transaction records to official registration dates from the National Enterprise Credit Information Publicity System (NECIPS). This yields startup age in months at investment, crucial for identifying strategic behavior near the 60-month eligibility cutoff. The data are further enriched with 293,960 patent records from the China National Intellectual Property Administration (CNIPA) (2015-2024) and 48,813 job posting records from Zhaopin.com (2022-2024) to track real firm outcomes.

We begin by documenting investor responses to the policy's discontinuous incentive structure. Visual and statistical evidence reveals significant reactions to the 60-month age threshold. Following implementation, investment concentration spikes dramatically just below the eligibility cutoff—a pattern entirely absent in pre-policy years. This bunching demonstrates that the policy successfully attracts investor attention. Yet a striking asymmetry emerges: while the policy works, it works selectively—investment bunches near the threshold but the youngest startups aged 0–24 months experience significant crowding out.

To quantify VC responses to the tax incentive, we apply the bunching framework of Kleven (2016). We find 132% excess mass strategically bunched just below the eligibility threshold. Further examination of investment amount changes across age groups reveals significant capital reallocation. For mature firms aged 84-96 months (beyond the eligibility line), VC investment declined by 33.8%. For firms aged 24-60 months approaching the threshold, investment increased by 14% to 43%. For the youngest firms aged 0-24 months—the policy's explicitly intended beneficiaries—investment amounts did not increase significantly. This pattern reveals a critical paradox: while crowding out overage firms, the policy fails to direct capital to the youngest firms, instead concentrating

[2]U.S. QSBS relies on asset caps (USD 75 million post-2025), active business requirements, and C-corporation structures. Australia's VCLP sets asset limits (AUD 250 million) and industry exclusions. Canada's LSVCC requires 8-year holding. Unlike China, these programs lack mandatory age cutoffs, screening targets through asset size and industry type instead.

investment on relatively mature yet still-eligible targets near the threshold.

Why would a policy designed to help young startups inadvertently crowd out the youngest ones? A theoretical framework based on heterogeneous survival risk is proposed to explain this incentive distortion. The core mechanism lies in the interaction between the 24-month holding period and firm age, creating an age gradient in effective tax incentives. Although the policy nominally provides a uniform 70% tax deduction to all firms within 60 months, realization of the tax benefit depends on firm survival through the holding period. Investing in the youngest firms thus carries higher risk: the firm may fail before satisfying the holding period, forfeiting the tax benefit.[3]

A structural model of VC portfolio choice under capital constraints is constructed and calibrated to rigorously test and quantify this mechanism. The model closely matches empirically observed moments of survival rates and investment density, validating the mechanism's robustness, and enables precise quantification of economic impact. Three sets of counterfactual simulations are conducted. First, eliminating the holding period requirement such that all eligible firms receive an unconditional 70% tax deduction reveals that the survival constraint from the holding period alone reduces the investment share in firms aged 0-30 months by 5.15 percentage points. Second, comparing different holding period lengths (6 to 36 months) demonstrates that longer holding periods exacerbate the crowding-out effect on the youngest firms. Third, varying the tax deduction rate (50% to 90%) shows that while higher deduction rates increase overall investment, they cannot reverse the allocation distortion; both crowding-out and bunching effects scale proportionally. These counterfactual exercises collectively confirm that the survival-contingent constraint drives the crowding-out effect.

Do these financial distortions affect startup performance? Exploiting heterogeneous policy exposure across the age distribution, we employ difference-in-differences (DiD) estimation. We classify firms into three groups by age at investment: the crowded-out group aged 0-24 months, the non-bunching group aged 24–45 months, and the bunching group aged 45–60 months.

Results show that policy increases patent applications by 19.4% and salary offers by 6.4%-7.9% among eligible firms overall. Yet crowded-out young firms benefit far less than the non-bunching group. The policy's impact on patents for crowded-out firms is less than half that of the non-bunching group. Patent quality and scope similarly deteriorate. Human capital effects follow the same pattern: salary offers rise significantly in the non-bunching group but remain flat among crowded-out firms. While effective on average, the survival-contingent holding period substantially weakens the policy's impact on the youngest startups it aims to support.

[3]In Section 4 We show that the expected survival probability of the youngest enterprises (0-6 months)—approximately 32% over 24 months—is significantly lower than that of enterprises nearing the threshold (54-60 months, approximately 53%). Consequently, the minimum holding period substantially dilutes the anticipated value of tax relief for the youngest enterprises.

This paper makes contributions to the literature on tax incentives and entrepreneurship. While prior research demonstrates that investor-level incentives increase aggregate investment(Denes et al., 2023; Güçeri et al., 2024) and overall entrepreneurial outcomes (Chen and Farre-Mensa, 2023) , we move beyond whether these policies work to examine how specific design features create unintended allocation distortions. A novel form of within-group crowding out is documented for the first time. Denes et al. (2023) find that angel tax credits crowd out other financing channels; our study shows that VCs themselves are not crowded out but rather that the policy design induces capital reallocation from the youngest firms to safer, older yet still-eligible firms to maximize the expected subsidy value. This highlights a previously unobserved policy design paradox: when holding period requirements interact with survival rate heterogeneity within the eligible pool, the policy not only fails to direct resources to the highest-risk firms most in need of support but systematically excludes them through the survival constraint mechanism.

Second, we provide a novel mechanistic explanation for the mixed results of investor incentive policies: the interaction between policy parameters and firm survival probability. Prior literature typically attributes poor policy performance to investor types or motives. Acs et al. (2016) and Lerner (2020) note that entrepreneurship policies struggle to target firms with genuine high-growth potential; Denes et al. (2023) show that incentives may be exploited by inexperienced investors or insiders for tax avoidance or self-dealing; Lerner (2013) argues that they may merely increase sophisticated investors' existing returns.

Our research proposes a more fundamental structural channel operating independently of investor experience or motives. The 24-month minimum holding period requirement interacts unexpectedly with startups' inherent survival probability, which varies with age. This mechanism echoes Keuschnigg and Nielsen (2003) emphasis on the role of startup survival rates in tax policy; our structural model validates that this survival-contingent mechanism is the primary driver of capital reallocation. This contribution extends traditional tax impact analysis(Akcigit et al., 2022) by providing the first evidence of how policy microstructure features interact with the endogenous risk of startups to systematically distort capital allocation away from the policy's original intent (Poterba, 1989).

Third, our analysis directly links policy-induced financial distortions to real effects on firm development through rigorous causal identification. The literature offers mixed evidence on the real economic effects of investor incentives. Some studies show that tax policies can affect investment behavior(Zwick and Mahon, 2017) and innovation output (Akcigit et al., 2022; Dimitrova and Eswar, 2023) or influence human capital accumulation (Campello et al., 2024), while other evidence emphasizes VC's positive contribution to the economy (Gornall and Strebulaev, 2021); overall effects remain inconclusive. Exploiting the heterogeneous impact of the policy across different firm age groups constructs a DiD strategy showing that crowded-out young firms lag significantly behind threshold-adjacent

firms in both innovation output and human capital accumulation. This speaks to Denes et al. (2023), who find angel investment credits produce no real economic effects. Our results suggest the problem may lie not with incentives per se, but with design flaws—like holding period requirements—that generate allocative distortions offsetting the policy's intended benefits.

Finally, our study offers important lessons for policy design. While substantial literature calls for supporting early-stage entrepreneurship through tax incentives (Haltiwanger et al., 2013; Akcigit et al., 2022), achieving this goal remains challenging (Lerner, 2022). We demonstrate that well-intentioned policies can backfire when they ignore how incentive structures interact with the economic characteristics of target firms. Our findings quantify a specific design failure: the holding period requirement not only fails to direct capital to the youngest startups but actively crowds them out. This reveals a critical oversight—policymakers focused on tax rates while neglecting microparameters like holding periods, age thresholds, and eligibility rules. These seemingly technical details determine whether policies support or inadvertently penalize the high-risk, high-growth ventures they aim to help. The lesson is clear: effective entrepreneurship policy requires careful calibration of all design parameters, not just generous tax breaks.

The remainder of the paper is organized as follows. Section 2 describes the institutional background and data. Section 3 documents bunching at the 60-month threshold and crowding out of firms aged 0-24 months. Section 4 builds a structural model showing how the holding period interacts with survival probability to drive this reallocation. Section 5 examines real effects on innovation and human capital. Section 6 concludes.

2 Institutional Background and Data

2.1 Institutional Background

Using tax incentives to encourage venture capital investment in startups has become standard practice across major economies. In the United States, the Qualified Small Business Stock (QSBS) regime offers capital gains tax exemptions of up to 100%. The United Kingdom's Enterprise Investment Scheme (EIS) and Seed Enterprise Investment Scheme (SEIS) provide income tax relief of 30% and 50%, respectively. France offers an 18% income tax deduction for investments in young innovative enterprises.

These policies share a common design element: minimum holding period requirements. Table A.1 in Appendix compares these tax incentive schemes across countries and shows that investors must hold their equity stakes for a specified period—typically three to five years—before they can fully claim tax benefits.

This design reflects two policy objectives. First, holding periods screen for investors willing to provide patient capital rather than pursue short-term gains. Second, they align

tax benefits with the long-term, high-risk nature of startup growth, encouraging sustained post-investment support from Venture Capitalists (VCs).

The holding period requirement creates an important but often overlooked effect: firm survival becomes an implicit precondition for claiming tax benefits. Investors realize benefits only when their portfolio companies survive through the entire holding period. Because the youngest startups exhibit substantially lower survival rates over two to five years than expansion-stage firms, nominally uniform tax incentives generate systematic variation in effective incentive strength across firm age. This survival-based mechanism underpins our theoretical model in Section 4 and explains our key empirical finding in Section 3: capital reallocates from the youngest startups toward those approaching the age threshold.

China first introduced tax incentives for venture capital in 2009. The State Administration of Taxation's Circular No. 87 [2009] allowed VC enterprises to deduct 70% of their investment amounts from taxable income. Circular No. 81 [2015] expanded the policy's geographic coverage and extended eligibility to venture capital firms registered as corporate entities nationwide, but maintained the restrictive requirement that investees be officially certified as small and medium-sized high-tech enterprises.

These early policies, however, had significant limitations. First, deductions applied only to investments in small and medium-sized high-tech enterprises—a narrow category with stringent qualification requirements that excluded most seed- and early-stage startups. Second, only corporate-form funds qualified for benefits. Limited partnerships, which dominate the VC market, and their partners remained ineligible. Angel investors were also excluded. These restrictions severely limited policy effectiveness.

The Ministry of Finance and the State Administration of Taxation addressed these limitations in May 2018 with Circular No. 55 [2018], the Notice on Tax Policies for VCs and Angel Investors. Implemented nationwide, this policy introduced three key advances. First, it redefined the target from small and medium-sized high-tech enterprises to early-stage technology startups, using criteria that covered younger firms with smaller asset bases. Second, it expanded eligibility to three investor types: corporate VC enterprises, limited partnership VC enterprises, and individual angel investors. Third, it linked tax benefits explicitly to firm survival. Qualifying investors can deduct 70% of their investment from taxable income after holding equity in early-stage technology startups for at least 24 months.

Circular No.55 [2018] creates a compelling quasi-natural experiment for identifying causal effects. The policy defines early-stage technology startups using five criteria listed in Table 1. Of these, one stands out for identification purposes: startups must be no more than five years (60 months) old.

Firm age is exogenous. Unlike assets, revenues, employees, or R&D spending—all of which firms can manipulate—age advances mechanically from the registration date.

Table 1: Eligibility Criteria for Qualified Startups

Criterion	Requirements
Registration	Registered resident enterprise in mainland China
Size Thresholds	• Employees ≤ 200 • Bachelor's degree holders $\geq 30\%$ • Total assets $\leq$ RMB 30 million • Annual revenue $\leq$ RMB 30 million
Age Threshold	Age ≤ 5 years (60 months)
Listing Status	Unlisted during investment and subsequent 2-year period
R&D Intensity	R&D / Total Costs $\geq 20\%$

Notes: This table presents the eligibility criteria for qualified startups under China's Circular No.55 [2018], which provides tax incentives for venture capital investments.

Neither firms nor investors can alter it. The 60-month cutoff therefore creates a sharp, non-manipulable discontinuity that enables clean identification of the tax policy's causal effect on investment decisions. Discontinuous changes in investment behavior around this threshold can be attributed to investors' strategic responses to tax incentives.

More importantly, the policy's 70% deduction depends on firm survival: portfolio companies must survive 24 months. Combining an exogenous age threshold (60 months) with a survival-dependent holding period (24 months) generates this study's central insight. The expected after-tax return from investing in a 59-month-old qualifying startup substantially exceeds that from investing in a one-month-old qualifying startup, because the older firm has a much higher probability of surviving the 24-month holding period. What appears to be uniform treatment thus creates an age gradient in effective tax incentives within the 0-60 month eligibility window, driven entirely by age-related differences in survival probability.

This institutional design directly motivates our research question. It explains why we observe bunching near the 60-month threshold and provides the foundation for our Section 4 model of how tax incentives crowd out investment in the youngest startups. Exploiting this unique policy structure, we quantify how age-based survival differentials reshape VC allocation.

2.2 Data

This section describes our data and sample construction. To comprehensively examine how tax incentives affect VC investment and startup outcomes, we integrate four independent data sources, each serving a distinct analytical purpose.

VC Transaction Data. Our primary dataset comes from CVSource database and the Private Equity Database (www.pedata.cn), the two most comprehensive commercial databases covering China's VC market. We collect VC deals in mainland China from

2010 to 2022. Each transaction record contains the portfolio company name, investor name, investment amount, transaction date, and financing round. The initial dataset includes over 100,000 transactions before cleaning.

Firm Registration Data. To construct our key independent variable—firm age at investment—we obtain firm registration data from the National Enterprise Credit Information Publicity System (NECIPS), maintained by the State Administration for Market Regulation. This official administrative database covers all registered firms in China, providing full legal names, unified social credit codes, establishment dates, registered capital, addresses, industry codes, and operating status. Critically, the comprehensive coverage of this database enables us to precisely measure firm age, which is essential for our identification strategy.

Patent Data. To assess innovation outcomes, we obtain patent data from the China National Intellectual Property Administration (CNIPA), collecting all patent applications and grants from 2015 to 2024. This yields approximately 450,000 patent records. We further acquire citation data from Google Patents to construct quality measures. Due to name variations and organizational changes, matching patent applicant names to firm names requires substantial manual verification.

Job Posting Data. Finally, to measure human capital investment, we obtain job posting data from Zhaopin.com, one of China's largest recruitment platforms. Our sample covers full-time postings from 2022 to 2024. Each record includes job title, location, salary range, and education requirements, directly capturing firms' talent acquisition strategies and human capital intensity.

Having assembled these datasets, we proceed to construct our analysis sample through careful matching and screening. Our identification strategy requires precise measurement of firm age at investment. We match VC transactions to firm registration records using exact legal names. Given that Chinese firm names often contain special characters, abbreviations, and legal form suffixes, careful standardization is necessary. Through this process, we successfully match 71,844 transactions to registration records.

We construct our analysis sample following three criteria. First, we focus on the period from 2015 to 2022. Since Circular No. 55 [2018] took effect in July 2018, we define 2015-2017 as the pre-policy period and 2019-2022 as the post-policy period, ensuring sufficient observations before and after policy implementation. Second, we exclude cross-border transactions to isolate domestic policy effects. Third, we exclude firms with missing data or cancelled/revoked status.

This process yields a final sample of 71,844 deals involving 20,492 portfolio companies and 22,155 investors. Crucially, we measure firm age in months as the difference between the deal date and the establishment date. This measure is exogenous—firms cannot manipulate establishment dates and investors cannot alter time.

Beyond VC transactions, our real effects analysis requires matching these firms to

outcome data. To test whether the policy improves resource allocation, we link VC-backed firms to job postings on Zhaopin.com. The recruitment data span 2022 to 2024, covering the post-policy period when effects should materialize. We retain full-time positions and exclude part-time or internship postings, ultimately linking 1,582 firms to 48,813 job postings. Key variables include minimum salary, maximum salary, and education requirements, which collectively measure firms' talent acquisition strategies and human capital intensity.

Similarly, for innovation outcomes, we match VC-backed firms to CNIPA patent records. Because patent applicant names often differ from legal names due to abbreviations or organizational changes, we use fuzzy matching combined with manual verification. This approach allows us to match 29,396 firms to their patents from 2015 to 2024, yielding approximately 450,000 patents. We then aggregate to the firm-year level, creating a balanced panel of 293,960 observations. Our measures include patent counts, forward citations, and technology breadth.

To provide context for our subsequent analysis, Table 2 presents summary statistics by policy period, documenting both the characteristics of VC transactions and the outcomes we examine. Panel A reveals important shifts in deal characteristics surrounding the policy change. Pre-policy, average firm age was 63.9 months and 60.8% of deals involved firms under 60 months old. Post-policy, average age rose to 73.7 months and the qualifying share fell to 55.4%. More striking, however, is the reallocation of capital. Despite fewer qualifying deals, investment in eligible firms increased dramatically: average deal size for firms under 60 months jumped from RMB 0.056 billion to RMB 0.141 billion (152% increase). This pattern—fewer eligible deals but larger investments—previews the strategic reallocation we document in Section 3.

Turning to human capital outcomes, Panel C shows recruitment patterns for the subset of firms we successfully match to job posting data. Average log salaries range from 8.96 to 9.42, corresponding to approximately RMB 7,800-12,300 per month. Notably, more than 33% of postings require bachelor's degrees or higher, substantially exceeding national averages.[4] This skill intensity reflects the high-tech nature of VC-backed firms and provides meaningful variation for our human capital analysis in Section 5.

Finally, Panel D shows innovation activity as measured by patent filings. Patent counts are highly right-skewed; the median and 75th percentile are both zero. While this may seem concerning, such concentration in a small subset of high-growth startups is typical in innovation studies (Hsu et al., 2024) and reflects the reality that most startups do not patent while a few innovate intensively. Citation and breadth measures show similar patterns, indicating that innovation outcomes exhibit considerable heterogeneity across firms—heterogeneity we exploit when examining treatment effects.

[4]The 2023 China Population and Employment Statistical Yearbook reveals key findings from the 2022 labor force survey: 24.1% of China's employed population had received higher education.

Table 2: Descriptive Statistics

	Obs.	Mean	SD	Min	P25	Med.	P75	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: VC Investments Pre-Policy Period (2015-2017)								
FirmAge(months)	38,487	63.911	64.109	0.000	15.000	39.000	100.000	484.000
VCInvest(billion RMB)	38,487	0.141	0.410	0.001	0.010	0.050	0.100	3.239
RegCap (billion RMB)	38,487	0.218	0.779	0.000	0.009	0.035	0.107	6.335
Eligible Firm (Age$\leq$ 60)	38,487	0.608	0.488	0.000	0.000	1.000	1.000	1.000
InvestYoung (billion RMB)	38,487	0.056	0.175	0.000	0.000	0.005	0.050	1.400
Panel B: VC Investments Post-Policy Period (2019-2022)								
FirmAge (months)	33,357	73.733	62.452	0.000	31.000	54.000	98.000	472.000
VCInvest(billion RMB)	33,357	0.271	0.540	0.001	0.050	0.100	0.300	3.542
RegCap(billion RMB)	33,357	0.149	0.525	0.001	0.007	0.019	0.070	4.000
Eligible Firm(Age$\leq$ 60)	33,357	0.554	0.497	0.000	0.000	1.000	1.000	1.000
InvestYoung(billion RMB)	33,357	0.141	0.423	0.000	0.000	0.010	0.100	3.300
Panel C: Job Postings by VC-Backed Firms (2022-2024)								
Salary (Lower Bound)	48,813	8.930	0.473	6.908	8.700	8.854	9.210	12.388
Salary (Upper Bound)	48,813	9.403	0.489	7.601	8.987	9.393	9.616	12.429
Education	48,813	0.333	0.471	0.000	0.000	0.000	1.000	1.000
Panel D: VC-Backed Firm Patenting Data (2015-2024)								
PatentNum	293,960	0.219	0.684	0.000	0.000	0.000	0.000	8.625
Citation	293,960	0.032	0.231	0.000	0.000	0.000	0.000	6.198
PatentWidth	293,960	0.059	0.202	0.000	0.000	0.000	0.000	0.987

Notes: This table reports descriptive statistics for the main analysis samples. Panels A and B present deal-level characteristics of venture capital investments in the pre-policy period (2015-2017) and post-policy period (2019-2022), respectively. The unit of observation is a VC investment transaction. *FirmAge* is the age of the portfolio firm in months at the time of investment. *VCInvest* is the investment amount in billion RMB. *RegCap* is the firm's registered capital in billion RMB. *Eligible Firm* is an indicator variable equal to one if the firm is younger than 60 months at the time of investment, and zero otherwise. *InvestYoung* is the total investment amount in billion RMB directed to firms younger than 60 months. Panel C presents job-level recruitment data from VC-backed firms during 2022-2024. The unit of observation is a job posting. *Salary Lower Bound* and *Salary Upper Bound* are the natural logarithms of the lower and upper bounds of the advertised monthly salary. *Education* is an indicator variable equal to one if the position requires a bachelor's degree or above, and zero otherwise. Panel D presents innovation outcomes for VC-backed firms from 2015 to 2024, matched with patent data and aggregated at the firm-year level. *PatentNum* is the natural logarithm of one plus the number of patent applications. *Citation* is the natural logarithm of one plus the total forward citations received by the firm's patents. *PatentWidth* measures the breadth of the firm's technological knowledge, calculated as a diversity index based on the distribution of the firm's patents across IPC technology classes, with values ranging from 0 to 1.

3 Empirical Facts of VC Responses to Tax Notches

3.1 Bunching at Threshold but Crowding out of the Youngest

We begin by examining how the firm age distribution changed after policy implementation. This provides direct evidence of tax incentive effects.

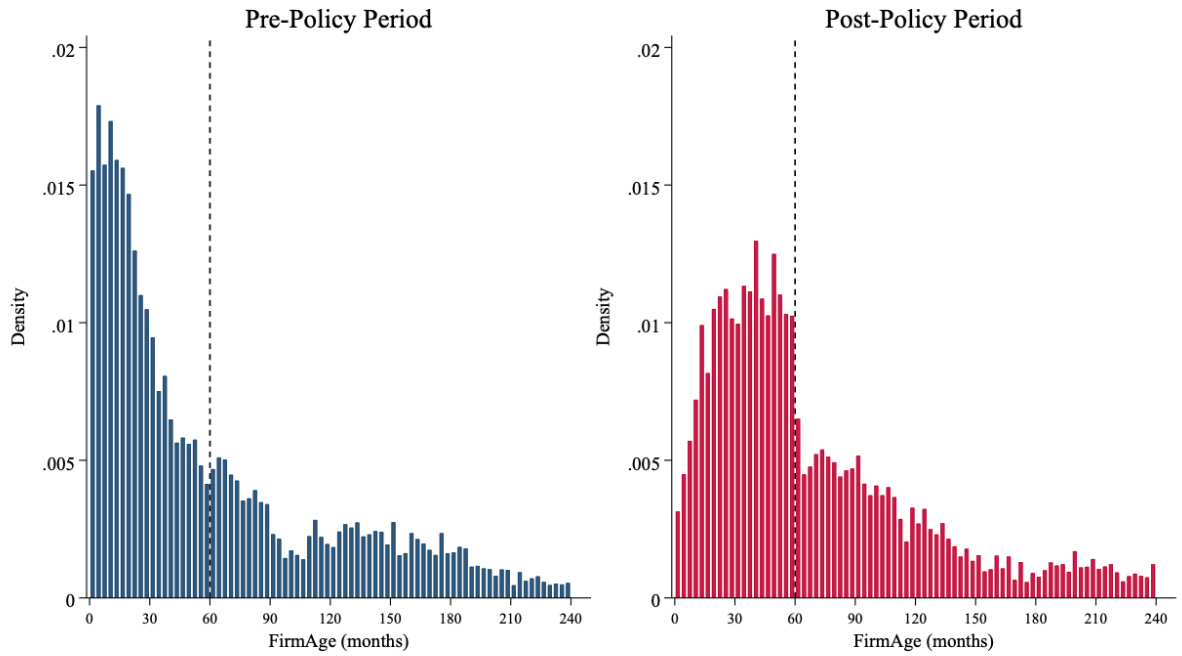


Figure 1: Firm Age Distribution (Before and After 2018 Tax Incentive Policy)

Notes: This figure plots histograms of the age distribution of firms receiving venture capital investment. The unit of observation is a VC-firm investment deal. The left panel shows the distribution for the pre-policy period (2015-2017), and the right panel shows the distribution for the post-policy period (2019-2022). The horizontal axis represents the firm's age in months at the time of investment, grouped into 3-month bins. The vertical axis represents the density of all deals within each age bin. The vertical dashed line indicates the 60-month age threshold.

Figure 1 plots the age distribution of VC-backed startups before and after the policy. Pre-policy, the distribution is smooth and decreasing, consistent with VCs' well-known preference for younger firms. Critically, no discontinuity exists at 60 months. Absent the tax incentive, this age cutoff holds no special significance. Post-policy, the distribution transforms. A sharp spike emerges just below 60 months, while deal frequency drops just above it. This bunching is precisely what we would expect if VCs respond strategically to the tax deduction. To qualify for the 70% deduction, investors prioritize firms near the cutoff or accelerate negotiations to close deals before firms age out of eligibility.

Figure 2 overlays both distributions to highlight the contrast. Two patterns stand out. Bunching is evident at the threshold—a pronounced peak appears below 60 months post-policy, whereas the pre-policy distribution crosses this point smoothly. Equally important, investment density in the 0-30 month range falls in the post-policy period. This suggests capital is reallocated away from the youngest, riskiest startups toward older

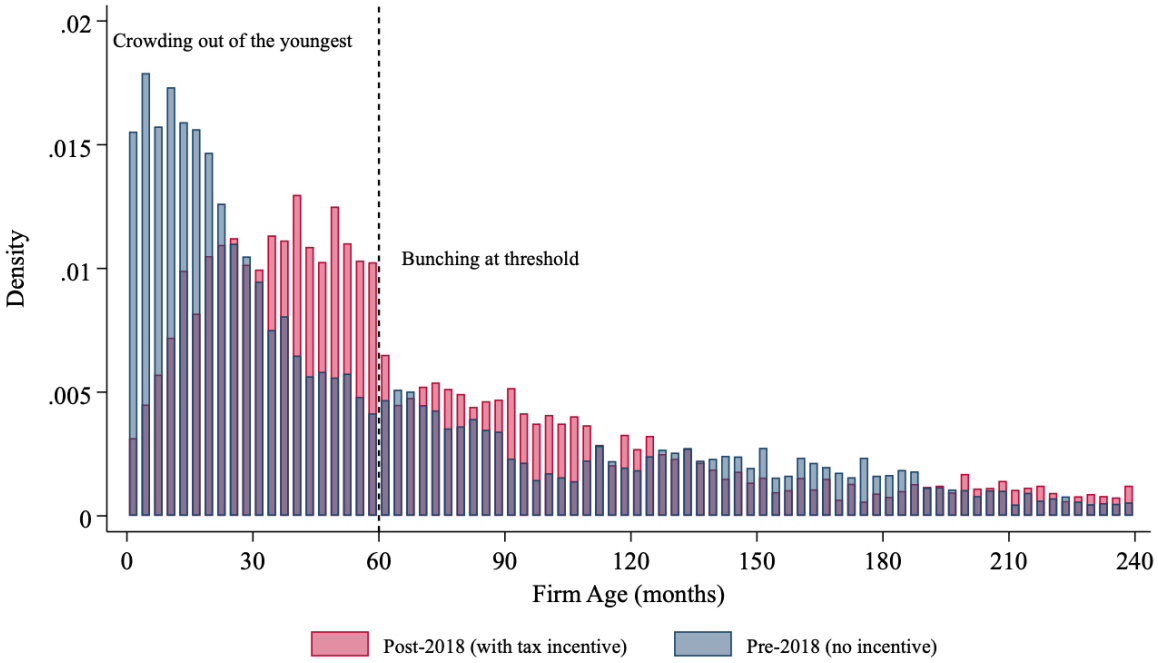


Figure 2: Policy-Induced Distortion in Firm Age Distribution

Notes: This figure overlays the age distributions of firms receiving venture capital investment in the pre-policy period (2015-2017) and post-policy period (2019-2022). The unit of observation is a VC-firm investment deal. The horizontal axis represents the firm's age in months at the time of investment, grouped into 3-month bins. The vertical axis represents the density of all deals within each age bin. The vertical dashed line indicates the 60-month age threshold. The overlapping visualization reveals two distinct policy-induced distortions: (1) a pronounced bunching of investments immediately below the threshold in the post-policy period, and (2) a relative decrease in the density of investments in the youngest firms.

firms closer to the threshold. Together, these patterns tell a coherent story. Bunching confirms that the tax incentive works—VCs clearly respond to it. But crowding out points to an unintended cost: the policy shifts capital toward relatively mature firms rather than supporting the earliest-stage ventures it ostensibly targets.

A natural concern is that the post-policy period (2019–2022) overlaps heavily with the COVID-19 pandemic, which disrupted financing conditions, firm survival, and industry structure in ways that could independently alter the observed firm age distribution. To address this, Figure 3 restricts the post-policy panel to 2019 alone, the first post-policy year and the last full year prior to the pandemic outbreak, serving as a pre-COVID placebo window. The bunching pattern below the 60-month threshold remains clearly visible in 2019 data, with investment density dropping sharply above the cutoff, mirroring the full post-policy pattern. This confirms that the distributional distortion emerges immediately upon policy introduction and cannot be attributed to pandemic-era disruptions. The core mechanism of VCs strategically concentrating investments below the tax eligibility threshold is already operative before COVID-19.

The distributional evidence in Figures 1 and 2 motivates our subsequent analysis. We next provide formal statistical tests and quantify these effects.

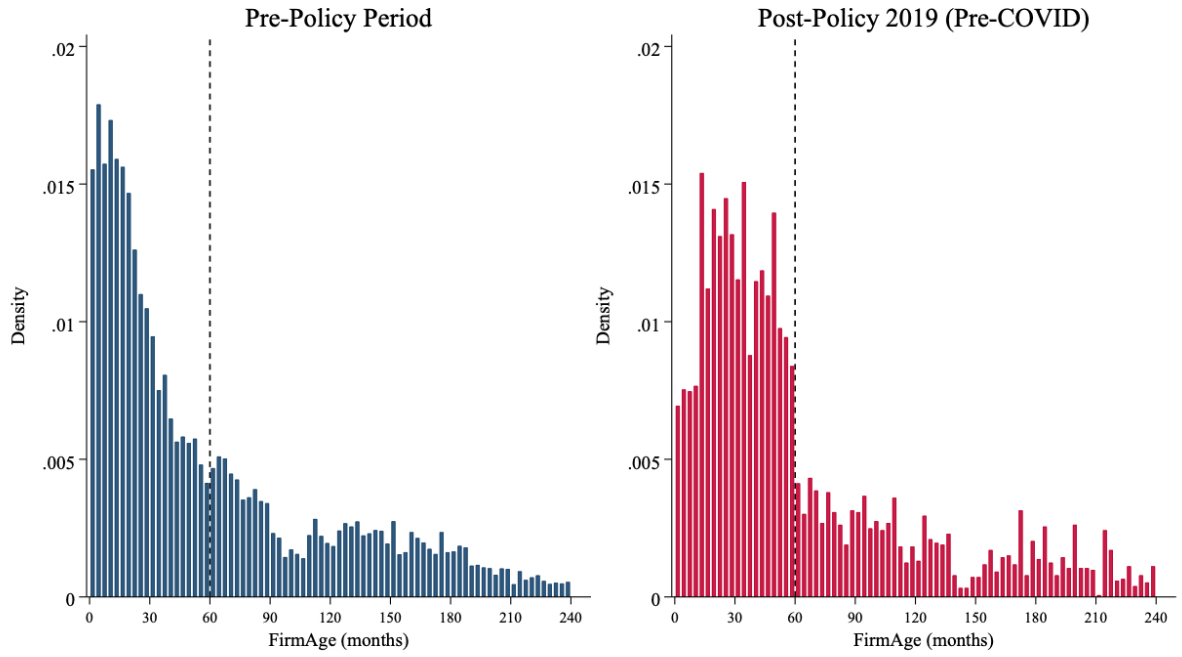


Figure 3: Firm Age Distribution: Pre-Policy Period vs. Post-Policy 2019 (Pre-COVID Placebo)

Notes: This figure plots histograms of the age distribution of firms receiving venture capital investment. The unit of observation is a VC-firm investment deal. The left panel shows the distribution for the pre-policy period (2015–2017), and the right panel shows the distribution for 2019 only—the first post-policy year and, crucially, the final year prior to the COVID-19 outbreak—serving as a pre-pandemic placebo window. The horizontal axis represents the firm's age in months at the time of investment, grouped into 3-month bins. The vertical axis represents the density of all deals within each age bin. The vertical dashed line indicates the 60-month age threshold.

3.2 Bunching Estimation

Section 3.1 documents substantial distortions in the investment distribution at the 60-month threshold. We now formally test and quantify these patterns.

3.2.1 Methodology

We apply the bunching estimation framework of Kleven (2016) and Kleven and Waseem (2013). This approach hinges on constructing a counterfactual by estimating the smooth shape of the investment distribution that would prevail without tax incentives. By comparing this counterfactual benchmark to the observed distribution, the resulting difference reveals the policy-induced behavioral distortions.

We begin by dividing firm age into equal-width bins of h months. To construct the counterfactual, we estimate the following polynomial model:

$$c_j = \sum_{k=0}^{p} \beta_k d_j^k + \sum_{i=d_L}^{d_U} \gamma_1 \mathbb{1}\left[d_j = i\right] + \varepsilon_j \tag{1}$$

where c_j denotes the density of VC investments in bin j at firm age d_j. The first term—a p-th order polynomial—captures the smooth trend in investment density across firm ages without policy intervention. The second term comprises dummy variables $\mathbb{1}[d_j = i]$ for bins within the manipulation region $[d_L, d_U]$, which capture local deviations from trend.

The counterfactual construction requires excluding the manipulation region from estimation. We fit equation (1) using only bins outside $[d_L, d_U]$, preventing strategic bunching from contaminating the trend estimate. The counterfactual density is then:

$$\hat{c}_j^{CF} = \sum_{k=0}^{p} \beta_k d_j^k \tag{2}$$

Two parameters require calibration: polynomial order p and manipulation bounds $[d_L, d_U]$. Following Bachas et al. (2021), we select both using data-driven methods. For polynomial order, we apply K-fold cross-validation, choosing $p \in [2, 8]$ to minimize out-of-sample mean squared error. For the manipulation region, we employ a grid search algorithm that identifies the interval simultaneously minimizing polynomial fit error outside the region and satisfying the integration constraint (excess mass equals missing mass) within it.

Our bunching estimator is:

$$b = \frac{\sum_{j=d_L}^{d^*} \left(c_j - \hat{c}_j^{CF}\right)}{c_{d^*}^{CF} h} \tag{3}$$

The numerator sums excess mass to the left of threshold d^*—observed investments minus counterfactual predictions. The denominator normalizes by counterfactual density $\hat{c}_{d^*}^{CF}$ and bin width h. Thus b measures the proportional increase in investment just below the eligibility cutoff. To ensure reliable statistical inference, we use 500 Bootstrap resamples, which generate the standard errors and confidence intervals for all estimators. We then apply the Wald test to assess the statistical significance.

3.2.2 Results

Figure 4 presents the core bunching results. The left panel plots the pre-policy distribution (2015-2017). The empirical and counterfactual distributions overlap closely, with a bunching estimate of -0.603 and statistically insignificant. This confirms no pre-existing distortion at the age threshold.

The right panel plots the post-policy distribution (2019-2022). A sharp spike emerges just below 60 months. The bunching estimate is 1.323, significant at the 1% level. Relative to the counterfactual, 132% excess investment now concentrates below the threshold. Tax incentives clearly induce strategic retiming.

Table 3 tests robustness across bin widths. Panel A reports pre-policy estimates

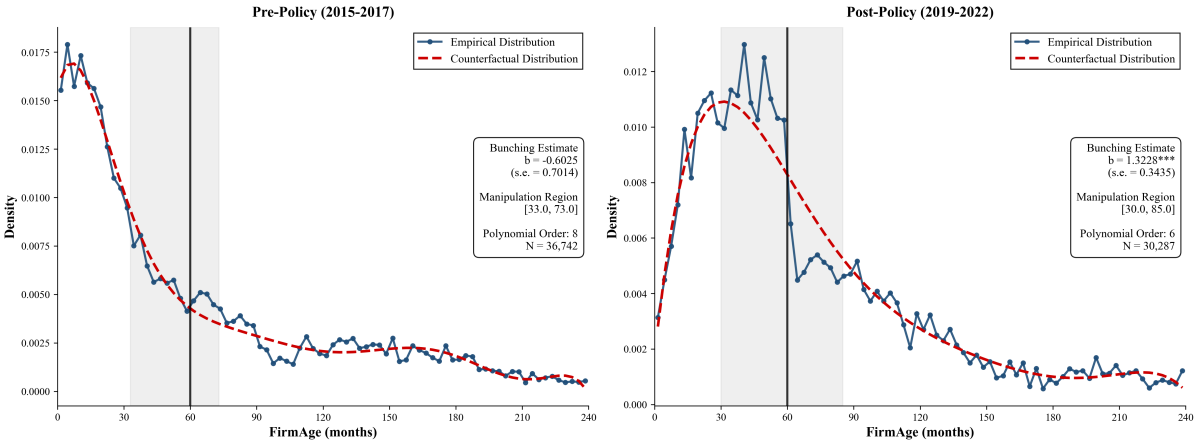


Figure 4: Bunching Evidence at the 60-Month Age Threshold

Notes: This figure presents bunching estimates at the 60-month age threshold for the pre-policy period (2015-2017) and post-policy period (2019-2022). The unit of observation is a VC investment transaction. The horizontal axis represents firm age in months at the time of investment, grouped into 3-month bins. The vertical axis shows the density of investment transactions. The solid blue line plots the empirical distribution, and the dashed red line shows the estimated counterfactual distribution constructed by fitting a polynomial to the data outside the manipulation region. Gray shaded areas indicate the estimated manipulation regions. The bunching estimate b, standard error, manipulation region boundaries, and polynomial order are reported in each panel.

Table 3: Bunching Estimates

Bin	Bunching (b)	Std. Error	Manipulation Region	Polynomial Order	Excess Mass	Missing Mass	N
Panel A: Pre-Policy Period (2015–2017)							
1	-3.110	2.058	[30, 70]	8	-0.014	-0.010	36,742
2	-1.274	0.995	[33, 70]	8	-0.006	-0.005	36,742
3	-0.603	0.701	[33, 73]	8	-0.003	-0.004	36,742
5	-0.015	0.039	[54, 64]	8	-0.000	-0.001	36,742
6	-0.103	0.176	[42, 64]	8	-0.000	-0.001	36,742
Panel B: Post-Policy Period (2019–2022)							
1	4.713***	1.019	[39, 88]	8	0.038	0.032	30,287
2	2.357*	0.930	[30, 85]	8	0.019	0.016	30,287
3	1.323***	0.343	[30, 85]	6	0.011	0.013	30,287
5	0.893*	0.434	[30, 85]	8	0.007	0.006	30,287
6	0.706***	0.102	[36, 82]	6	0.006	0.006	30,287

Notes: This table reports bunching estimates under five alternative bin widths. The bunching parameter b measures the excess mass at the threshold relative to the average counterfactual density, normalized by bin width. Standard errors are computed using the bootstrap method with 500 replications. *Manipulation Region* indicates the range of firm age (in months) around the 60-month eligibility threshold where bunching is detected. *Polynomial Order* specifies the order of the polynomial used to fit the counterfactual density. *Excess Mass* is the total density above the counterfactual within the manipulation region. *Missing Mass* is the total density below the counterfactual within the manipulation region. Panel A presents estimates for the pre-policy period (2015–2017), when the tax incentive policy was not yet implemented. Panel B presents estimates for the post-policy period (2019–2022), following the implementation of Circular [2018] No. 55. The sample includes all VC investment transactions during these periods. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

(2015-2017). All five specifications yield negative, insignificant coefficients, confirming distributional smoothness. Panel B reports post-policy estimates (2019-2022). Bunching is positive and significant across all bin widths, ranging from 4.713 to 0.706. The declining

pattern reflects a mechanical property: finer bins capture sharper peaks. Taken together, the results demonstrate policy-induced bunching. To obtain the 70% deduction, investors concentrate investments just below the eligibility cutoff. This response is both statistically robust and economically meaningful.

3.3 Investment Size and Capital Reallocation

Tax incentives change the relative attractiveness of firms at different ages, leading to capital reallocation. We examine this reallocation with the following regression:

$$Y_{ijt} = \beta_k \sum_{k=1,k\neq 5}^{10} (Bin_{k,ij} \times Post_t) + \theta \times Age \leq 60_{ij} + FEs + \varepsilon_{ijt} \tag{4}$$

where i, j, and t index firms, VCs, and years. The dependent variable is log investment amount. We group firms into age bins based on years since establishment. The 5-year bin is the baseline group. We estimate coefficients β_k for each age bin interacted with $Post_t$, which equals one after the policy. $Age \leq 60_{ij}$ equals one for firms under 60 months old. We include firm, VC, and year fixed effects to control for time-invariant characteristics.

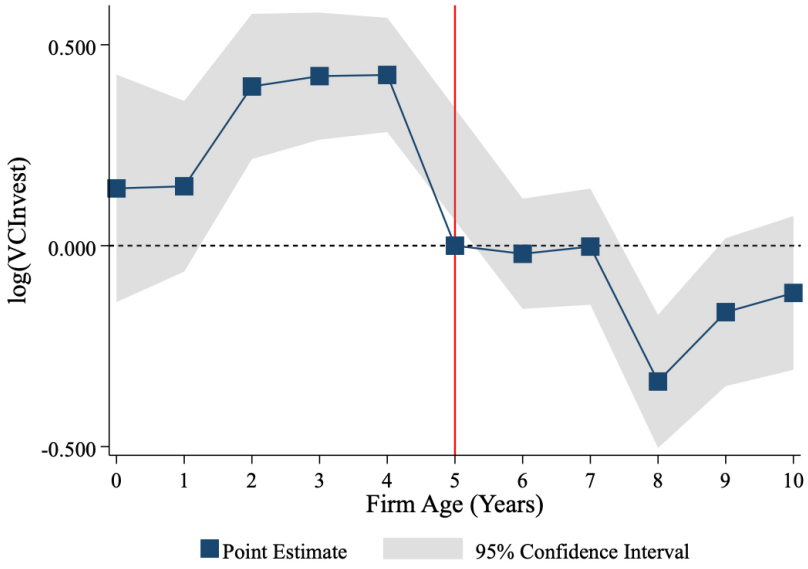


Figure 5: Venture Capital Investment Allocation under Tax Incentives

Notes: This figure plots the estimated coefficients β_k from the regression specification (4). The vertical axis shows the policy effect on the log of VC investment amount. Blue squares represent point estimates, and the gray shaded area depicts the 95% confidence interval based on standard errors clustered at the firm level. The specification includes firm fixed effects, VC fixed effects, and year fixed effects.

Figure 5 plots the β_k coefficients. For ages 2-4 (24-60 months), point estimates range from 0.142 to 0.425. The 95% confidence intervals exclude zero. Investment increased by

14%-43% for firms in this range. The tax incentive substantially raised funding for firms near the threshold. In contrast, investment in the youngest firms (ages 0-24 months) did not increase significantly.

Crucially, the policy exhibits negative effects on firms just beyond the eligibility cutoff. For ages 7–8 (84–96 months), the point estimates are negative. At age 8, the coefficient is -0.338 and statistically significant, suggesting a 34% decline in funding. This suggests VCs facing capital constraints strategically shifted funding away from older, newly ineligible firms toward younger firms that still qualify for the deduction.

These patterns show strategic reallocation rather than a uniform increase in early-stage investment. VCs move capital from firms that just lost eligibility toward firms where tax benefits are largest. This confirms the policy works but also shows it reshapes portfolio composition.

4 Why Do Tax Incentives Crowd Out the Youngest Firms

Section 3 documents an unintended consequence of the tax policy: investment decreases for the youngest startups (0-12 months old) but increases significantly for startups nearing the 60-month age threshold. This section develops a theoretical framework to explain this phenomenon.

The core insight is that the tax incentive imposes two conditions on investors. Eligibility requires that startup age not exceed 60 months, but claiming the benefit also requires that the startup survives the 24-month holding period. Because VCs hold diversified portfolios, they can use deductions from qualifying investments to offset portfolio-wide taxable income. If a portfolio startup exits before satisfying the holding requirement, however, the associated tax benefit is forfeited entirely.

This survival constraint generates an age gradient in effective incentives. Since startup exit risk declines with age (Adelino et al., 2017), younger startups are substantially less likely to survive the holding period. The effective tax incentive—defined as the expected deduction conditional on survival—is therefore lower for young startups than for startups approaching the eligibility threshold.

To quantify this mechanism, we develop and calibrate a model of VC portfolio choice under heterogeneous survival risk. Counterfactual simulations reveal that the survival constraint crowds out 5.15% of investment in startups aged 0-30 months.

4.1 Theoretical Framework

4.1.1 Environment and Firm Dynamics

We consider a discrete-time economy, indexed by time periods $t = 0, 1, 2, \ldots$. Startups are characterized by age $a \in [0, \bar{a}]$ measured in months and observable quality φ, drawn from a distribution $G(\varphi)$. The state of each startup evolves according to $s_t \in \{\text{Active, Exit}\}$, where Exit denotes bankruptcy, acquisition, or liquidation.

The framework focuses on age-dependent survival probabilities. Following the empirical literature on firm dynamics (Ericson and Pakes, 1995; Sedláček and Sterk, 2017), we specify the exit hazard rate for a startup moving from age a to age $a + 1$ as:

$$\lambda(a) = \lambda_0 \exp(-\gamma a) \tag{5}$$

Where, the baseline exit rate parameter $\lambda_0 > 0$ captures the inherent risk faced by startups. The age effect parameter $\gamma > 0$ reflects the speed at which the firm's exit rate declines with age. Importantly, this decline reflects the improvement in survival capability achieved through accumulated experience, built customer relationships, and refined business models during the growth process.

The key metric for VCs is whether a startup survives the mandated holding period. Let H denote this period in months. The cumulative hazard from age a to $a + H$ is:

$$\chi(a, a + H) = \int_a^{a+H} \lambda(t)\, dt \tag{6}$$

The survival probability, $S(a, H)$ is then given by:

$$S(a, a + H) = exp(-\chi) = \exp\left(-(\lambda_0/\gamma)\left[e^{-\gamma a} - e^{-\gamma(a+H)}\right]\right) \tag{7}$$

Crucially, survival probability is increasing in initial age: $\partial S/\partial a > 0$. Older startups are more likely to survive the holding period, having weathered the high-risk early years. This monotonic relationship between investment age and survival underpins our tax incentive mechanism.

4.1.2 Venture Capital Investment

Consider an economy with a continuum of heterogeneous VCs indexed by $i \in [0, 1]$. Each VC manages capital K_i and allocates it across investment opportunities every period. VCs face a capital constraint: total investment in any period t cannot exceed available capital.

In the baseline scenario without tax policy, the value function for a VC firm investing amount I in a firm of age a and characteristics (φ) is given by:

$$V^0(a, \varphi; I) = \mathbb{E}[R] \cdot I \cdot (1 - \tau_c) - C(I, a) \tag{8}$$

where $\mathbb{E}$ denotes the expected return and τ_c denotes the corporate income tax rate. Investment costs include the opportunity cost of capital as well as substantial due diligence, post-investment management, and monitoring expenses. Young startups typically lack established financial records, standardized operations, and proven business models, which requires VCs to invest additional resources in information gathering and risk assessment. We model the investment cost function as:

$$C(I, a) = [c_0 + c_1 \cdot \exp(-\delta \cdot a)] \cdot I \tag{9}$$

With tax incentives, the value function is modified. The policy permits VCs to deduct a fraction Φ of their investment from taxable income if two conditions are satisfied: the startup's age does not exceed threshold a^*, and the VC holds the investment for H months. Critically, this tax benefit is contingent on an implicit survival constraint—the deduction is realized only if the startup survives the holding period. The value function becomes:

$$V^1(a, \phi) = V^0 + \text{ TaxBenefit}(a, I) \tag{10}$$

We specify the tax benefit function to explicitly capture this survival contingency. The expected tax deduction is:

$$\text{TaxBenefit}(a, I) = \mathbb{1}\{a \leq a^*\} \cdot S\{a, a + H\} \cdot \Phi \cdot I \tag{11}$$

where $\mathbb{1}\{a \leq a^*\}$ is the indicator function for the age qualification criterion.

4.2 The Crowding Out Mechanism

4.2.1 Age Gradient in Marginal Value

The tax policy changes the marginal value structure across startup ages. We show how this creates a wedge between young and near-threshold startups.

Consider two startup types: young startups with investment age a^y and near-threshold startups with age a^o, where $0 < a^y < a^o < a^*$. For clarity, assume both types have identical quality ϕ. Without tax incentives, the marginal values are:

$$\frac{V(a^y)}{I} = \mathbb{E}[R] \cdot (1 - \tau_c) - [c_0 - c_1 \cdot exp(-\delta \cdot a^y)] \tag{12}$$

$$\frac{V(a^o)}{I} = \mathbb{E}[R] \cdot (1 - \tau_c) - [c_0 - c_1 \cdot exp(-\delta \cdot a^o)] \tag{13}$$

With the policy, the marginal value function changes in two ways. Tax incentives add marginal benefits for eligible startups, and because $S(a, H)$ increases with age, this benefit varies across ages:

$$\Delta \frac{V\left(a^{o}\right)}{I} = S\left(a^{o}, a^{o}+H\right) \cdot \Phi \tag{14}$$

$$\Delta \frac{V\left(a^{y}\right)}{I} = S\left(a^{y}, a^{y}+H\right) \cdot \Phi \tag{15}$$

Note that the difference in marginal value increments is:

$$\Delta^{policy}\left(a^{o}\right) - \Delta^{policy}\left(a^{y}\right) = \left[S\left(a^{o}, a^{o}+H\right) - S\left(a^{y}, a^{y}+H\right)\right] \cdot \Phi > 0 \tag{16}$$

Since $\partial S/\partial a > 0$ and $a^{o} > a^{y}$, this expression is strictly positive. Although the policy treats all eligible startups equally, the survival constraint makes near-threshold startups gain more in marginal value than young startups.

4.2.2 Portfolio Reallocation under Capital Constraints

Capital scarcity forces VCs to reallocate investments across ages. We model the VC portfolio as a continuous age distribution with density $f_i(a)$. This density function denotes the portfolio weight of age-a firms for VC firm i, subject to the normalization constraint:

$$\sum_{0}^{a} f_i\left(a\right) da = 1 \tag{17}$$

Portfolio adjustment is costly. Finding targets requires due diligence, exiting positions incurs transaction costs, and reorganizing takes time. We introduce adjustment cost κ and let $\mathbf{f_0}(\mathbf{a})$ denote the pre-policy investment density. The VC firm's portfolio optimization problem is:

$$\max_{f^{1}(a)} \int_{0}^{\bar{a}} \left[V^{1}(a) \cdot f^{1}(a) - \frac{\kappa}{2}\left(f^{1}(a) - f^{0}(a)\right)^{2}\right] da \tag{18}$$

where $V^{1}\left(a\right) = V^{0}\left(a\right) + \Delta^{policy}\left(a\right)$ is the post-policy marginal value and $\Delta^{policy}\left(a\right) = \mathbb{1}\{a \leq a^{*}\} \cdot S\{a, a+H\} \cdot \Phi$ is the effective tax incentive. The first-order condition yields the reallocation response (Appendix A):

Proposition 1 (Portfolio Reallocation): The post-policy investment density satisfies:

$$f^{1}\left(a\right) = f^{0}\left(a\right) \cdot \exp\left(\left[\frac{1}{\kappa} \cdot \left(\Delta^{policy}\left(a\right) - \bar{\Delta}^{policy}\right)\right]\right) \tag{19}$$

where $\bar{\Delta}^{policy} = \frac{1}{a}\sum_{0}^{a} \Delta^{policy}\left(a\right) da$ is the mean effective incentive and $\frac{1}{\kappa}$ is the investment elasticity.

This expression shows that changes in density are proportional to deviations from the

mean incentive, $\Delta^{policy}(a) - \bar{\Delta}^{policy}$. Startups with above-mean incentives attract capital inflows; those with below-mean incentives experience outflows. Since total investment is fixed, gains in some age groups require losses in others.

The magnitude of reallocation depends on adjustment costs. Lower κ implies more aggressive reallocation, while higher κ dampens the response.

4.3 Quantitative analysis

4.3.1 Calibration and model fit

The model has ten parameters calibrated in two steps. In the first step, we set four parameters directly from policy documents: the tax deduction rate $\Phi = 0.7$, holding period $H = 24$ months, age threshold $a^* = 60$ months, and corporate tax rate $\tau_c = 0.25$. We also calibrate the cost parameters (c_0, c_1, δ) directly via nonlinear regression on pre-policy investment patterns across startup ages. This approach is appropriate because our mechanism focuses on survival risk rather than cost heterogeneity.

The second step estimates three core structural parameters: $\Theta \equiv \{\lambda_0, \gamma, \kappa\}$. The baseline exit intensity λ_0 captures exit risk for new startups. The age attenuation rate γ measures how quickly exit risk declines as startups age. The adjustment cost parameter κ governs portfolio rebalancing. A lower κ implies greater sensitivity of capital allocation to effective tax incentives. Together, these parameters determine the age gradient in survival probability and the investment redistribution induced by the policy.

Identification exploits three sets of moment conditions. The first set uses the age profile of 24-month survival probabilities to pin down (λ_0, γ). We compute survival rates from actual startup outcomes in the business registration database spanning ages 0-120 months at 6-month intervals. Because these moments reflect only the natural exit process, they identify the risk parameters independently of the policy.

The second set identifies κ from changes in the investment distribution across ages. We compare investment shares in the pre-policy (2015-2017) and post-policy (2019-2022) periods for startups aged 0-120 months.

The third set exploits post-policy investment densities across the same age range. These moments provide over-identifying restrictions that improve precision. They also ensure the model matches both the direction and magnitude of investment shifts.

We estimate parameters via simulated method of moments (SMM), which minimizes the weighted distance between simulated and empirical moments. Let m_{data} denote the empirical moments and $m_{model}(\Theta)$ the model-implied moments for parameter vector Θ. The SMM objective is:

$$Q(\Theta) = [m_{model}(\Theta) - m_{data}]' W [m_{model}(\Theta) - m_{data}] \tag{20}$$

Table 4: Parameters of the Model

	Parameter	Description	Equation	Identification	Value
1	H	Holding period (months)	(7)	Policy document	24
2	Φ	Tax credit rate	(11)	Policy document	0.70
3	τ	Corporate income tax rate	(8)	Policy document	0.25
4	a^*	Age threshold (months)	(11)	Policy document	60
5	c_0	Investment cost parameter	(9)	Nonlinear regression	0.300
6	c_1	Investment cost parameter	(9)	Nonlinear regression	0.412
7	δ	Investment cost parameter	(9)	Nonlinear regression	0.018
8	λ_0	Baseline exit intensity	(5)	Survival moments (SMM)	-
9	γ	Age decay rate	(5)	Survival moments(SMM)	-
10	κ	Portfolio adjustment cost	(19)	Investment distribution(SMM)	-

Notes: This table presents the 10 parameters of the structural model and their calibration strategy. Parameters 1-4 are set according to the policy document (National Tax Bureau Circular No. 18, 2018). Parameters 5-7, which govern investment costs, are calibrated to match the pre-policy age pattern of VC investment amounts using nonlinear regression. The baseline exit intensity (λ_0) and age decay rate (γ) jointly determine the survival probability gradient across firm ages. The adjustment cost parameter (κ) captures portfolio reallocation frictions.

where W is the weighting matrix. We follow a two-step procedure. Step one uses an identity matrix to obtain preliminary estimates. Step two re-estimates using an optimal weighting matrix constructed from first-step residuals, which yields asymptotically efficient estimates.

We compute standard errors via bootstrap with 500 replications. Each replication draws from the original sample with replacement, preserving the pre-post policy ratio. We then recompute moments and re-estimate parameters. This procedure accounts for both sampling uncertainty in the empirical moments and simulation error. Table 4 describes the parameters and calibration strategy.

Table 5 reports parameter estimates. The baseline exit intensity is $\lambda_0 = 0.054$. The attenuation rate is $\gamma = 0.011$, implying exit risk falls roughly 1% per month. This aligns with existing evidence that early-stage startups face elevated risk that diminishes with experience (Haltiwanger et al., 2013). The adjustment cost is $\kappa = 0.075$, indicating low frictions in portfolio rebalancing. All estimates are significant at the 1% level.

Table 5: Parameter Estimates from Simulated Method of Moments

	Baseline Exit Rate λ_0	Age Attenuation of Exit Risk γ	Portfolio Adjustment Cost κ
Estimate	0.054***	0.011***	0.075***
	(0.006)	(0.002)	(0.013)

Notes: This table presents parameter estimates from the Simulated Method of Moments (SMM). Standard errors are computed using 500 bootstrap replications and reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 6 shows the model fit for survival probabilities. Simulated rates track empirical rates closely, capturing the nonlinear rise in survival with age. At age 0, the 24-month survival rate is 32.2%; by age 54, it reaches 52.98%. This 20 percentage point gap underpins the age gradient in effective tax incentives.

Figure 7 shows investment distributions. Panel A plots post-policy densities by startup age. Panel B plots changes in density. The model replicates the key empiri-

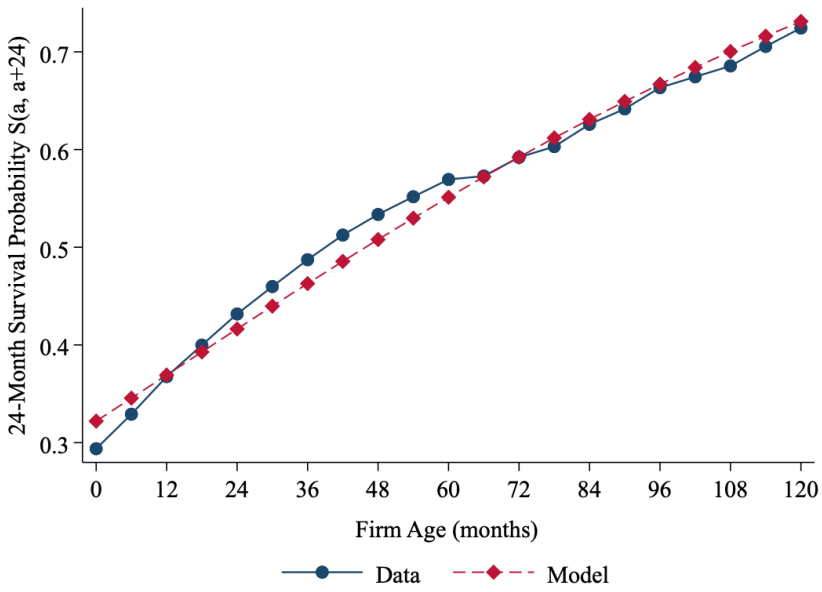


Figure 6: Distribution of 24-Month Survival Rate

Notes: This figure shows the model fit for 24-month survival probabilities. The horizontal axis measures startup age in months and the vertical axis measures the probability of surviving 24 months from the investment date. The sample covers ages 0-120 months at 6-month intervals. Empirical survival rates are computed from the business registration database tracking actual firm survival status. The solid line with circles shows the data and the dashed line with diamonds shows model predictions.

cal patterns: density falls for young startups (0-24 months) and rises for startups near the 60-month threshold (48-60 months). Bunching is most pronounced at ages 54-60, where density increases by roughly 5 percentage points. This close match validates the portfolio rebalancing mechanism.

4.3.2 Simulation

We use the calibrated parameters to conduct counterfactual simulations quantifying how the holding period and tax deduction rate affect investment allocation. These simulations identify the drivers of crowding out and provide quantitative guidance for policy design.

We first simulate how the age gradient in effective incentives drives investment reallocation (Figure 8). The 24-month survival probability $S(a, a+24)$ rises with startup age: from 32% at age 0 to 53% by age 54. Because effective incentives scale with survival probability, this survival gradient translates directly into an incentive gradient.

The deviation of effective incentives from the mean, $\Delta^{policy}(a) - \bar{\Delta}^{policy}$, governs reallocation. Young startups (0-24 months) receive below-mean incentives, reducing their investment share—the source of crowding out. Startups near the age threshold receive above-mean incentives, attracting capital inflows. The relative incentive crosses zero around month 24, marking the turning point for rebalancing. These patterns reveal the

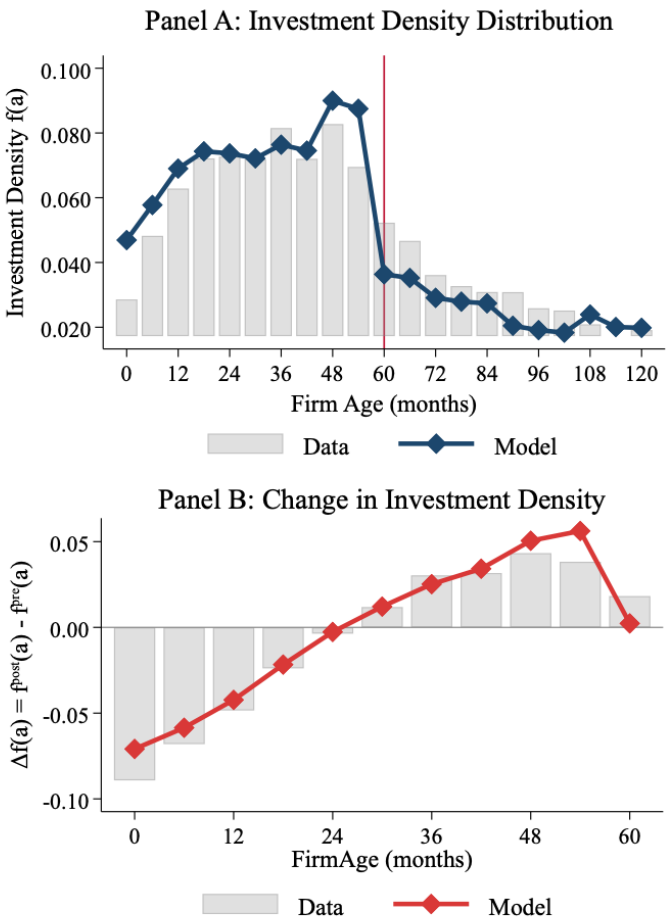


Figure 7: VC investment distributions

Notes: This figure shows changes in investment distribution following policy implementation. Panel A displays the post-policy density of VC investments across startup ages. Panel B plots the change in investment density, $\Delta f(a) = f^{post}(a) - f^{pre}(a)$, where $f^{post}(a)$ and $f^{pre}(a)$ denote post-policy and pre-policy densities. Bars represent empirical data and lines show model predictions. Negative values indicate crowding out, while positive values indicate bunching. The vertical dashed line marks the 60-month age threshold. The pre-policy period is 2015-2017 and the post-policy period is 2019-2022.

transmission mechanism. The survival constraint generates an age gradient in survival probability, which creates an incentive gradient. Survival risk heterogeneity then channels capital from high-risk young startups to low-risk older startups.

To isolate the survival constraint's role, we simulate a counterfactual without a holding period ($H = 0$). Table 6 reports the results. Columns (1)-(3) show how the survival constraint creates the incentive gradient. With $H = 24$, startups aged 0-6 months face an effective rate of 22.54%—only 32% of the 70% rate under $H = 0$. Startups aged 54-60 months face a rate of 37.08%—61% of the $H = 0$ level. Columns (4)-(5) compare investment density changes. Column (4) isolates the holding period's effect: young startups

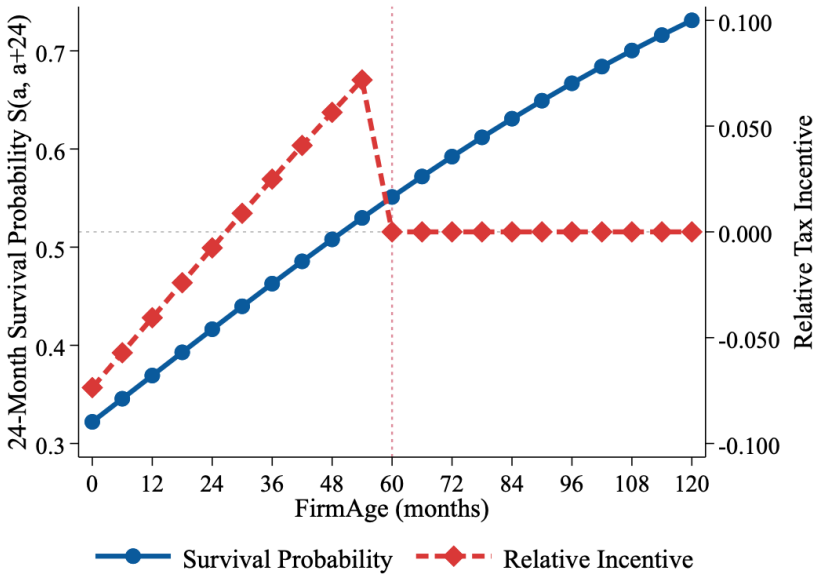


Figure 8: Survival Probability and Relative Tax Incentives

Notes: This figure plots the age profiles of survival probability and relative tax incentives. The blue curve shows the 24-month survival probability $S(a, a+24)$, which rises with startup age. The red curve shows the deviation of effective incentives from the mean, $\Delta^{policy}(a) - \bar{\Delta}^{policy}$. The horizontal axis measures startup age in months. Negative values correspond to crowding out and positive values correspond to bunching. Parameters are from Table 5.

lose 5.15 percentage points on average, while startups near the threshold gain 5.01 points.

Table 6: Crowding-Out Effects of Holding Period Requirements

	24-Month Survival Rate (%)	Effective Incentive Rate (%)		Change in Investment Density (pp)		Crowding-Out Effect(pp)
		H=0	H=24	H=0	H=24	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Young Firms (0-30 Months)						
0-6 months	32.20	70	22.54	+4.14	−5.33	−9.47
6-12 months	34.56	70	24.19	+4.08	−3.69	−7.77
12-18 months	36.92	70	25.84	+3.91	−1.64	−5.55
18-24 months	39.28	70	27.50	+3.37	+0.62	−2.76
24-30 months	41.64	70	29.15	+2.68	+2.50	−0.18
Mean	36.92	70	25.84	+3.64	−1.51	−5.15
Panel B: Near-Threshold Firms (30-60 Months)						
30-36 months	43.97	70	30.78	+2.11	+3.92	+1.81
36-42 months	46.28	70	32.40	+1.80	+5.38	+3.59
42-48 months	48.55	70	33.99	+1.42	+6.22	+4.80
48-54 months	50.79	70	35.55	+1.39	+8.42	+7.04
54-60 months	52.98	70	37.08	+1.10	+8.90	+7.80
Mean	48.51	70	33.96	+1.56	+6.57	+5.01

Notes: This table identifies the causal role of survival constraints in the crowding-out mechanism through counterfactual comparisons. Under the H=0 scenario, all eligible firms receive an unconditional 70% tax credit. Under the H=24 scenario, the tax benefit is conditional on a 24-month holding period requirement. Changes in investment density are measured in percentage points (pp). The crowding-out effect in column (6) is calculated as the difference between columns (5) and (4), representing the net impact of imposing the holding period requirement. Parameter estimates are based on Table 4. Panel A reports results for young firms aged 0-30 months at the time of VC investment, while Panel B reports results for near-threshold firms aged 30-60 months. Negative values indicate crowding-out effects, where the holding period requirement discourages VC investment relative to the unconstrained policy.

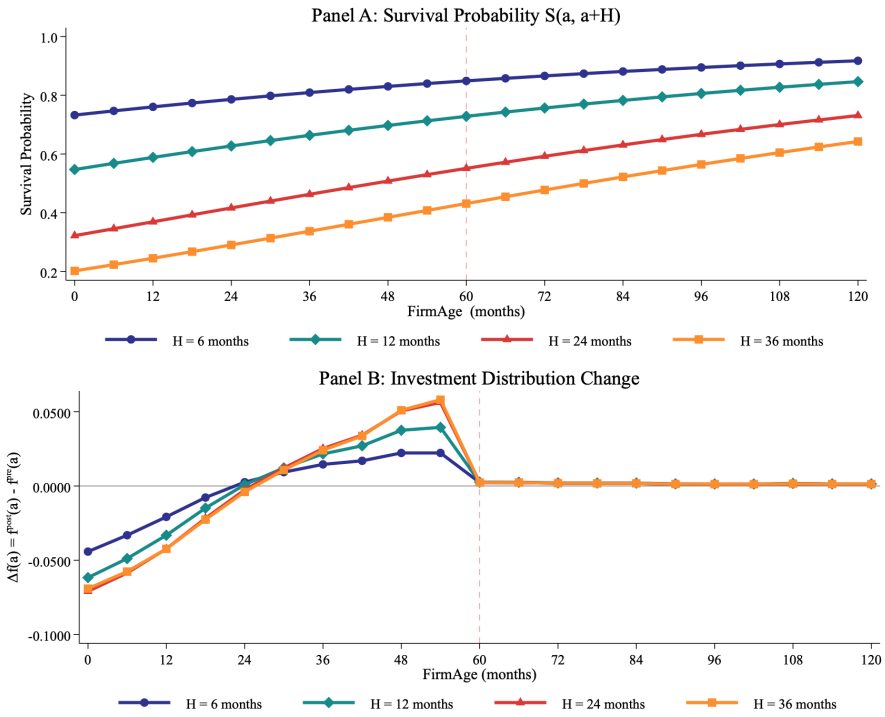


Figure 9: Survival Rates and Crowding Out Under Different Holding Periods

Notes: This figure shows how holding period length affects investment allocation through the survival constraint. Panel A plots survival probability from investment age a to $a + H$ under four holding periods ($H = 6, 12, 24, 36$ months). Panel B plots the corresponding change in investment density, $\Delta f(a) = f^{post}(a) - f^{pre}(a)$. Negative values indicate crowding out and positive values indicate bunching.

The holding period is a core design parameter. Lengthening it screens for committed investors but intensifies crowding out by tightening the survival constraint. To quantify this tradeoff, we simulate reallocation under three holding periods ($H = 18, 24, 30$ months). Figure 9 reports the results.

Panel A shows that longer holding periods reduce survival probabilities and steepen the age gradient. For age-0 startups, 6-month survival exceeds 70%, 24-month survival falls to 32%, and 36-month survival drops to 20%. Panel B shows how this translates into reallocation. With $H = 6$, density at age 0 falls 4.4 percentage points and density at age 54 rises 2.2 points. At $H = 24$, crowding out at age 0 reaches 7.1 points and bunching at age 54 reaches 5.6 points. At $H = 36$, crowding out is 6.9 points and bunching is 5.8 points.

Two forces drive this pattern. First, longer holding periods compress effective rates for young startups. Second, they widen the incentive wedge across ages. The result: longer holding periods reduce survival rates, weaken effective incentives, and amplify crowding out.

The deduction rate Φ controls incentive generosity. Does raising it benefit all startups

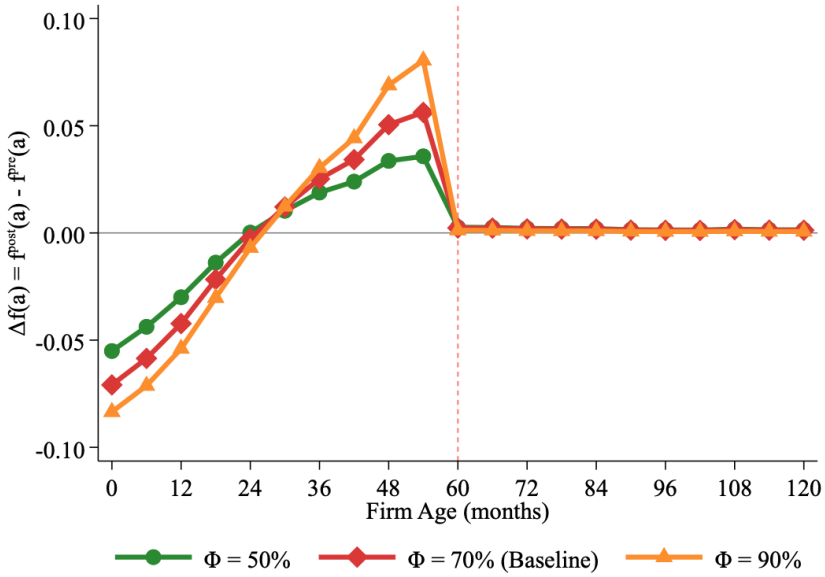


Figure 10: Investment Reallocation Under Different Tax Deduction Rates

Notes: This figure shows investment reallocation under three tax deduction rates ($\Phi = 50\%, 70\%, 90\%$) with the holding period fixed at H=24 months. The vertical axis measures the change in investment density, $\Delta f(a) = f^{post}(a) - f^{pre}(a)$. The horizontal axis measures startup age in months. The vertical dashed line marks the 60-month age threshold.

equally? To find out, we simulate reallocation under three rates ($\Phi = 50\%, 70\%, 90\%$) holding the period fixed at $H = 24$ months. Figure 10 reports the results.

The simulations reveal proportional scaling. All three curves exhibit the same age profile: density falls for young startups and rises near the threshold, peaking at ages 54-60. Raising the rate scales both effects proportionally. When the rate rises from 50% to 90%, crowding out at age 0 grows from -5% to -8% and bunching at ages 54-60 grows from 3% to 8%.

This has important policy implications. Raising the deduction rate increases nominal benefits for all eligible startups, but the survival constraint distributes gains unevenly across ages. Simply boosting generosity cannot fix the allocation distortion. To reduce crowding out of young startups, policy must target the survival constraint directly—through age-varying rates or partial deductions for early exits.

5 Policy effects on Startup Performance

Our earlier analysis shows that tax incentives significantly alter VC allocation. Whether these financial market effects translate into real economic outcomes—specifically, changes in firm-level inputs and innovation—remains an open question. This section addresses this gap by examining the policy's impact on startup human capital investment and

technological innovation.

Our analysis faces two main identification challenges. First, VC-backed firms are positively selected: they possess higher growth potential ex ante. Comparing outcomes between funded and unfunded firms confounds financing effects with selection effects. Second, strategic manipulation contaminates our treatment assignment. Section 3 documents that investors strategically time investments within the 45-85 month age window to maximize tax benefits. Investment timing for these firms is endogenous, complicating our causal identification.

We address these challenges by restricting the sample to VC-backed firms and exploiting within-VC variation in portfolio company age at investment. Crucially, we separately identify firms in the strategic manipulation window, allowing us to purge estimates of timing-induced bias. We partition firms into three groups based on age at initial VC investment. The **Bunching group** (45-60 months) comprises firms in the manipulation window identified in Section 3. The **Crowding group** ($\leq$24 months) includes firms in the crowding-out region predicted by our model in Section 4. The **NonBunching group** (24-45 months) provides clean identification, as these firms fall outside both the manipulation and crowding-out windows.

5.1 Effects on Human Capital Investment

We use job posting data from Zhaopin.com (2022-2024) matched to VC-backed firms. The sample contains 48,813 positions posted by 1,582 firms, with each observation representing a firm-position pair. Since all observations occur post-policy, we cannot implement a standard panel DiD design. Instead, we adopt a cohort DiD approach (Chen et al., 2020), exploiting cross-cohort variation in policy exposure. Firms receiving VC funding at different ages and times face different treatment intensities, even when observed in the same calendar year.

Treatment status depends on two dimensions: eligibility and timing. Firms are treated if they received investment before age 60 months and were funded in 2019 or later. Control firms received VC funding but could not claim tax benefits due to either age or timing constraints. For example, within our 2022-2024 observation window, a firm funded at 50 months in 2020 posts jobs alongside a firm funded at 70 months in 2020 and a firm funded at 50 months in 2018.

We estimate the following Cohort DiD specification:

$$Y_{ijt} = \beta \times Age \leq 60_{ij} \times Post2019_i + \gamma \cdot Controls_{ijt} + FEs + \varepsilon_{ijt} \tag{21}$$

where i, j, and t denote firms, VCs, and year. We use three measures of human capital investment. *Salary (Lower Bound)* is the log minimum salary. *Salary (Upper Bound)* is the log maximum salary. *Education* equals one if the position requires a bachelor's degree

or higher, zero otherwise. Higher salaries and stricter education requirements indicate stronger demand for quality human capital.

The interaction term $Age \leq 60_{ij} \times Post2019_i$ identifies the treated cohort—firms that were both eligible and funded post-policy. The coefficient β captures the policy's causal effect. Controls include firm size, financing intensity, and firm age. We include city, year, and industry fixed effects. City fixed effects absorb local labor market conditions; year fixed effects control for aggregate trends; industry fixed effects account for sector-specific wage structures. Salary regressions additionally include education fixed effects. Standard errors are clustered by city.

We also estimate the following model to examine effects across age groups:

$$Y_{ijt} = \beta \times Age \leq 60_{ij} \times Post2019_i \times Group_{ij} + \gamma \cdot Controls_{ijt} + FEs + \varepsilon_{ijt} \tag{22}$$

Specification (22) interacts the DiD term with three age-group indicators: Bunching, Crowding, and Nonbunching. The triple-interaction coefficients identify policy effects within each group, isolating strategic manipulation and crowding-out from the true causal effect.

Table 7 reports results. Panels A and B show results for salary bounds. In column (1), the baseline coefficients are 0.100 and 0.079, both significant at 1%. Treated firms offer salaries 10.0% and 7.9% higher than control firms. This suggests the policy enables firms to pay more by easing financing constraints. However, this estimate combines effects across age groups and may be influenced by manipulation and crowding-out.

Columns (2)-(4) reveal heterogeneity across age groups. In columns (2) and (3), the Bunching and Crowding coefficients are insignificant. One explanation is that firms in the manipulation window receive mistimed investments. Their investment timing results from delays or acceleration rather than optimal development needs, which may offset policy benefits. The youngest firms face crowding-out and may receive smaller or lower-quality investments, limiting their ability to improve human capital. In column (4), the NonBunching coefficient is 0.079 and 0.064, significant at 1% and 5%. This is our core estimate. In the age window free from manipulation and crowding-out, the policy increases salaries by 7.9% and 6.4%.

The salary increase reflects two mechanisms. First, relaxed financing constraints allow firms to pay more. Second, venture capital often brings better governance and planning, shifting firms from cost control to talent competition.

Panel C shows results for education requirements. The baseline coefficient is 0.184, significant at 1%. Treated firms increase positions requiring bachelor's degrees by 18.4 percentage points. Triple-difference results show coefficients of 0.132, 0.093, and 0.107 for the three groups. The policy increases demand for educated talent by about 10 percentage points across eligible firms. Since 31.4% of sample positions require bachelor's degrees, a

Table 7: Impact of Tax Policy on Human Capital Investment in Startups

Panel A	*Salary (Lower Bound)*			
	(1)	(2)	(3)	(4)
Age≤60×Post	0.100***			
	(0.023)			
Age≤60×Post×Bunching		0.020		
		(0.031)		
Age≤60×Post×Crowding			0.072	
			(0.051)	
Age≤60×Post×NonBunching				0.079***
				(0.028)
Controls	YES	YES	YES	YES
Under 60 months	YES	YES	YES	YES
Mean of Dependent Variable	8.925	8.925	8.925	8.925
S.D. of Dependent Variable	0.468	0.468	0.468	0.468
Panel B	*Salary (Upper Bound)*			
	(1)	(2)	(3)	(4)
Age≤60×Post	0.079***			
	(0.027)			
Age≤60×Post×Bunching		0.001		
		(0.033)		
Age≤60×Post×Crowding			0.071	
			(0.055)	
Age≤60×Post×NonBunching				0.064**
				(0.031)
Controls	YES	YES	YES	YES
Under 60 months	YES	YES	YES	YES
Mean of Dependent Variable	9.406	9.406	9.406	9.406
S.D. of Dependent Variable	0.479	0.479	0.479	0.479
Panel C	*Education*			
	(1)	(2)	(3)	(4)
Age≤60×Post	0.184***			
	(0.028)			
Age≤60×Post×Bunching		0.132***		
		(0.033)		
Age≤60×Post×Crowding			0.093***	
			(0.035)	
Age≤60×Post×NonBunching				0.107***
				(0.023)
Controls	YES	YES	YES	YES
Under 60 months	YES	YES	YES	YES
Mean of Dependent Variable	0.314	0.314	0.314	0.314
S.D. of Dependent Variable	0.464	0.464	0.464	0.464

Notes: This table reports the impact of tax policy on human capital investment in startup technology firms. The dependent variables are: Panel A - log of lower bound salary; Panel B - log of upper bound salary; Panel C - education requirement (bachelor's degree or above = 1). *Age≤60* indicates firms younger than 60 months at the time of VC investment. *Post* is a dummy variable for post-2019. *Bunching*, *Crowding*, and *NonBunching* correspond to firm ages of 45-85 months, ≤24 months, and 24-45 months at the time of investment, respectively. Control variables include firm size, VC investment, and firm age. Regressions control for city, year, and industry fixed effects (Panels A and B additionally control for education fixed effects). Sample period is 2022–2024, with 42,859 job posting observations. Standard errors clustered at the city level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

10 percentage point increase represents a 30% relative gain.

5.2 Effects on Innovation

We use patent data from the CNIPA for 2015-2024, matched to VC-backed firms. The data form a balanced panel of 293,960 firm-year observations covering 29,396 firms. Unlike hiring data, patent data span periods before and after the policy. This allows us to observe changes in innovation for the same firm over time. We use a standard panel DiD specification:

$$Y_{it} = \beta \times Age \leq 60_i \times Post_t + \gamma \cdot Controls_{it} + FEs + \varepsilon_{it} \tag{23}$$

where i and t denote firms and year. We use three innovation measures. *PatentNum* is the log number of patent applications. *Citation* is the log number of citations received. *PatentWidth* measures patent breadth based on IPC classifications, ranging from 0 to 1. Higher values indicate broader technological coverage.

$Age \leq 60_i$ equals one if the firm was younger than 60 months at first VC investment. $Post_t$ equals one for years 2019 and after. β measures the change in innovation for eligible firms after the policy relative to ineligible firms. Control variables include firm size and financing intensity, both interacted with time trend. The model includes firm and year fixed effects. Standard errors are clustered at the firm level.

We also estimate heterogeneous effects across age groups:

$$Y_{it} = \beta \times Age \leq 60_i \times Post_t \times Group_i + \gamma \cdot Controls_{it} + FEs + \varepsilon_{it} \tag{24}$$

The grouping follows specification (22).

Table 8 presents estimates. Panel A shows the policy increased patent applications by 19.4%. Heterogeneity analysis reveals that the Crowding coefficient (0.087) is substantially smaller than the Bunching (0.225) and NonBunching (0.215) coefficients. The weakest innovation response among the youngest firms confirms crowding-out: lower effective subsidies translate into smaller financing improvements and muted innovation gains. Panels B and C document similar patterns for citations and patent breadth.

In summary, the tax policy successfully channels venture capital to eligible startups, easing their financing constraints and generating measurable improvements in firm-level outcomes. We document significant increases in both human capital investment—as evidenced by higher salaries and stronger educational requirements—and innovation output, with patent applications rising 19.4% among treated firms. On average, the policy achieves its intended goals.

However, this aggregate success masks important heterogeneity. The crowded-out cohort—firms aged 0-24 months at investment—exhibits substantially weaker treatment effects than their older counterparts. For these youngest startups, the policy's benefits are muted: patent growth is less than half that of the non-bunching group, and human capital improvements remain statistically insignificant. This reveals a design flaw: the holding period requirement, by creating survival-contingent incentives, systematically weakens the policy's impact on the highest-risk firms it ostensibly aims to support. Effective policy design must account for how structural features like holding periods interact with age-varying survival probabilities to avoid inadvertently penalizing the most vulnerable beneficiaries.

Table 8: Impact of Tax Policy on Innovation Capability of Startups

Panel A	*PatentNum*			
	(1)	(2)	(3)	(4)
Age≤60×Post	0.194***			
	(0.009)			
Age≤60×Post×Bunching		0.225***		
		(0.019)		
Age≤60×Post×Crowding			0.087***	
			(0.013)	
Age≤60×Post×NonBunching				0.215***
				(0.015)
Controls	YES	YES	YES	YES
Mean of Dependent Variable	0.235	0.235	0.235	0.235
S.D. of Dependent Variable	0.706	0.706	0.706	0.706
Panel B	*Citation*			
	(1)	(2)	(3)	(4)
Age≤60×Post	0.043***			
	(0.003)			
Age≤60×Post×Bunching		0.048***		
		(0.006)		
Age≤60×Post×Crowding			0.025***	
			(0.004)	
Age≤60×Post×NonBunching				0.044***
				(0.005)
Controls	YES	YES	YES	YES
Mean of Dependent Variable	0.034	0.034	0.034	0.034
S.D. of Dependent Variable	0.238	0.238	0.238	0.238
Panel C	*PatentWidth*			
	(1)	(2)	(3)	(4)
Age≤60×Post	0.045***			
	(0.003)			
Age≤60×Post×Bunching		0.052***		
		(0.005)		
Age≤60×Post×Crowding			0.019***	
			(0.004)	
Age≤60×Post×NonBunching				0.052***
				(0.004)
Controls	YES	YES	YES	YES
Mean of Dependent Variable	0.064	0.064	0.064	0.064
S.D. of Dependent Variable	0.209	0.209	0.209	0.209

Notes: This table examines the impact of the 2019 tax policy on innovation in startup technology firms at the firm-year level. The dependent variables are: Panel A - log of patent count; Panel B - log of patent citations; Panel C - patent knowledge breadth. *Age≤60* indicates firms younger than 60 months at the time of VC investment. *Post* is a dummy variable for the period of 2019 and after. *Bunching*, *Crowding*, and *NonBunching* correspond to firm ages of 45-85 months, ≤24 months, and 24-45 months at the time of investment, respectively. Control variables include firm size and VC investment intensity, in the form of interactions between baseline values and time trends. Regressions control for firm and year fixed effects. Sample period is 2015–2024, with 262,610 observations. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

6 Conclusion

This paper examines whether tax incentives can effectively channel capital toward the youngest and riskiest startups. Our analysis of this age-threshold and holding-period tax incentive yields several important conclusions.

First, the tax incentive significantly influences VC allocation, as evidenced by pronounced bunching behavior at the 60-month eligibility cutoff. This pattern confirms that the policy effectively shapes investor behavior. Second, the policy design unintentionally shifts VC project selection toward lower-risk startups. Specifically, VCs favor longer-established firms that still qualify for tax benefits because these firms have higher survival probabilities and therefore generate higher expected tax relief value. This shift significantly crowds out the youngest startups aged 0-24 months. Third, while the policy increases innovation and human capital investment among eligible firms overall, these benefits concentrate near the age threshold. The crowded-out youngest startups lag significantly behind—experiencing less than half the innovation gains of non-bunching startups. This reveals how survival-contingent holding periods systematically distort policy impact, weakening effectiveness precisely where support is most needed.

Our findings deepen understanding of how tax policy shapes entrepreneurial finance markets in two important ways. First, we demonstrate that the interaction between policy parameters and firm survival probabilities decisively shapes policy effectiveness. We are the first to show that tax incentives may systematically distort capital allocation through holding periods that directly link tax benefits to startup survival. Second, we reveal a critical implication: poorly designed policies may paradoxically worsen financing barriers by systematically penalizing the highest-risk ventures. While critics argue that tax incentive programs merely boost returns for sophisticated investors, our evidence reveals a different pattern. Overly simplified incentive structures—uniform age thresholds combined with holding periods—alter the risk-return tradeoff in ways that narrow the domain of entrepreneurial investment, steering capital away from the policy's original targets.

While our setting is China, the survival constraint mechanism we identify characterizes holding-period-based investor tax incentives globally, making our findings directly relevant to ongoing policy debates in the U.S., Europe, and other OECD economies. Future research should explore optimal calibration of these tax incentives. Our study offers a clear warning: when designing tax incentives to promote entrepreneurship, policymakers must look beyond tax rates and carefully calibrate holding periods, age restrictions, and eligibility thresholds. Such calibration is essential to prevent unintended penalties on high-risk, high-growth innovative activities.

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Appendix

Table A.1: Tax Incentive Schemes for Venture Capital Investment Across Countries

Country	Tax Policy	Incentive Structure	Minimum Holding Period
U.S.	Qualified Small Business Stock (QSBS)	100% capital gains tax exclusion	5 years
UK	Enterprise Investment Scheme (EIS)	30% income tax relief on investment amount; Capital gains tax exemption	3 years
UK	Seed Enterprise Investment Scheme (SEIS)	50% income tax relief on investment amount; Capital gains tax exemption	3 years
Canada	Labour-Sponsored Venture Capital Corporation (LSVCC)	Federal (15%) + provincial tax credits	8 years
Australia	Venture Capital Limited Partnership (VCLP)	Tax exemption on capital gains and income for foreign investors; Flow-through tax treatment	12 months
France	IR-PME (Investment Tax Reduction for SMEs)	18%-50% tax reduction on investment amount	5 years
China	Circular [2018] No. 55	70% of investment amount deductible from taxable income	2 years

Notes: This table summarizes key tax incentive programs designed to stimulate venture capital investment and entrepreneurship across major economies. The policies represent supply-side interventions aimed at reducing the cost of capital for early-stage enterprises through investor tax benefits.

Appendix A: Derivation of Proposition 1

This appendix provides the complete mathematical derivation of Proposition 1, demonstrating how the exponential response function for investment density is derived from the first-order conditions of the portfolio optimization problem.

The portfolio adjustment problem faced by venture capital firms is:

$$\max_{f^1(a)} \int_0^{\bar{a}} \left[V^1(a) \cdot f^1(a) - \frac{\kappa}{2}(f^1(a) - f^0(a))^2 \right] da \quad \text{(A.1)}$$

subject to:

$$\int_0^{\bar{a}} f^1(a) da = 1 \quad \text{(A.2)}$$

Construct the Lagrangian function:

$$\mathcal{L} = \int_0^{\bar{a}} \left[V^1(a) \cdot f^1(a) - \frac{\kappa}{2}(f^1(a) - f^0(a))^2 \right] da - \lambda \left(\int_0^{\bar{a}} f^1(a) da - 1 \right) \quad \text{(A.3)}$$

where λ is the Lagrange multiplier corresponding to the normalization constraint. Taking the functional derivative with respect to $f^1(a)$ and setting it equal to zero, we compute the variation of each term:

$$\frac{\delta}{\delta f^1(a)} \int_0^{\bar{a}} V^1(a) \cdot f^1(a) da = V^1(a)$$

$$\frac{\delta}{\delta f^1(a)} \int_0^{\bar{a}} \frac{\kappa}{2}(f^1(a) - f^0(a))^2 da = \kappa(f^1(a) - f^0(a))$$

$$\frac{\delta}{\delta f^1(a)} \lambda \int_0^{\bar{a}} f^1(a) da = \lambda$$

Combining these yields the Euler-Lagrange equation:

$$V^1(a) - \kappa \left(f^1(a) - f^0(a) \right) - \lambda = 0 \quad \text{(A.4)}$$

Rearranging, we obtain:

$$f^1(a) = f^0(a) + \frac{1}{\kappa} \left(V^1(a) - \lambda \right) \quad \text{(A.5)}$$

The Lagrange multiplier λ is endogenously determined by the normalization constraint. Integrating both sides of equation (A.5) over $[0, \bar{a}]$:

$$\int_0^{\bar{a}} f^1(a) da = \int_0^{\bar{a}} f^0(a) da + \frac{1}{\kappa} \int_0^{\bar{a}} \left(V^1(a) - \lambda \right) da$$

Applying the normalization conditions:

$$\int_0^{\overline{a}} f^1(a)da = 1, \quad \int_0^{\overline{a}} f^0(a)da = 1$$

we have:

$$1 = 1 + \frac{1}{\kappa}\left(\int_0^{\overline{a}} V^1(a)da - \lambda\overline{a}\right)$$

Solving for λ:

$$\lambda = \frac{1}{\overline{a}}\int_0^{\overline{a}} V^1(a)da \equiv \overline{V}^1 \quad \text{(A.6)}$$

Substituting equation (A.6) into equation (A.5):

$$f^1(a) = f^0(a) + \frac{1}{\kappa}\left(V^1(a) - \overline{V}^1\right) \quad \text{(A.7)}$$

Equation (A.7) provides a linear approximation of the change in investment density. However, the linear form may produce negative densities. To ensure the economic constraint $f^1(a) \geq 0$, we apply a logarithmic transformation to equation (A.7). Define the log density:

$$\ln f^1(a) = \ln f^0(a) + \frac{1}{\kappa}\left(V^1(a) - \overline{V}^1\right) \quad \text{(A.8)}$$

Exponentiating equation (A.8):

$$f^1(a) = f^0(a) \times \exp\left[\frac{1}{\kappa}\left(V^1(a) - \overline{V}^1\right)\right] \quad \text{(A.9)}$$

The validity of this transformation can be verified through a first-order Taylor expansion.

When $\frac{1}{\kappa}\left(V^1(a) - \overline{V}^1\right)$ is small:

$$\exp\left[\frac{1}{\kappa}\left(V^1(a) - \overline{V}^1\right)\right] \approx 1 + \frac{1}{\kappa}\left(V^1(a) - \overline{V}^1\right)$$

Substituting into equation (A.9):

$$f^1(a) \approx f^0(a)\left[1 + \frac{1}{\kappa}\left(V^1(a) - \overline{V}^1\right)\right] = f^0(a) + \frac{1}{\kappa}\left(V^1(a) - \overline{V}^1\right)$$

Decompose the marginal value into the baseline level and the policy shock:

$$V^1(a) = V^0(a) + \Delta^{\text{policy}}(a) \quad \text{(A.10)}$$

Calculate the average marginal value after the policy:

$$\overline{V}^1 = \frac{1}{\overline{a}} \int_0^{\overline{a}} \left[V^0(a) + \Delta^{\text{policy}}(a) \right] da = \overline{V}^0 + \overline{\Delta}^{\text{policy}} \quad \text{(A.11)}$$

where:

$$\overline{V}^0 = \frac{1}{\overline{a}} \int_0^{\overline{a}} V^0(a) da, \quad \overline{\Delta}^{\text{policy}} = \frac{1}{\overline{a}} \int_0^{\overline{a}} \Delta^{\text{policy}}(a) da$$

Substituting equations (A.10) and (A.11) into equation (A.9):

$$f^1(a) = f^0(a) \times \exp \frac{1}{\kappa} \left[\left(V^0(a) + \Delta^{\text{policy}}(a) \right) - \left(\overline{V}^0 + \overline{\Delta}^{\text{policy}} \right) \right]$$

$$= f^0(a) \times \exp \frac{1}{\kappa} \left[\left(V^0(a) - \overline{V}^0 \right) + \left(\Delta^{\text{policy}}(a) - \overline{\Delta}^{\text{policy}} \right) \right] \quad \text{(A.12)}$$

We assume that the portfolio is already at its optimum prior to the policy implementation. This implies that the pre-policy investment density $f^0(a)$ also satisfies similar first-order conditions. In long-run equilibrium, this requires that the marginal values across all ages are equalized:

$$V^0(a) = \overline{V}^0, \quad \forall a \in [0, \overline{a}] \quad \text{(A.13)}$$

That is, the marginal productivity of capital is equalized across all age groups (no-arbitrage condition). Under this assumption, $V^0(a) - \overline{V}^0 = 0$, and equation (A.12) simplifies to:

$$f^1(a) = f^0(a) \times \exp \left[\frac{1}{\kappa} \left(\Delta^{\text{policy}}(a) - \overline{\Delta}^{\text{policy}} \right) \right] \quad \text{(A.14)}$$

This completes the proof.