Picking Winners or Building Them? Central and Local Government Venture Capital in Chinese Semiconductors*

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Abstract

Could governments be good venture capitalists? I compare Chinese semiconductor firms backed by local government, central government, and private venture capital (VC). Central and private VCs invest in the most productive firms, while local VCs back smaller, less productive local champions. Yet local-backed firms gain about 34% in revenue productivity after investment relative to not-yet-invested firms, while central- and private-backed firms show no detectable change. Local VCs hold smaller portfolios than central VCs, sit closer to their firms, and add directors with graduate degrees and foreign education. In a model of VC selection, firm productivity, capital responses, and import competition, 2023 domestic sales would have been 11.6% lower had private VCs allocated government VCs' deals and 4.0% lower had the central government allocated local investments. Post-investment productivity growth from local government VCs outweighs the selection of central and private VCs on larger, more efficient firms.

1 Introduction

Many well-intentioned industrial policies failed due to political frictions. Governments regularly direct support to declining sectors that lobbied for protection (Krueger, 1990; Beason and Weinstein, 1996; Baldwin and Robert-Nicoud, 2007; Bombardini et al., 2023) and, within sectors, to connected firms that are less productive (Khwaja and Mian, 2005; Fang et al., 2023). Subsidized firms often

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fail to improve afterward (Luzio and Greenstein, 1995; Branstetter et al., 2023). State-owned enterprises and "national champions" tasked with industrial policy goals have lagged private firms in productivity in China and elsewhere (Shleifer and Vishny, 1994; Shleifer, 1998; Megginson and Netter, 2001; Brandt et al., 2012).

Yet, state intervention in firms has also had some prominent successes. Taiwan's TSMC, now the world's leading chipmaker, and many other leading Taiwanese chip companies were spun off from the government's Industrial Technology Research Institute (ITRI) with minority state ownership (Mathews, 1997; Chu, 2013). Different experiences with state investment suggest that the incentives, information and capabilities of government agencies that allocate industrial policy resources are critical determinants of policy success (Rodrik, 2004; Juhász and Lane, 2024). This paper studies an important instance of this organizational problem: for a large country committed to funding a strategic sector, whether the decision to allocate industrial policy spending should be centralized or delegated to local governments. Local governments favor locally connected firms that a central planner may not want to support (Bardhan and Mookherjee, 2000; Fang et al., 2022). At the same time, the proximity and institutional links of local governments with local firms may provide them with superior information on the right companies to target and the appropriate tools to support them (Huang et al., 2017). This question is especially salient in China, where industrial policy is implemented through a highly decentralized system in which provincial and municipal governments retain substantial discretion over the actual allocation of fiscal resources (Xu, 2011; Luo et al., 2025; Fang et al., 2025).

Chinese industrial policy in semiconductors presents an ideal setting in which to study this institutional design problem. As the semiconductor sector provides critical inputs to downstream sectors (Liu, 2019) and exhibits learning-by-doing properties (Irwin and Klenow, 1994; Goldberg et al., 2024), developing a homegrown semiconductor supply chain has long been a national priority for China. Following the adoption of the "National Integrated Circuit Industry Development Promotion Guidelines", central and local governments invested heavily in the industry through state-backed venture capital and other investment vehicles (Branstetter and Li, 2023), which became the primary means for Chinese governments to finance private entrepreneurs in the sector.

I compare which firms central and local government funds invest in, and how those firms perform afterward, to understand the incentives of the two tiers of government and the potential effectiveness of their investments. I constructed a panel of Chinese semiconductor firms from 1998 to 2024 by combining registered shareholder data, firm balance sheets, board and senior management members' tenure and biographies, intellectual property records, and commercial plant-level information. The merged dataset allows me to identify when a firm first received equity investment from a local government, central government, or private VC, and to track productivity, innovation, and board composition before and after investment.

The first set of results documents how private, central and local government VCs select investments

among firms they have not yet invested in. Consistent with the central government implementing industrial policy to maximize national revenue, central government funds are more likely to invest in firms with higher revenue productivity (TFPR) within the nation. Despite targeting relatively productive firms in their province, local governments still invest in less productive firms on average relative to both central government and private VCs. This is due to the fact that productive firms are not equally distributed across localities. This pattern is consistent with a decentralized industrial policy system where different levels of government face different incentives. Local governments are evaluated on relative local output performance, while the national government focuses on promoting established national champions. From the viewpoint of the national government, decentralized government investment appears to generate misallocation of fiscal resources unless local governments screen firm potential better or provide additional value to their firms.

This motivates the second set of results on post-investment firm performance. I study the productivity and innovation outcomes of firms invested by local and central government VCs through event study analyses. To account for the fact that a firm may be invested by local government, central government, and private VCs simultaneously or at different times in the data, I implement de Chaisemartin and D'Haultfœuille (2023)'s event study design for multiple staggered treatments. The results suggest that local government VC-invested firms experienced faster growth in revenue productivity relative to firms not yet invested by local government VCs. There is little evidence of differential trends before local government investment, especially when comparing within firms that had not received any prior VC investment. Firms invested by central government and private VCs instead do not exhibit significantly different productivity growth relative to firms not yet invested by the respective VCs. Other measures correlated with productivity, such as sales per worker, patents, and intellectual property measures, follow similar patterns. This result is surprising because state ownership is associated with lower productivity in China (Hsieh and Klenow, 2009; Brandt et al., 2012; Chen et al., 2021; Lian and Zhang, 2026). Furthermore, local government VCs back firms that are smaller, behind the national productivity frontier, and connected via alumni or career ties to local government VC board members, the type of firms the literature suggests to receive protection due to crony favoritism rather than merit. Yet these firms become more productive after investment. This suggests that the professional managers of local government venture capital are doing something different from bureaucrats and SOE managers in both allocating state capital and engaging with invested firms.

Leveraging rich data on the members of the senior management and corporate boards, I further show that relative to central government VCs, local government VC funds are more likely to bring their managers onto the board of invested firms, and expand the number of directors with post-graduate degrees, foreign education, and finance backgrounds. This is plausibly related to the fact that VC fund managers enter their invested firm's board/management more often if the firm is geographically closer to the fund and if the VC invested in fewer firms. The overall picture suggests that local government VCs do not merely inject capital, but appear to mobilize organizational and managerial support that helps invested firms grow. A decomposition exercise suggests that board

composition and managerial turnover account for 44% of the estimated local-central government VC effect gap on productivity, while paid-in capital, subsidies, procurement, and patents each account for less than 10%.

Domestic production's share of semiconductor consumption in China was rising but remained small throughout the sample period. As a result, the increase in government-invested firms' revenue relative to non-invested domestic firms identified in the event study should largely come from imports rather than other domestic competitors. Thus, the equilibrium effect of government investment on the aggregate size of the domestic industry would not be too small (Rotemberg, 2019). I quantify the extent to which the documented effects matter for aggregate industry size via a model motivated by previous empirical analyses. The model combines Cobb-Douglas firm production with (a) semiconductor demand that treats domestic output and imports as imperfect substitutes and (b) simultaneous local government, central government, and private VC investment in firms. Each type of VC has a limited number of new investments that it can make each year, which it allocates according to observed firm characteristics. VC investments have different effects on firm productivity and capital.

Comparing simulated counterfactuals to the status quo regime, I find that the Chinese domestic semiconductor industry would have had 11.6% less revenue in 2023 if private VCs had made the government VCs' investments. If all local government investment had gone to the central government under the "centralization" counterfactual, aggregate revenue would have been 4.0% less. Although central government investments do not improve firm productivity, their allocation to larger and more efficient firms would raise industry revenue relative to the status quo initially. The superior growth of local government-invested firms eventually catches up, allowing the status quo's total industry revenue to surpass that under the centralization counterfactual. This exercise further clarifies the principal tradeoff of decentralization this paper highlights: local governments' allocation to less productive and smaller local firms could result in lower output initially, but the static misallocation could be outweighed by dynamic growth if local government-invested firms grow faster.

Related Literature and Contributions. The paper is directly relevant to the growing literature on industrial policy (Juhász and Lane, 2024; Juhász et al., 2024; Lashkaripour and Lugovskyy, 2023; Liu, 2019; Lane, 2025), in particular on the partial and equilibrium effects of firm-level subsidies (Choi and Levchenko, 2025; Rotemberg, 2019; Criscuolo et al., 2019). The impressive scale and variety of China's industrial policy programs have generated a vibrant literature (Aghion et al., 2015; Barwick et al., 2024; Branstetter and Li, 2023). A strand of work estimates production and entry subsidies from the output and entry patterns of Chinese versus international firms and infers the equilibrium effects of subsidies, which necessarily requires ruling out endogenous productivity improvement from subsidies (Barwick et al., 2025; Kalouptsidi, 2017). Recent literature identified rich variations in local government industrial policy documents, and exploited staggered adoption of different sets of policy tools across localities and time to identify their respective effects (Fang et al., 2025; Banares-Sanchez et al., 2026). Other literature using direct firm-level balance sheet and

subsidies data has found that government subsidies have had little effect on firm-level productivity or innovation (Branstetter et al., 2023; Garcia-Macia et al., 2025). I contribute by showing that the level of government that allocates matters in determining which firms receive support and supported firms' subsequent performance. Furthermore, I show that Chinese governments affect firm performance not simply through monetary support but also by participating in corporate boards via government VCs, a novel non-monetary form of intervention in firms that is less understood.

The paper primarily relates to a growing literature on government venture capital as an alternative industrial policy instrument (Beraja et al., 2024; Chen et al., 2026; Aragoneses and Saxena, 2025; Zhang et al., 2024; Colonnelli et al., 2024; Lerner, 2009). I contribute by showing that the government can influence a firm's board and management as a shareholder, a distinguishing feature of government VC relative to conventional subsidies. The type of personnel government funds place in their portfolio firms' management could drive firm performance. Therefore, this paper also speaks to the literature on management as a determinant of productivity (Bertrand and Schoar, 2003; Bloom and Van Reenen, 2007; Bloom et al., 2013; Syverson, 2011), and how venture capital monitoring could contribute to firm performance (Bernstein et al., 2016; Kaplan and Stromberg, 2001; Chemmanur et al., 2011; Lerner, 1995; Bottazzi et al., 2008; Chemmanur et al., 2021).

I contribute to the Chinese government VC literature by explicitly contrasting the differences between local and central government VCs on both the firms they invest in and invested firms' subsequent performance. My evidence on how local government VCs could help firms grow faster by engaging in corporate governance clarifies the mechanisms behind several results: Colonnelli et al. (2024) find that general partner (GP) firms that manage VC funds dislike central government investors, or limited partners (LPs) in venture capital terminology, in particular and show a mild preference for local government LPs. Beraja et al. (2024) and Zhang et al. (2024) both find that government VCs invest more in firms with weaker initial productivity signals and in more remote places that tend to be neglected by private VCs, yet government-invested firms subsequently generate more intellectual property. I show that in the Chinese semiconductor industry, this is primarily driven by local government VCs. The central government behaves more like private investors that chase stronger ex ante performance. This adds a third dimension to the literature's usual comparison between government and private VCs.

My work also directly speaks to the literature on decentralization and federalism. Seminal theoretical work characterizes decentralization as a problem of delegation to informed but self-interested local governments that ignore the externalities their actions impose on other localities (Oates, 1999; Besley and Coate, 2003; Alonso et al., 2008). The literature on the Chinese economy has documented numerous inefficiencies arising from the Chinese "tournament model", including the erection of local trade & investment barriers (Barwick et al., 2021; Fang et al., 2022), misrepresentation to extract central government favors (Wang and Yang, 2023), and excessive leverage (Song and Xiong, 2026). In contrast, other work emphasizes local initiative and experimentation as a fundamental driver of past Chinese growth and dynamism (Li et al., 2025; Luo et al., 2025). My

results suggest that while decentralized investment induces investments in initially weaker local firms, local governments may have better information on firm potential and better capabilities to help firms grow.

This paper is also tied to a large literature on state ownership and firm productivity in China (Hsieh and Klenow, 2009; Brandt et al., 2017, 2012, 2022, 2026). The literature shares a broad consensus that private firms are more productive than SOEs, and that privatized SOEs became more productive (Chen et al., 2021). There is less evidence on how private firms fare after becoming partially state-owned, which became increasingly common in the Xi Jinping era. Lian and Zhang (2026) found that firm productivity decreased after firms sold minority stakes to state-owned companies in data from 1998–2013, while studies of state equity investments in the post-2013 Xi Jinping era found positive effects of government investment on measures of firm size and intellectual property (Beraja et al., 2024; Chen et al., 2026; Zhang et al., 2024). The paper contributes by focusing on the differential incentives of central and local government investors, and investigating the heterogeneous impact of different state investors on capital allocation and productivity growth.

The paper further engages with the literature on venture capital selection and syndication. A set of literature studies what observable characteristics VCs use in selecting targets and whether those characteristics also predict firm performance via regressions and machine learning methods (Gompers et al., 2020; Lyonnet and Stern, 2024; Hellmann and Puri, 2002; Jang and Kaplan, 2025). Another strand of work models how venture investors match with startups, and uses realized and counterfactual matches to distinguish investor effects from startup quality (Sørensen, 2007; Uetake, 2012; Fox et al., 2018; Ewens et al., 2022; Zhang et al., 2024). My reduced form analysis and quantitative model build upon the tradition of this literature to understand how government VCs might behave differently from private VCs due to industrial policy objectives.

The rest of the paper proceeds as follows. Sections 2 and 3 discuss the institutional setting and the data. Section 4 first establishes that both the Chinese central government and local governments set total industry sales as policy targets, which requires subsidizing higher productivity firms in a benchmark model. It then tests the claim by showing how central government, local government, and private VCs invest based on a firm's relative productivity rankings and personal ties. Section 5 presents the main event study results on productivity, firm size, innovation, and board/management composition. Section 6 probes the determinants of government VC managers' participation in the corporate governance of portfolio firms and decomposes the observed productivity effects. Section 7 introduces a model of demand, firm production, and VC investment by central government, local government, and private VCs, as well as the estimates and the counterfactual. Section 8 concludes.

2 Setting: Chinese Government Venture Capital in Semiconductors

In the 1990s, local governments in major cities pioneered government venture capital specializing in high-tech investments. Prominent examples include Shanghai Science & Technology Venture Capital established in 1992 and Shenzhen Capital Group founded in 1999. Government venture

capital was institutionalized at the national level via a series of policy decrees in the 2000s. In 2005 the National Development and Reform Commission (NDRC) formally defined the "Government Guidance Fund" as a government "mother fund" that invests as a "limited partner" (LP) in venture capital funds managed by professional private or state-owned "general partner" (GP) investors (Wei et al., 2023). The State Council in 2008 further specified the purpose of government guidance funds as "correcting market failures resulting from private allocation of startup capital". It authorized local governments above the prefectural level to fund venture capital that invests in early startups in priority high-tech sectors. Government LPs monitor their GPs to ensure they operate according to policy guidance, but do not interfere in the GPs' daily operations. Such institutional arrangements allow government capital to take advantage of the GP's market expertise in investing while adhering to industrial policy objectives (Luong et al., 2021).

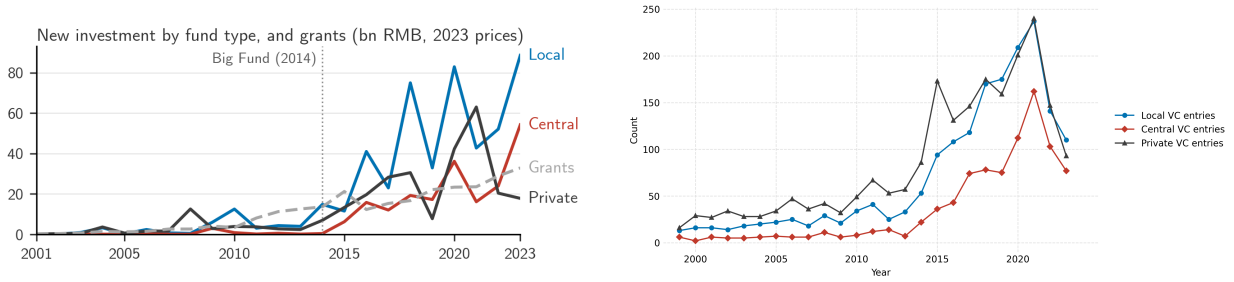
Government venture capital at both the national and sub-national levels proliferated after 2014 as a consequence of two major policy changes. First, "Made in China 2025" cemented the support of the capital- and technology-intensive manufacturing sectors as a central priority. Second, the State Council's "Document No. 62" in 2014 barred local governments from giving out fiscal subsidies and tax incentives to firms without explicit legal authority. This spurred a movement to "replace subsidies with (equity) investment" (Cheng et al., 2026).

Foreign venture capital backed China's first private semiconductor startups in the 2000s, which grew to rival state-owned national champions (Fuller, 2016). Private financing mainly targeted asset-light firms with foreseeable commercial prospects, with little interest in uncertain long-duration projects in capital- and technology-intensive sectors that face globally dominant competitors (Fuller, 2019). The rapid rise of the Chinese electronics sector following trade liberalization in the 2000s helped cultivate homegrown firms across distinct segments of the supply chain, but the market share of domestic firms remains limited (Chu, 2013).

The watershed moment of Chinese semiconductor industrial policy arrived in June 2014 when the central government promulgated the "National Integrated Circuit Industry Development Promotion Guidelines". This foundational document of Chinese semiconductor industrial policy today aimed for total industry revenue to grow by a 20% year-on-year growth rate through 2020. To achieve the stated objectives, the central government established the "National Integrated Circuit Industry Investment Fund", nicknamed the "Big Fund", which raised around 138.7 billion RMB in its initial funding round ("Phase I") in September 2014 from the Ministry of Finance and central SOEs like the China Development Bank and China Tobacco. The fund is managed by state-owned Sino IC Capital and was the largest government venture capital/private equity (VC/PE) fund. "Phase I" of the fund invested primarily in notable national leaders in semiconductor manufacturing and design. The Made in China 2025 plan, issued in 2015, later set a target for homegrown producers to supply 70% of domestic demand by 2025.

Following the Big Fund, local governments at the provincial and municipal levels also instituted

government guidance funds and venture capital dedicated to investing in local semiconductor firms. Figure 1a documents the dramatic rise of government VC investment relative to private VC and traditional fiscal subsidies since 2014 in semiconductors. Annual new equity investment by local government funds reached about 89 billion RMB ($12.5 billion) in 2023; central equity investment was about 54 billion RMB ($7.6 billion) and grants about 33 billion RMB ($4.6 billion) that year. Cumulatively over 2014–23, Chinese local governments' equity investment totals about $66 billion, the majority of China's estimated industrial policy expenditures in semiconductors. The scale is comparable to the U.S. CHIPS Act in 2022, which promises to spend $52.7 billion with $39 billion on funding semiconductor manufacturing plants. After 2014, an increasing number of private firms have received equity investments from government VC funds. Figure 1b plots the count of new investment events, defined as the first year an initially private firm receives investment by a particular VC type over time.



(a) New Equity Investments and Grants **(b)** New Investment Events

Figure 1: Local and Central Government Equity Investment in Semiconductor Firms

Notes. Panel (a) plots annual flows of new equity investment by local government, central government, and private VC funds, and grants, into Chinese semiconductor firms (billions of RMB, 2023 prices); panel (b) plots the annual count of new investment events by local government funds, central government funds, and private venture capital. Equity investment is measured as new paid-in capital from each fund type; grants are total grants reported by Chinese listed firms and grants for all firms reported by Qizhidao. The dotted vertical line in panel (a) marks 2014, the launch of the National Integrated Circuit Industry Investment Fund (the "Big Fund") and State Council Document No. 62. Author's calculations from business-registration records on Qichacha and Tianyancha (equity) and subsidy disclosures on Wind and Qizhidao (grants).

Government venture capital in semiconductors has produced visible failures at both levels of government. The Big Fund came under an anticorruption investigation in 2022, with several of the fund's senior managers being indicted or replaced. Around 2019–22, several semiconductor startups funded by local governments across the country also declared bankruptcy. On the other hand, several Chinese semiconductor firms nurtured by government VCs have grown to be globally competitive. One example is CXMT, a memory chipmaker that received equity investment from the Hefei city government in 2016, followed by the Big Fund in 2020, and became the most valuable company listed in mainland China by market capitalization upon its initial public offering (IPO) in 2026. The empirical analysis in the following sections tests whether the high-profile failures reflect fundamental pitfalls of government equity investment or are particular edge cases.

3 Data

Business registration data. To document Chinese government equity investments, I leverage Chinese business registration data published by the National Enterprise Credit Information Publicity System and available on the business intelligence platforms Qichacha and Tianyancha. The platforms provide information on capital invested and shareholding percentage by all shareholders, main personnel (board members and senior management), and intellectual property of the universe of firms in China across time. This enables me to track the equity share and paid-in capital contribution over time of the immediate shareholders of firms, as well as that of the immediate shareholders' shareholders, and so on. For each shareholder of the firm, the data platform identifies the "ultimate controller" of the corporate shareholder via shareholding and/or voting rights. I am thus able to identify whether a given venture capital/private equity (VC/PE) fund is controlled by a central (typically the State Council, the Ministry of Finance, or the State Council State-owned Assets Supervision and Administration Commission (SASAC)) or a local government entity (provincial/municipal people's government, finance bureaus, or provincial/municipal SASAC).

Following the methodology of Bai et al. (2020b) and Beraja et al. (2024), I identify government VC/PE funds by looking through the shareholding chain of the firms. I collect the ultimate controllers of the shareholders of each direct corporate shareholder of a firm. Following Chen et al. (2026), a direct corporate shareholder is a "central", "provincial", or "municipal" investment fund if it is a VC/PE fund and has over 20% of its shares controlled by shareholders identified by Qichacha to be ultimately controlled by a central, provincial, or municipal entity respectively. Appendix Figure E.3 illustrates this logic by showing the shareholding chain behind the major shareholders of Shanghai Enflame Technology, a graphics processing unit (GPU) designer for artificial intelligence (AI) applications. Enflame's major shareholders include the Big Fund, which invested in the firm in 2022, and Shanghai Wuyuefeng Phase II Integrated Circuits Equity Investment Limited Partnership, which invested in 2020. As documented in the figure, Shanghai Wuyuefeng's major shareholders, Shanghai Venture Capital Co. and Shanghai Shuangchuang Tech Investment Center, are both investment companies ultimately controlled by the Shanghai municipal and district-level SASACs. Thus, I identify Shanghai Wuyuefeng as a local government fund of Shanghai.

Balance sheet data. I focus on the set of firms belonging to the following 4-digit sectors in China's National Economic Industry Classification: Integrated Circuits Design (I6520), Integrated Circuits Manufacturing (C3973), Discrete Semiconductor Manufacturing (C3972), Semiconductor Lighting Devices (C3975, "Optoelectronics" hereafter), Semiconductor Equipment (C3562), and Materials for Electronic Manufacturing (C3985). I combine and harmonize multiple data sources to build a panel of semiconductor firms in China from 1998 to 2024.

I obtain data on firm revenue, noncurrent assets (fixed assets including physical assets and intangibles), the number of employees, and cost of goods sold from Bureau van Dijk's Orbis database. For publicly listed firms, Orbis' data agrees with that from Wind, the equivalent of Compustat for China. I further augment and corroborate the Orbis panel with a source widely used in the

Chinese manufacturing firm literature: the National Bureau of Statistics Survey of Above-Scale Industrial Firms (ASIF), which contains survey outcomes for all Chinese manufacturing firms with sales exceeding 5 million RMB before 2011 and 20 million RMB in 2011–13 (Brandt et al., 2014). I join the ASIF series to the Orbis series by adjusting the ASIF series by the within-firm ratio of observations where Orbis and ASIF overlapped. Appendix Section A discusses the fit between the two sources, which are generally similar. The resulting dataset has 6,241 firms with 49,823 observations with revenue, capital, and employee data.

Personnel data. To characterize the people who run semiconductor, government VC, and private VC companies, I collect from the same business registration platforms the "main personnel" histories of every semiconductor and VC general partner (GP) firm in the sample. All firms are required to report current and new changes in the roster of their "main personnel", which are members of the senior management and board of directors. For each person, the records list their name, position, and the start and end dates of each appointment, which allows me to construct a panel of director and executive term spells across firms and funds over time. The platforms also contain biographical profiles for these individuals, describing their education and prior career history. I further augment the data by collecting additional biographies using Anthropic Claude's web search tool. I use large language models (LLMs), namely Claude Haiku 4.5 and DeepSeek-V3, to encode the unstructured biographies into a consistent set of characteristics and a career history of dated education and employment stints with normalized institution names.

With the coded biographies, I further identify personal "connections" between a pair of firm and VC personnel via a shared past employer or alma mater. This allows me to link each firm to a VC GP via such personal ties and test whether government and private VCs' investment decisions are shaped by such linkages. Concretely, I define a *connection* as a pair of distinct individuals who share a past affiliation with the same institution, either as alumni or as employees in each year. Appendix Table E.1 reports the institutions through which firm and VC personnel are most often connected for private, central government, and local government VC GPs. Across all three fund types, connections are formed overwhelmingly through elite universities.

Other data. The data is further supplemented with commercial datasets from SEMI's global semiconductor plant-level data from 1996–2024. Commercial platforms Aiqicha and Qizhidao list publicly announced information on firms' grants, subsidies, and government recognitions. Appendix Section B discusses the details.

4 VC Selection: Who do Central and Local Governments Target?

This section starts by establishing that both central and local governments set industry sales as one major target for their respective industrial policies. This implies that governments should support more productive firms within their jurisdiction to maximize industry revenue. I then show that, consistent with their mandates, central government VCs target more productive firms in the nation, while local government VCs invest in more productive firms in their provinces. As top firms in

each province are not equally productive, the average local government VC-invested firm is less productive than the average central government and private VC-invested firm upon investment. If local government VC investments do not differentially change firm productivity, this suggests resource misallocation from the central government's perspective: the national industry size should increase if investments by less productive provinces are reallocated to productive firms.

4.1 Industry Revenue as Policy Target

What do Chinese governments aim to do by investing in semiconductors? Policy documents issued by central and local governments describe in detail the objectives and tools of industrial policy directed towards semiconductors. In the 2014 National Integrated Circuit Industry Development Promotion Guidelines, the central government targets domestic substitution and a 20% year-on-year industry sales growth rate. To characterize the objectives of provincial and city governments' semiconductor policies, I collected 323 policy documents on semiconductors from PKU Law, an authoritative database of Chinese laws, regulations, and government policies maintained by the Peking University Law School (Luo et al., 2025). Figure 2 shows that among the 280 major policy documents released by various levels of government from 2000 to 2023, 132 explicitly set industry revenue or scale as a policy goal, while 218 target or support productivity upgrading. Such a policy target is present not only at the national level but also throughout provincial and city-level documents, where the objective is total industry revenue at the local level. Appendix C.5 shows in detail local governments' headline revenue targets across places and years.



Figure 2: Major Semiconductor Policies Targeting Revenue and Productivity

Notes. Counts of new *major* Chinese semiconductor policy documents issued each year, 2000–2023. A document is "major" if it introduces at least one new target, support instrument, or concrete execution provision, as opposed to merely transmitting or implementing a previously announced major policy. "Tech. & self-sufficiency" marks documents that target or support production-efficiency or total-factor-productivity gains—including through R&D, equipment upgrading, or process and quality improvement, and also support the use and market share of domestic products. "Output / scale targets" marks documents that set an explicit revenue or output-scale target. The plotted data comprise 280 policy documents released between 2000 and 2023, of which 277 are provincial or municipal and 3 are national; the series therefore predominantly reflect sub-national policymaking.

The central government's domestic substitution target and local governments' focus on within-

jurisdiction industry sales motivate the paper's focus on revenue productivity (TFPR) as a core outcome. If government investment only provides additional capital, Appendix Section H shows that, under the following standard assumptions of firm production:

1. TFPR follows a common stochastically increasing Markov process (expected next-year TFPR strictly increasing in current TFPR)
2. a firm's investment rate ($\frac{I}{K}$) is increasing in TFPR,
3. constant returns to scale

government VCs should invest in firms with higher TFPR to maximize the jurisdiction's sales. In the next subsection, I test whether government VC funds invest in high-productivity firms as the model predicts, conditioning on other rich observables such as firm-VC board connections. Appendix Section C discusses how I estimate firm TFPR with balance sheet variables using Ackerberg et al. (2015).

4.2 Who do Government and Private VCs Invest In?

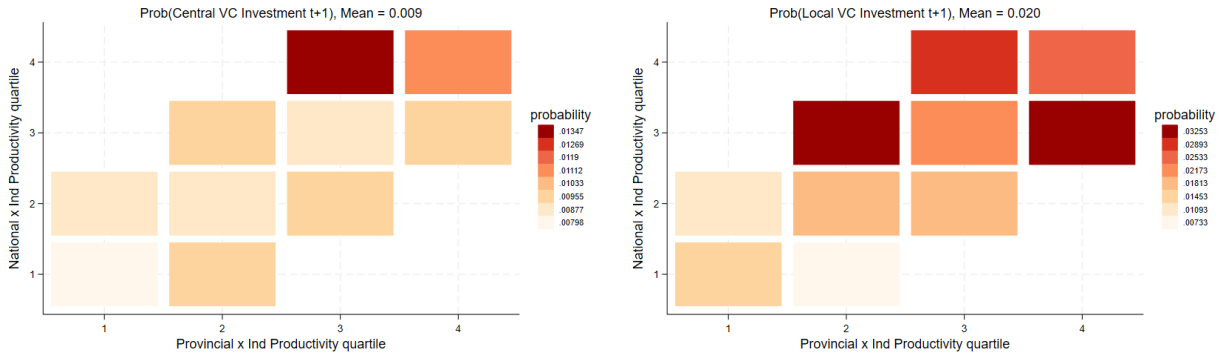
For the central government interested in maximizing national industry revenue, decentralization by allowing local governments to invest in semiconductor firms may result in the misallocation of fiscal resources if local governments invest too much in unproductive firms. Local governments may invest in inefficient firms due to corruption and local ties, or more fundamentally, some localities do not have productive enough firms to start with. Total national industry revenue could improve if unproductive provinces' budgets could be redistributed to firms in productive places, which justifies centralizing investment decisions.

This concern is not purely theoretical and has been expressed by central government officials publicly. At an October 2020 press conference, the National Development and Reform Commission warned that firms "with no experience, no technology, and no talent" had rushed into the semiconductor industry, that some localities "launch projects blindly" without an understanding of the industry, and that the risk of duplicating redundant investment in low-technology projects had begun to surface. It announced a "whoever supports, bears responsibility" principle, under which local authorities backing projects that cause major losses would be held to account.[1] The statement reflects concerns about the downsides of decentralized investment: local governments finance local firms regardless of firms' actual competitiveness in the national market, resulting in misallocation of fiscal resources.

Figures 3a and 3b plot the raw probability of receiving central and local government VC investment in the next year by being in a particular national and provincial productivity quartile, among same-sector firms that have not received any government VC investment. The probability of central

[1]National Development and Reform Commission regular press conference, 20 October 2020. https://www.ndrc.gov.cn/fggz/fgzy/shgqhy/202010/t20201021_1248556.html

government VC investment rises with a firm's national productivity quartile, represented by the vertical axis of Figure 3a. The gradient of local investment probability, on the other hand, shifts more strongly with the firm's provincial TFPR quartile, on the horizontal axis. Local government VCs may invest in weaker firms, ranked by the national productivity percentile, if the firms nevertheless are relatively productive within their own province. The figures thus provide suggestive visual evidence that a wedge between central and local government incentives may be present.



(a) Central Fund Investment Probability by National × Provincial Productivity Quartiles

(b) Local Fund Investment Probability by National × Provincial Productivity Quartiles

Figure 3: Government Fund Investment Probability by National and Provincial Productivity Quartiles

Notes. Within a panel, each block represents the percentage of not government fund invested firm-years that will receive first-time central (Panel a) or local (Panel b) government fund investment next year, conditional on being in a particular national (vertical axis) and provincial (horizontal axis) productivity rank quartile (1–4, 4 being the highest). The color represents the frequency of next-year central investment for Panel (a), and the frequency of next-year local investment for Panel (b) in the sample.

I formally test the differential investment incentives of private, local government, and central government VCs on the sample of firms the VC type has not yet invested in. The sample is the "choice set" of VC funds deciding on the firms to allocate to for the first time. I run the following linear probability model with fixed effects:

$$\begin{aligned} 1(\text{VC type k investment in year t+1})_{it} = {} & \alpha^{\text{nat}} \ nat_TFPR_pctl_{it}^{k} \\ & + \alpha^{\text{prov}} \ prov_TFPR_pctl_{it}^{k} \\ & + \beta^{\text{central}} \#central_conn_{it} + \beta^{\text{local}} \#local_conn_{it} \\ & + \beta^{\text{private}} \#private_conn_{it} + \boldsymbol{\gamma}' \mathbf{x}_{it} + \delta_{s(i),t} + \epsilon_{it} \end{aligned}$$

where $nat_TFPR_pctl_{it}^{k}$ is firm i's national productivity percentile (normalized to 0–1 scale with 1 being the highest) among same-sector firms in VC k's choice set in year t, and $prov_TFPR_pctl_{it}^{k}$ is the corresponding provincial productivity percentile within VC k's choice set. I also test how a firm's personnel ties to a VC fund's GP could influence investment by including the number of directors or management connected to a director in the central (#central conn_{it}), local government fund GP (#local conn_{it}) or private VC GP (#private conn_{it}). $\mathbf{x}_{it}$ denotes a vector of firm char-

acteristics, and $\delta_{s(i),t}$ is the sector × year fixed effect to control for variation in each VC type's investment intensity across sector-years.

The coefficients of interest $\alpha^{\text{nat}}, \alpha^{\text{prov}}$ are identified by the relative productivity between provinces. Holding a firm's national percentile fixed, the firm has a higher provincial TFPR percentile if it is in a less productive province with weaker firms. A positive α^{prov} implies that firms in less productive provinces receive more of the VC type's investments. Analogously, α^{nat} is identified by comparing firms with the same provincial rank. The firm with the higher national productivity rank is in a more productive province, and hence a positive α^{nat} implies that the VC type invests in more productive provinces. The sector × year fixed effects absorb differences in each VC type's investment rate across sector-years.

Table 1: Productivity Percentiles and Director Ties as Predictors of VC Investment

	Central government VC		Local government VC		Private VC	
	(1)	(2)	(1)	(2)	(1)	(2)
National TFPR percentile (0–1)	0.012**	0.012**	-0.004	-0.005	0.018***	0.018***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)
Provincial TFPR percentile (0–1)	-0.006	-0.008	0.014**	0.010*	0.006	0.002
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
# directors tied to the GP of a:						
central government VC	0.002*	0.001	-0.003*	-0.003**	-0.001	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
same-province local VC	0.001	0.001	0.005***	0.005**	-0.000	-0.002*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
private VC	0.000	-0.001	0.003***	-0.001	0.003***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mean dependent variable	0.01	0.01	0.02	0.02	0.01	0.01
Observations	22,533	22,472	23,964	23,902	20,874	20,874
R^2	0.04	0.04	0.04	0.05	0.02	0.04
Province × industry clusters	175	175	177	177	174	174
Industry × year fixed effects	Y	Y	Y	Y	Y	Y
Firm characteristics controls	N	Y	N	Y	N	Y

Notes. Linear probability models of investment by the named VC type in year $t+1$, on firms that type has not yet invested in. Percentiles rank revenue productivity (TFPR) among same-industry firms nationally and within the firm's province in year t. A tie is a link through education or an employment stint between a member of the firm's main personnel and a member of the main personnel of the VC type's GP. Both columns include industry × year fixed effects and indicators of whether the firm is already invested by the other VC types. Column (2) adds ownership indicators (foreign, SOE); firm age, log capital, log employment, and registered capital; patent, IC layout, and software stocks, production capacity, and an indicator for the industry's most advanced process; board size and the numbers of directors with government, SOE, finance, or R&D experience, a master's degree, or foreign education; High-Tech Enterprise and national specialized-SME status, total subsidies (grants and equity), and the number of central and local procurement contracts. Appendix Table E.4 shows the estimates for other covariates. Standard errors clustered by province × industry in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The first two columns of Table 1 suggest that central government VC investment probability rises with the national TFPR percentile. The coefficient remains significant after controlling for an extensive battery of firm characteristics including intellectual property, firm size, board member composition, and government grants/procurement variables. The middle columns show instead that local government VC investment has the opposite pattern: the probability of local investment increases only with the provincial productivity percentile. The last two columns show that a higher national TFPR percentile strongly predicts private VC investment, consistent with private VCs favoring more efficient and likely profitable firms. The estimates suggest that moving from the bottom to the top of the national productivity distribution raises the probability of central gov-

ernment VC investment by 1.2 percentage points on a base of about 1 percent, while moving from the bottom to the top of the provincial distribution raises the probability of local government VC investment by 1.0 to 1.4 percentage points on a baseline of about 2 percent.

Figure 4 visualizes what the productivity percentile coefficients imply for the investment behavior of central and local governments. Each dot is a firm in the discrete semiconductor manufacturing sector in 2016, representing its productivity percentile within its province (horizontal axis) and within the nation (vertical axis). Shanghai firms (purple) mostly lie above the diagonal. The median firm in Shanghai is above the national median, and similarly for other percentiles, suggesting that firms in Shanghai are generally more productive. Firms in Shandong province (orange) lie below the diagonal and represent the opposite case. A random Shanghai firm is more productive than a random Shandong firm 77% of the time. The vertical dashed line links a Shanghai firm and a Shandong firm that both rank at about the 80th percentile in their own province. The Shanghai firm ranks at the 95th percentile nationally and the Shandong firm at the 58th. The central government VC is more likely to invest in the Shanghai firm. The horizontal dashed line instead links two equally productive firms at about the 58th percentile in the nation. The firm from Shandong, the less productive province, ranks near the top of its province (79th percentile) while the Shanghai firm ranks below the provincial median (42nd). The Shandong firm is more likely to receive local government investment. Thus, Table 1 suggests that central and local government VCs target firms differentially due to their different objectives: central government VCs target more productive firms in the nation and thus prefer firms in more productive provinces holding fixed the provincial rank. Local government VCs instead favor local champions. Fixing national productivity rank and hence the productivity level, the firm in a less productive province is more likely to get local government investment. This creates potential for misallocation if less productive provinces like Shandong invest in a lot of their firms.

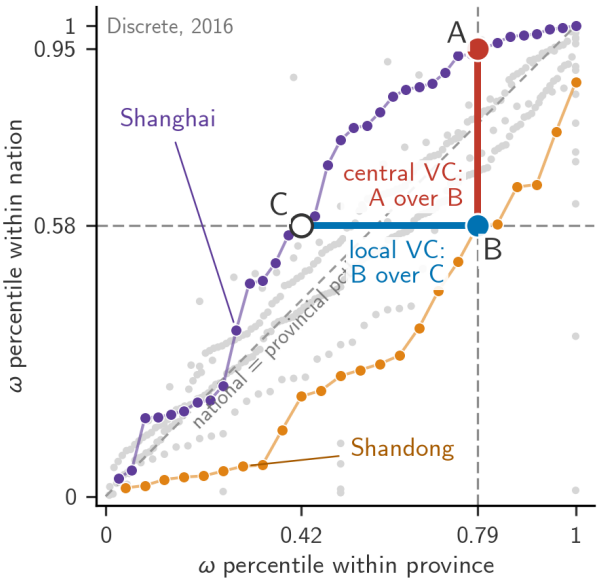


Figure 4: Visualizing Central and Local Selection on National vs Provincial Productivity Percentiles

Notes. Each dot is a discrete semiconductor firm in 2016 not yet invested by a government VC. Axes: the firm's TFPR (ω^R) percentile within its province (horizontal) and within the whole nation (vertical). Grey dots are firms in other provinces, purple dots indicate Shanghai firms and orange dots represent Shandong firms. The vertical dashed line fixes the provincial percentile at 0.79 to compare a Shanghai and a Shandong firm with the same provincial rank but different national rank. The central government VC is more likely to invest in the more productive Shanghai firm. The horizontal dashed line instead fixes the national TFPR percentile at 0.58 and compares another Shanghai firm with the Shandong firm. The Shandong firm has a higher provincial rank and is more likely to be invested by a local government VC as implied by the estimates in Table 1.

Furthermore, the number of firm personnel with ties to a VC type predicts VC investment from the same type. While the effect of connections attenuates for central government and private VC investment under rich controls, the local government VC's connection effect remains significant at the 5% level accounting for rich firm observables. This further suggests that local government is unique among VCs in using personal networks from local alumni ties to make investment decisions on top of publicly available firm observables. Appendix Table E.5 reports estimates coming out of a conditional logit specification, and the coefficients tell the same story.

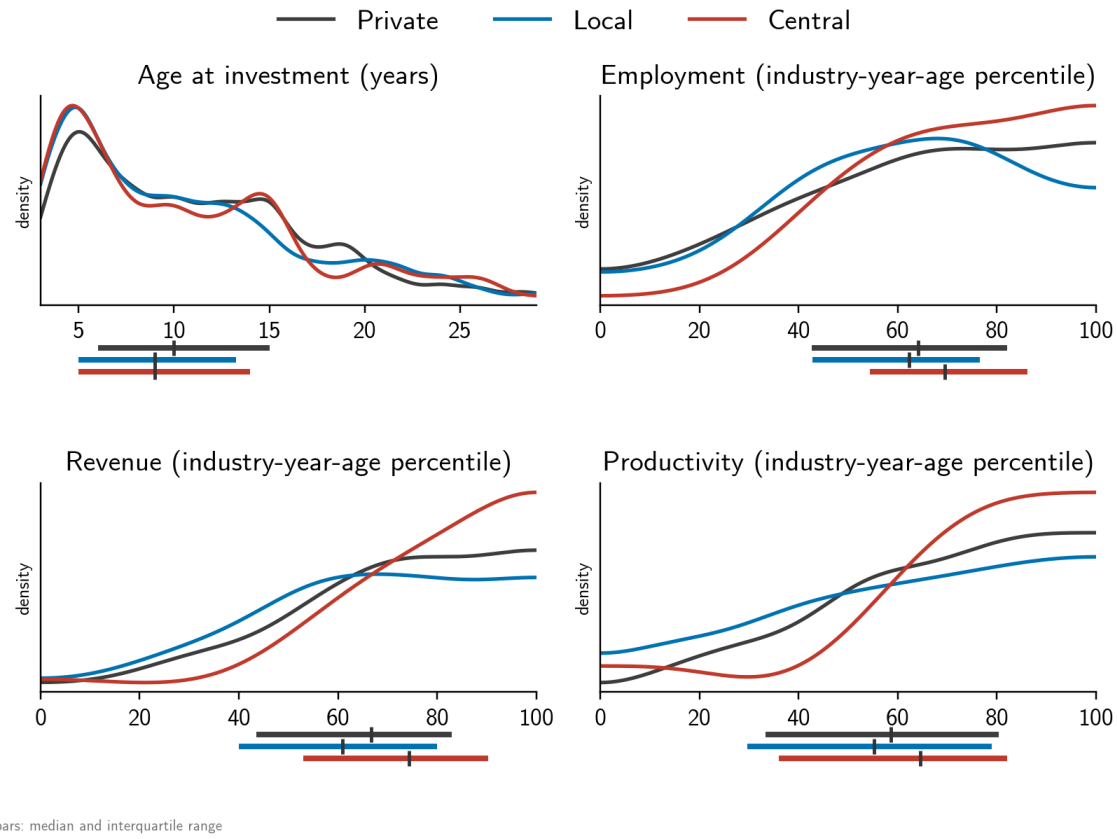


Figure 5: Firm Characteristics in the Year Before Entry, by VC Type as First Investor

Notes. Kernel densities of (a) age and within industry-age-year percentile of (b) revenue, (c) employment, and (d) productivity of firms that private/local government/central government VCs respectively will invest in next year as first investors. Appendix Figure E.5 and Table E.7 show the within industry-year distribution that does not condition on age.

Figure 5 further compares the distribution of age and within industry-year-age employment, revenue, and productivity percentile of firms that would receive local government, central government, and private VC investment in the next year. Private and central government VCs invest in more productive firms, but local government VCs invest in firms that are less productive and smaller. Central government VCs consistently pick larger firms by employment and revenue. These facts reflect that local governments have to invest among a more constrained choice set than that of private or central government VCs, and thus their average picks are ex ante weaker and smaller. Local governments may thus serve a distinct role in financing smaller and less established firms that are eschewed by private investors and the central government. Beraja et al. (2024) and Zhang et al. (2024) have previously documented that government VCs invest in weaker firms relative to private VCs. In Chinese semiconductors, this is primarily driven by local governments interested in maximizing local industry size. The central government instead targets large and productive national champions.

4.3 Following and Coordination Between VCs

Combination	First to enter	Firms	Share
Private only	Private	479	21.4%
Local only	Local	252	11.2%
Central only	Central	33	1.5%
Local and Private	Private	248	11.1%
($n = 664$, 29.6%)	Local	141	6.3%
	Jointly (same year)	275	12.3%
Central and Private	Private	25	1.1%
($n = 66$, 2.9%)	Central	13	0.6%
	Jointly (same year)	28	1.2%
Central and Local	Local	24	1.1%
($n = 58$, 2.6%)	Central	7	0.3%
	Jointly (same year)	27	1.2%
All three invested	Private	181	8.1%
($n = 688$, 30.7%)	Local	93	4.2%
	Central	19	0.8%
	Private and Local jointly	127	5.7%
	Private and Central jointly	45	2.0%
	Local and Central jointly	31	1.4%
	All three jointly	192	8.6%
Strictly first (total)	Local	510	22.8%
	Central	72	3.2%
	Private	933	41.7%
Ever invested	—	2,240	100.0%
Never invested	—	3,679	—

Notes. A type's first investment year is the first year it holds equity in the firm. "First to enter" names the type that invests earliest; "jointly" means the types first invested in the same year. Shares are of the 2,240 firms in the estimation sample that receive at least one investor type.

Table 2: Venture Capital Entry: Investor-Type Combination and Who Entered First

That central government and private VCs invest in more productive firms may also reflect that they tend to enter later in a firm's lifecycle when it is more mature and productive, while local government VCs invest earlier. However, Figure 5 shows that the age distributions of firms that receive different VC types' investments first are similar. Table 2 shows that there is substantial variation in the sequence and timing at which different types of VCs invest in firms, which I leverage for my event study analyses in Section 5.

In the largest group of firms, a private VC invested strictly first (933 out of 2,240, 41.7%), while a substantial number of firms received only local government VC investment in their first round (510

firms, 22.8%). Central government VCs typically follow local government and private VCs or jointly invest with them, but they also invested first in 72 firms. The patterns overall suggest that there is rich variation in the timing sequence by which firms receive investment. How do the differences in selection translate into outcomes on firm performance and growth? The next section examines how policy-relevant firm outcomes including revenue productivity and innovation evolve around entry by private, local government, and central government VCs, accounting for the presence and timing of other investors.

5 Event Study Analysis

5.1 Differences-in-Differences with Multiple Staggered Treatments

In this section, I present the headline empirical results on event studies of key firm outcomes such as productivity following different VCs' investments. In this setting, firms may receive investment from three different types of VCs $k \in \{\mathrm{C}, \mathrm{L}, \mathrm{P}\}$—central government, local government, and private, respectively—concurrently or in different years. When each VC's treatment effect is heterogeneous across cohorts, simple two-way fixed effects regressions on relative time indicators from multiple VC types' investments produce biased coefficients that are contaminated by other VC investments' effects (de Chaisemartin and D'Haultfœuille, 2023). To address this, I implement the procedure proposed by de Chaisemartin and D'Haultfœuille (2023) that is robust to heterogeneous treatment effects across cohorts of firms receiving investment in different years (de Chaisemartin and D'Haultfœuille, 2020; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021).

I estimate $\theta_k(\tau)$, the average change in outcome Y after $\tau \in \{-5, -4, \ldots, -2, 0, 1, \ldots, 4, 5\}$ years of investment by VC $k \in \{\mathrm{C}, \mathrm{L}, \mathrm{P}\}$ relative to $\tau = -1$, the year before VC k's investment. The year of investment g_i^k is defined as the first year firm i receives equity investment by a VC of type k. Following Callaway and Sant'Anna (2021), each $\theta_k(\tau)$ is a treated units-weighted average of 2×2 difference-in-differences estimates $ATT_{k,s}(g, \tau | \mathbf{g}^{-k})$. Specifically, it is defined as

$$ATT_{k,s}(g, \tau | \mathbf{g}^{-k}) = \underbrace{E[Y_{i,g+\tau} - Y_{i,g-1} \mid i \in \mathcal{T}_{k,s}(g, \mathbf{g}^{-}, \tau)]}_{\text{year } g-1 \text{ to } g+\tau \text{ difference for treated group}} - \underbrace{E[Y_{i,g+\tau} - Y_{i,g-1} \mid i \in \mathcal{C}_{k,s}(g, \mathbf{g}^{-}, \tau)]}_{\text{year } g-1 \text{ to } g+\tau \text{ difference for control group}}$$

The treated group $\mathcal{T}_{k,s}(g, \mathbf{g}^{-}, \tau)$ are firms in 4-digit sector s first invested by VC k in year g observed in year $g + \tau$. The control group $\mathcal{C}_{k,s}(g, \mathbf{g}^{-}, \tau)$ are firms in sector s not yet invested by VC type k by year $g + \tau$. Furthermore, both treated and control firms share the same treatment history from other VCs $\mathbf{g}^{-k} = \mathbf{g}^{-}$ in year g, and no other VC types have invested in either treated or control firms from year g to time $g + \tau$. Thus, the estimate $\theta_k(\tau)$ is interpreted as the average additional change in outcome τ years from VC k's investment. The details of the implementation are in Appendix Section D.

For the estimated coefficients to be interpreted as the average treatment effect on the treated (ATT) of different types of VC, the following assumptions for each VC type $k \in \{\mathrm{C}, \mathrm{L}, \mathrm{P}\}$ and year $g \in \{2003, 2004, ..., 2023\}$ of receiving k's investment need to hold:

1. firms' current outcomes do not depend on future VC investment ("No Anticipation");

2. treated firms' potential outcome would follow the same trend as that of the controls absent any VC investment ("Parallel Trends Prior to First Treatment");

3. the dynamic effect of receiving k's investment in year g evolves identically across firms first invested by k in year g ("Parallel Trends Following Earlier Treatment").

which are de Chaisemartin and D'Haultfœuille (2023)'s Assumptions 7–9 respectively. In particular, Assumption 3 ("Parallel Trends Following Earlier Treatment") requires the effect on firms invested by each VC type in the same year to follow the same trend. It allows identification of the effect of VC investment that occurs after earlier investments by other VC types. The VC's dynamic effect could vary across treatment years g, and the initial level effect upon investment could also vary within the cohort g. The following section presents the estimates with respect to key outcomes such as productivity that also test whether Assumptions 1–3 hold for each investor type k.

5.2 Productivity

I first test Assumptions 1–2 by focusing on investment events where treated firms are firms that received their first-ever VC investment, and only one particular VC type is the first investor. From Table 2, 933 firms received private VC investment, 510 received local VC investment, and 72 received VC investment from the central government only in their first round of VC investment. As these treated firms do not receive any VC investment prior to the treatment, the appropriate control group is firms that have not received any VC by event time. The results suggest that first, for both revenue productivity ω^R (Figure 6) and value-added productivity ω^{VA} (Appendix Figure F.1), firms that receive VC first from any of the three VC types do not experience detectable differential pre-trends in either productivity measure. Second, firms that receive local government VC investment see a significant increase in productivity in the first three years after investment. Firms invested by private and central government VCs do not see a significant increase in these measures of productivity relative to firms not invested by any VCs.

Appendix Figure F.2 plots instead the aggregated event time estimates for VCs that invest in the firm strictly after other VC types have invested. Therefore, the control group is firms that receive the same other VC types' investments in the same year, but do not receive the VC investment. Local government VCs' post-investment coefficients still stand above those of central government and private VCs, but are no longer significantly different. Assumption 3 seems to hold for local government investment, which, if anything, sees a relative decline in productivity prior to investment.

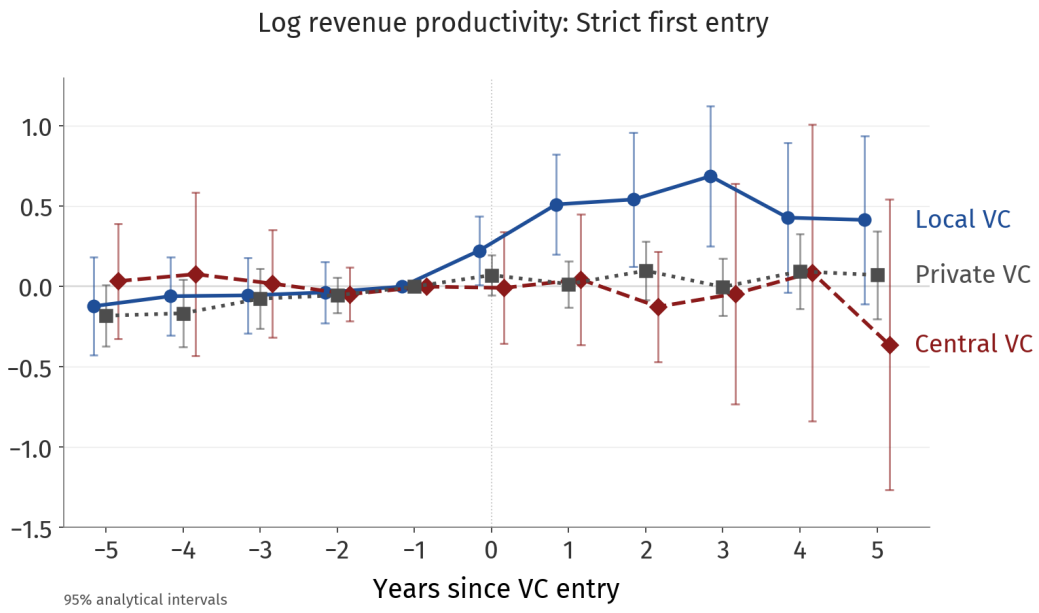


Figure 6: Revenue Productivity Event Study Estimates, Initial VC Investor

Notes. Central government, local government, and private VC ATT estimates $\theta_C(\tau), \theta_L(\tau), \theta_P(\tau)$ for years relative to investment $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% confidence intervals from analytical standard errors. The treated group are firms which receive their first VC investment from the VC type in question, and the controls are same-sector firms not yet invested by any VC. The estimates are treated-unit-weighted averages of primitive 2-period DiD estimates $ATT_{C,s}(g, \tau \mid \mathbf{g}^{-C})$, $ATT_{L,s}(g, \tau \mid \mathbf{g}^{-L})$ and $ATT_{P,s}(g, \tau \mid \mathbf{g}^{-P})$ respectively, which are group-time treatment effects of central, local, and private VC investment conditional on sector s and VC investment history $\mathbf{g}^{-}$.

Figure 7 presents the aggregate estimates that are weighted averages of the estimated coefficients from first VC investors and also subsequent investors. Local government VC-invested firms experience increases in productivity of about 35% (0.30 log points) one year after investment and about 44% (0.36–0.37 log points) two to three years after investment, reaching 66% (0.51 log points) in the fifth year after investment. Averaged over event times $\tau = 0, 1, \ldots, 5$ with treated-unit weights, the local government VC effect is 0.292 log points (about 34%). Central government-invested firms display sharp pre-treatment growth starting from $\tau = -3$, which is what one would expect from the selection results in Section 4.2, where central government VCs select on larger and more productive firms that have likely received positive productivity shocks years before investment. Appendix Figure F.3 shows similar results with value-added productivity. Appendix Figure F.6 shows that the local government VC's treated-unit-weighted average treatment effect over event times $\tau = 0, 1, 2, \ldots, 5$ is significantly different from that of private VCs ($p = 0.002$) and that of central government VC ($p = 0.045$) at 5%. To ensure that the result is not driven by the fact that local governments invest in smaller firms that could grow faster, I also run the same event study design comparing treated and control firms with below industry-median capital the year before investment, as well as above. Appendix Figure F.5 shows that both high- and low-capital firms after local government investment grew more productive relative to their peers at the same pre-investment capital bin.

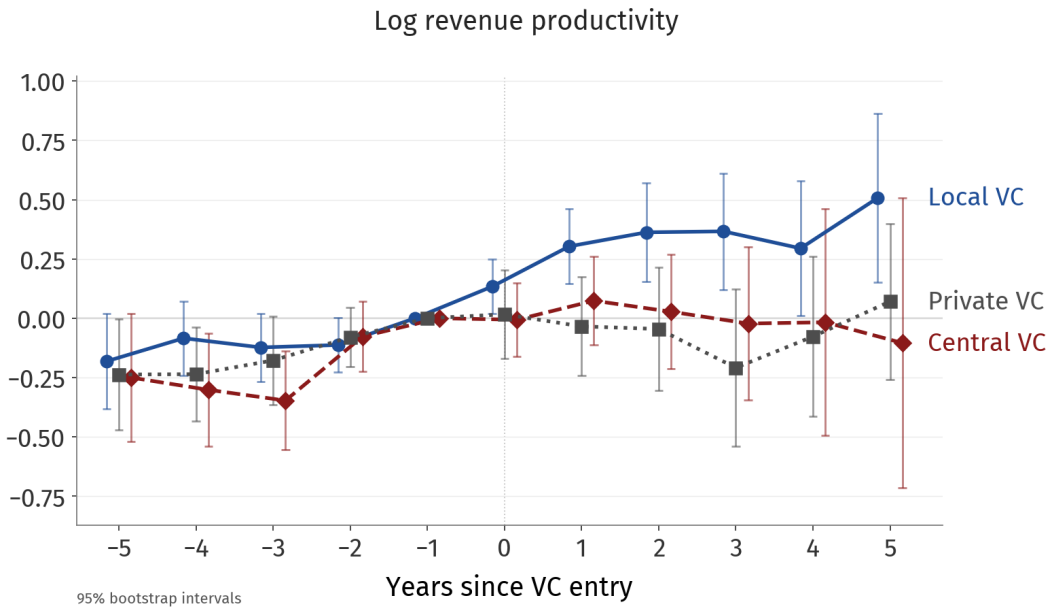


Figure 7: Revenue Productivity, Event Study Estimates

Notes. Central government, local government, and private VC investment average treatment effects $\theta_{\mathrm{C}}(\tau), \theta_{\mathrm{L}}(\tau), \theta_{\mathrm{P}}(\tau)$ estimates for $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% firm-block bootstrap confidence intervals. Following de Chaisemartin and D'Haultfœuille (2023), the estimates are treated-unit-weighted averages of primitive 2-period DiD estimates $ATT_{\mathrm{C},s}(g,\tau \mid \mathbf{g}^{-\mathrm{C}})$, $ATT_{\mathrm{L},s}(g,\tau \mid \mathbf{g}^{-\mathrm{L}})$ and $ATT_{\mathrm{P},s}(g,\tau \mid \mathbf{g}^{-\mathrm{P}})$ respectively, which are group-time treatment effects of central, local, and private VC investment conditional on sector s and VC investment history $\mathbf{g}^{-}$ (including never invested by the other VCs).

Appendix Figure F.4a plots the coefficients $\beta_{k,\tau}$ from the analogous two-way fixed effects event study specification:

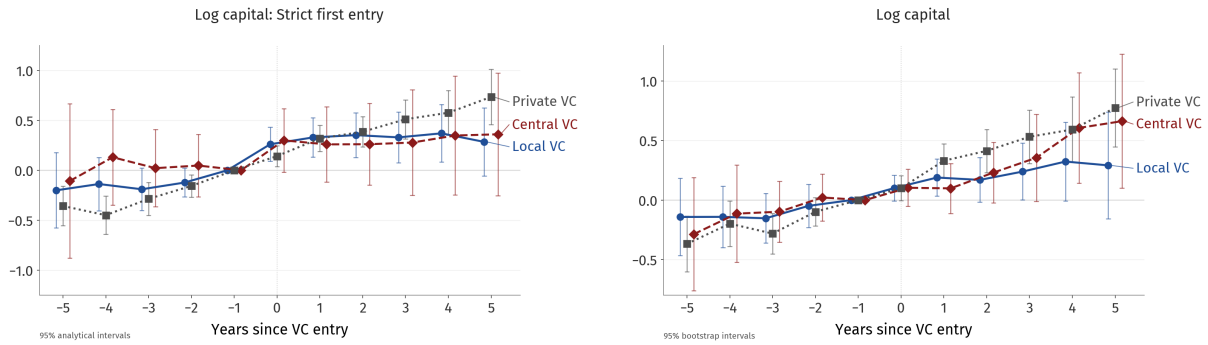
$$\omega_{it} = \alpha_i + \delta_{s(i),t} + \sum_{k\in\{\mathrm{C,L,P}\}} \sum_{\substack{\tau=-5 \\ \tau\neq -1}}^{5} \beta_{k,\tau} \mathbb{1}\{t - G_{ki} = \tau\} + \epsilon_{it}, \tag{1}$$

where I regress productivity on indicators of the leads and lags to each type k's investment along with firm and sector-year fixed effects $\alpha_i, \delta_{s(i),t}$. They qualitatively show a similar pattern, with coefficients of local and central government VCs rising from event time $\tau = 3$ to $\tau = 5$. Overall, the estimates suggest that firms invested by local government VCs become 35–66% (0.30 to 0.51 log points) more productive than not-yet-invested firms one to five years after local government VC investment. Averaged over event times 0 to 5, their gain exceeds that of central government and private VC-invested firms by 0.22 and 0.29 log points (Appendix Figure F.6).

5.3 Revenue and Capital

Appendix Figures F.8 and F.9 plot corresponding event study estimates on revenue per worker and log revenue. Consistent with the result on revenue productivity, firms invested by local government VCs also grew faster on these dimensions, with revenue about 69% ($e^{0.523} - 1$) higher than baseline three years after initial investment. There are also suggestive patterns of pre-investment revenue growth for central government and private VC-invested firms.

Figure 8 plots the corresponding estimates for log capital. Firms that receive private VC investment show a clear pre-trend in capital, while the corresponding pre-trends for local and central government VCs are milder. This suggests that government VCs relieve the financial constraints of firms, so government VCs materially change how invested firms expand capital. Private VCs instead tend to target firms that were already expanding capital faster than control firms, presumably financed from raising debt and other equity sources.



(a) Strict First Entry **(b)** Aggregate Estimates

Figure 8: Log (Capital), Event Study Estimates

Notes. Central government, local government, and private VC investment average treatment effects $\theta_{\mathrm{C}}(\tau), \theta_{\mathrm{L}}(\tau), \theta_{\mathrm{P}}(\tau)$ estimates for $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% confidence intervals (analytical in panel (a), firm-block bootstrap in panel (b)). Following de Chaisemartin and D'Haultfœuille (2023), the estimates are treated-unit-weighted averages of primitive 2-period DiD estimates $ATT_{\mathrm{C},s}(g,\tau \mid \mathbf{g}^{-\mathrm{C}})$, $ATT_{\mathrm{L},s}(g,\tau \mid \mathbf{g}^{-\mathrm{L}})$ and $ATT_{\mathrm{P},s}(g,\tau \mid \mathbf{g}^{-\mathrm{P}})$ respectively, which are group-time treatment effects of central, local, and private VC investment conditional on sector s and VC investment history $\mathbf{g}^{-}$. Panel (a) presents aggregated DiD estimates where treated and control firms had no other VC invested prior to the event, while Panel (b) presents estimates aggregated from both strict first entry and subsequent VC entries.

The post-treatment coefficients from Figure 8b suggest that firms increased capital by about 27% ($e^{0.239}-1$) three years after local government investment and 43% ($e^{0.355}-1$) three years after central government investment. There is some marked divergence afterwards, where central government-invested firms accumulate capital faster. To address the issue of pre-trends in capital for private VC in particular, I further implement a synthetic difference-in-differences design (Arkhangelsky et al., 2021) over a balanced sample with capital recorded for four pre-entry years. The estimator chooses control firms in the same sector so that their capital tracks each treated cohort over the four years before entry. The estimates plotted in Appendix Figure F.10 show that capital is higher by 57% ($e^{0.45}-1$) for central VC, 65% ($e^{0.5}-1$) for local VC and 58.4% ($e^{0.46}-1$) for private VC three years after investment.

5.4 Procurement

The previous results suggest that local government-invested firms see significant productivity increases, while central government and private VC-invested firms do not experience detectable changes in productivity relative to controls. The local government effect on revenue productivity could reflect higher production efficiency from process innovation and management, but could

also be due to higher prices and sales from favored treatment and local protectionism (Bai et al., 2020a; Barwick et al., 2021; Fang et al., 2022). I test this "local government protection" hypothesis via event studies on procurement contracts won by the firms. Appendix Figure F.11 instead suggests that, if anything, central government VC-invested firms win more procurement contracts from government agencies.

5.5 Manufacturing Technology and Innovation

Another way to investigate whether local government VC investment actually improves production efficiency is to test if measures of firm innovation change after VC investment. Specifically, I run event studies on whether firms register more semiconductor process improvements, patents, and copyrighted chip designs after different types of VC investment. From the SEMI plant-level data on process technologies, I observe the most advanced semiconductor process technology of manufacturing firms in the Integrated Circuits Manufacturing, Discrete Semiconductors, and Optoelectronics sectors. The semiconductor manufacturing process is measured in microns (1000 nanometers), which represents the density of transistors in chips produced by the process. A smaller number indicates more advanced and intricate technology. I convert the micron measures into 29 distinct technology generations from 5 microns (most mature) to 5 nanometers (most advanced). Appendix Figure F.12 shows that a manufacturing firm improves its manufacturing node generations after all VCs' investments. The point estimates for central government VC are higher than those of private VCs and local government VCs, but the differences are not statistically significant at the 10% level (p=0.39 for the $\tau = 3$ coefficient where the local-central gap is the largest).

Appendix Figures E.8 and E.9 show that among firms with manufacturing process nodes recorded by the SEMI data, central government VCs enter much later and concentrate investment on the more technologically advanced firms. Thus, although firms backed by central government VCs show higher but statistically insignificant process-node upgrading ($p = 0.39$), this difference may reflect both the central government's mandate to strengthen national technological capabilities and local government VCs' geographic investment constraints, which may limit their access to firms capable of pushing the technological frontier.

Appendix Figures F.13a and F.13b present results with respect to the number of newly published patents and integrated circuits (IC) design layouts, a special intellectual property right for chip designers' products introduced in China in 2001. Local government VC-backed firms subsequently publish more invention patents and more IC design layouts than firms after central government and private VC investment. The overall results suggest that the higher revenue productivity after local government VC investments is not merely reflecting higher market power or more intensive input use, but also product innovation, as measured by invention patents and IC layout designs. What could be driving the observed increase in productivity and innovation for local VCs relative to central government and private VCs? To probe this question, the next subsection studies whether government VCs as shareholders also compel firms to change the composition of their board members and management, and in doing so shape corporate governance and supply managerial and

technical talent to firms.

5.6 Personnel and Corporate Governance

What distinguishes government venture capital from conventional industrial subsidies is that, as shareholders, government VCs can appoint board members to monitor firms and participate in important managerial decisions. This section presents how the composition of a firm's management and board changes before and after government and private VC investment. As the outcomes of interest are count variables, I use Poisson DiD regressions as the primitives for my dynamic event study estimates (Wooldridge, 1999; Santos Silva and Tenreyro, 2006; Chen and Roth, 2024). Appendix Section D discusses the details. Figure 9a shows strikingly that firms' board size expands after VC, in particular for local government-invested firms. The estimates suggest that the average local government-invested firm's board expands in size by around 30% after investment.

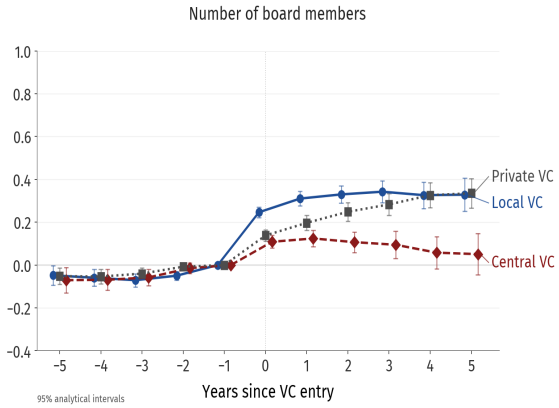
The evidence in principle could mean that government investment funds are a means through which the state extends its "grabbing hand" to innovative private companies. Yet I showed earlier that firms do not become less productive or innovative after receiving government VC investment. Local government-invested firms in particular see an increase in productivity and intellectual property outputs. Figures 9b, 9c, and 9d show furthermore that local government VCs also bring in board members with graduate degrees, foreign education, and finance backgrounds. Within firms, the number of foreign-educated directors is positively correlated with productivity (Appendix Table E.2). Thus, the results support the interpretation that local government VCs are not simply providing funding to their investees. Similar to Silicon Valley venture capital firms, they can complement founders' technical expertise by providing managerial talent and participating in corporate governance as active shareholders.

Anecdotal evidence from government VCs' publications supports the view that government VCs see themselves as playing an instrumental role in reforming corporate governance. For example, Shenzhen Capital Group, a municipal state-backed investor, invested in Xinchen Semiconductor, a laser-chip producer founded by two Chinese Academy of Sciences professors in 2022.[2] The local government VC helped design Xinchen's ownership and board structures, introduce performance evaluations and compensation systems, establish budgets and internal controls, and recruit finance personnel. These active intervention measures need not require VCs to insert their own managing team in the firms, but will encourage firms to expand their board and management committees to include more outside talent. The Shanghai semiconductor equipment producer AMEC, in its 2019 IPO prospectus, identified Shanghai Venture Capital as the nominating shareholder for two of its eleven directors. The directors also served on the board's strategy and remuneration and assessment committees that oversee strategic direction and managerial incentives.[3] These cases

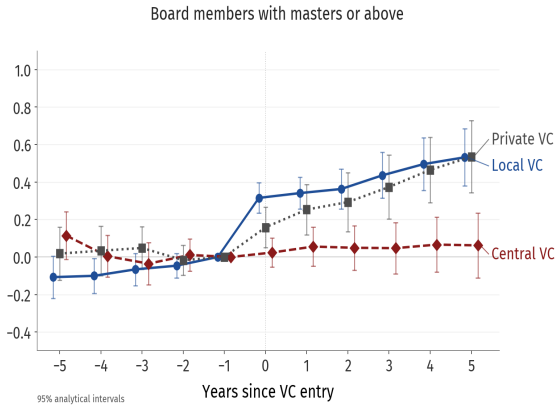
[2]See the story at https://www.szvc.com.cn/article/2620.

[3]See the IPO prospectus: https://money.finance.sina.com.cn/corp/view/vCB_AllBulletinDetail.php?id=5473221&stockid=688012.

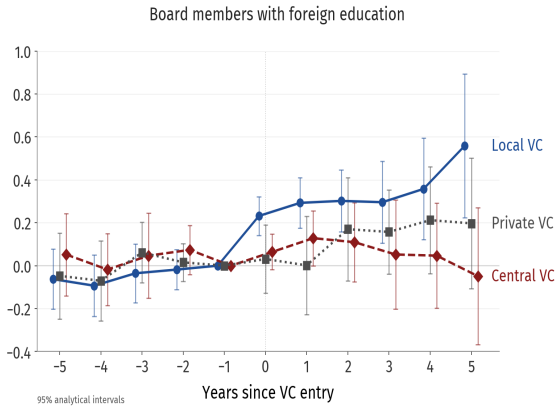
illustrate how state equity may advance industrial policy objectives via building firms' managerial capabilities and continued participation in corporate governance.



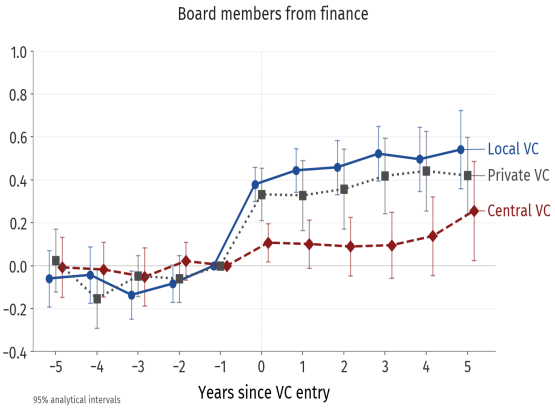
(a) Persons in Board or Management



(b) No. of Members with Graduate Degrees



(c) No. of Members with Foreign Education



(d) No. of Members with Finance Background

Figure 9: Board/Management Members and Composition
de Chaisemartin and D'Haultfœuille (2023) Event Study Estimates

Notes. Central government, local government, and private VC investment average treatment effects $\theta_{\mathrm{C}}(\tau), \theta_{\mathrm{L}}(\tau), \theta_{\mathrm{P}}(\tau)$ estimates for $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% analytical confidence intervals. Following de Chaisemartin and D'Haultfœuille (2023), the estimates are treated-unit-weighted averages of primitive 2-period Poisson DiD estimates $ATT_{\mathrm{C},s}(g,\tau \mid \mathbf{g}^{-\mathrm{C}})$, $ATT_{\mathrm{L},s}(g,\tau \mid \mathbf{g}^{-\mathrm{L}})$ and $ATT_{\mathrm{P},s}(g,\tau \mid \mathbf{g}^{-\mathrm{P}})$ respectively, which are group-time treatment effects of central, local, and private VC investment conditional on sector and VC investment history (including never invested by the other VCs).

5.7 Summary

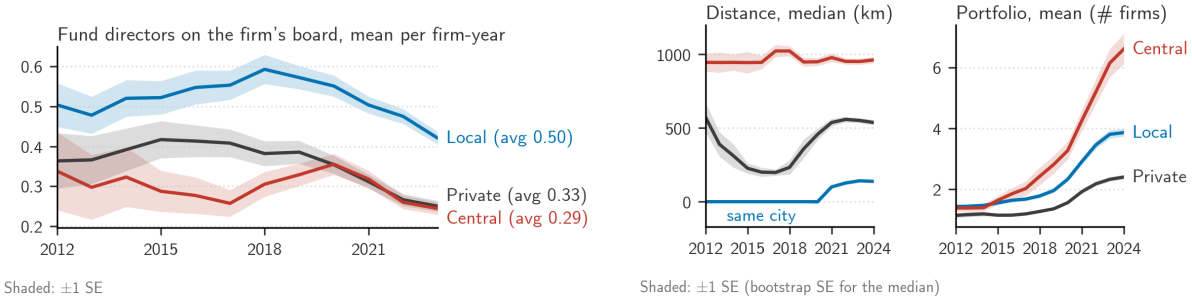
Across productivity, innovation, and personnel outcomes, the event study coefficients tell a consistent story. Local government VC-invested firms grow in productivity and revenue faster than central government and private VC-invested firms. I further show that local governments could improve firm productivity and innovation through a concrete treatment mechanism: the provision of managerial talent with advanced education and foreign experience. This added managerial oversight could be particularly helpful for smaller, initially less productive local firms as opposed to central government-invested firms that are already considered national champions. Faster ex-post firm growth suggests that there is value in delegating discretion and resources to local governments, and is another piece of evidence pointing towards the benefit of China's decentralized economic policy institutions (Luo et al., 2025).

Why would local government VCs in particular engage more in corporate governance relative to central government VCs? The next section suggests that geographic proximity and portfolio size explain why local government VCs may participate in firm management more than both private and central government VCs, and quantifies the extent to which the management channel contributes to observed productivity effects. Furthermore, the section quantifies the size of this observable channel relative to other explanations of local outperformance, such as local information and the provision of regulatory favors that I cannot measure.

6 Mechanisms: Active Management, Exit Likelihood, and Information

6.1 Local Governments Are More Active Due to Distance

Event study evidence suggests an organizational mechanism behind faster growth for local government-invested firms: local government funds intervene in their firms' management more, bringing in educated technical talent. Consistent with the event study evidence, Figure 10a shows that the average local government-invested firm has 0.50 directors who came from the board of its local government VC investors, about 1.7 times the 0.29 directors at the average central government VC-invested firm. The pattern remains at the extensive margin: 33.6% of local government-invested firm-years have at least one director linked to a local fund, versus 23.3% of central government-invested firm-years. Private VC funds fall in between at 0.33 directors per invested firm with 25.1% of firms in their portfolio with overlapping directors.



(a) Firm-Fund Management Overlap **(b)** Firm-Fund Pair Characteristics

Figure 10: Invested Firm-Fund Characteristics by Fund Type Over Time

Notes. Panel (a) contrasts private, central government, and local government VCs on the average number of persons sitting concurrently on the VC GP's board and the board of a firm the VC invests in. The unit of observation is a fund–invested-firm pair; each line plots the cross-sectional mean across all VC GP-portfolio firm pairs in a given year, 2012–2023, and shaded bands show ±1 standard error. Red denotes central government VC funds; blue denotes local government VC funds (provincial and city); dark grey depicts private VCs. Panel (b) plots the median firm–fund geographic distance in kilometers (left) and the mean number of portfolio firms per fund (right).

Figure 10b provides an intuitive explanation by plotting the median distance between local government, central government, and private VCs and their invested firms across all years, as well as the average size of the VC fund type's portfolio in semiconductors. The average central government

fund is further away from its invested firm and has more firms in its portfolio to attend to. Thus, it is costlier for a central government VC to intervene in the management of any given firm it invests in. The average private VC-invested firm is also further away from the private VC than that invested by a local government VC.

Table 3: Fund directors at the firm: comparing fund GPs within a firm and firms within a fund GP

	Dep. var.: # people on both the firm's and the fund GP's rosters	
	Firm FE	Fund GP FE
	(1)	(2)
Firm–fund distance (1,000 km)	-0.290^{***}	-0.233^{**}
	(0.060)	(0.102)
No. of firms in portfolio	-0.015^{***}	-0.010^{**}
	(0.004)	(0.004)
Fund equity stake (%)	$+0.030^{***}$	$+0.020^{***}$
	(0.004)	(0.005)
# pre-investment ties	$+0.003^{**}$	$+0.022^{***}$
	(0.001)	(0.005)
Firm TFPR percentile at entry	—	−0.377
		(0.247)
Firm size at entry (log employment)	—	−0.017
		(0.063)
Firm age at entry (years)	—	-0.021^{*}
		(0.013)
Entry characteristics jointly zero (p)		0.028
N (firm–fund GP years)	23,013	8,545
Pseudo R^2	0.28	0.32
Fixed effects	year, firm	year, fund GP
Firm controls	Y	Y

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Poisson, standard errors clustered by firm. Unit: invested firm × fund GP × year; outcome: # persons concurrently on firm and VC fund GP's board. Column (1) compares fund GPs within the same firm (year and firm fixed effects); column (2) compares firms held by the same fund GP (year and fund GP fixed effects), with entry characteristics measured the year before the GP's first investment in the firm (—: absorbed by the firm fixed effects). Both columns control for fund-type indicators, capital invested, fund board size and the firm controls of Table E.8.

Table 3 uses a firm–VC fund GP-year level panel to test what variables predict the number of persons the investing VC GP, the managing firm of the VC fund, puts on the investee firm's board. Within the same firm, distance to the VC fund GP and the VC GP's overall portfolio size negatively predict the number of persons the VC puts on the firm's board. With the full set of controls, an extra 1,000 km lowers the expected number of shared people by 0.29 log points across fund types, while one additional firm in the portfolio decreases the number by 0.015 log points. The specification controlling for GP fixed effects further shows that the invested firm's TFPR and size upon investment do not predict board placement, while younger firms upon investment receive more board placements from VC GPs. Appendix Tables E.8 and E.9 show that the negative gradient of distance and portfolio size on the number of VC GP persons in firms is shared between VC types. As central government VCs sit farther from their firms and hold larger portfolios (Figure 10b), the slopes imply fewer VC persons in the firm.

Local government VCs can draw on local industrial networks that local governments built, and their geographic proximity, to source investment opportunities through site visits and repeated engagement with prospective targets. These activities provide a potential channel through which investors obtain knowledge on latent firm potential and receptiveness towards government investment. Managers of the municipal investment platform of Zhangjiagang (a city in Jiangsu Province) were reported to have conducted regular visits to more than 100 local enterprises and investment roadshows involving more than 90 local projects.[4] Local government departments can complement investors' search efforts by identifying firms and facilitating direct access. In September 2023, Shenzhen's Longhua district screened 28 local strategic-emerging-industry projects and, after a matching procedure, organized 12 investment institutions to visit nine firms for face-to-face financing discussions.[5] Together, these accounts suggest that local investment networks can support a process of identifying potential targets and accumulating firm-specific information through repeated interaction. Geographic proximity and institutional connections may therefore reduce the costs of sourcing and evaluating investments, contributing to the documented effects of local government investment.

6.2 Private VCs Exit Quicker and More Often

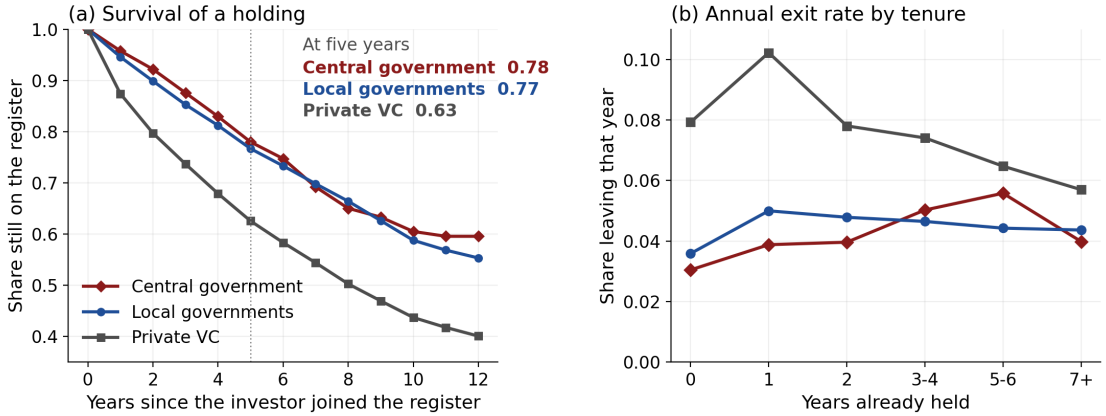


Figure 11: Survival Probability and Exit Rate by VC Type

Notes. Panel (a) plots the probability of a central government/local government/private VC GP remaining at a firm as its shareholder, directly or indirectly through any fund it manages, by the number of years since one of the government/GP's funds became the firm's shareholder. Panel (b) plots the share or probability of VC GPs leaving their portfolio firms as direct or indirect shareholders, by years already held.

The event studies in Section 5.6 show that private VC entry also predicts significant board expansion, and private VCs generally sit between local government and central government VC in their intensity in placing board directors on investee firms. Yet private VC-invested firms do not show a significant increase in productivity. Figure 11 suggests a possible reason: government VCs are more "patient" than private VCs. Specifically, 37% of private VC GPs will exit a firm completely

[4] https://szdushi.com.cn/news/1733363043197059.shtml.

[5] See the Longhua district government's report, published September 28, 2023: https://www.szlhq.gov.cn/lhtztgqyfwzx/gkmlpt/content/10/10862/post_10862492.html.

(through all of the funds they manage) by the fifth year of its holding, while the corresponding figure for local governments is 23% and for the central government 22%. Private VCs exit as a firm's shareholder with probability 8–10% in each of the first two years, while government VCs are at about 5%.

Appendix Table E.10 tests the predictors of an investing GP's exit using a firm-investor-year panel in which the investor is the central government, a provincial or city government, or a private VC GP. The results suggest that private VCs are differentially more likely to exit once a firm becomes publicly listed: In the years after the IPO, a private VC's annual exit probability is 22.1 percentage points higher than in firms that have not yet gone public, against 13.1 points for local governments and 8.0 points for the central government (government minus private: -9.8 points, $p < 0.01$). Furthermore, having the GP based in the invested firm's city lowers the annual exit probability of the central government by 1.6 points and of local governments by 1.2 points, but not of private VCs ($+0.8$; government minus private: -2.1 points, $p < 0.01$). Private VCs are less likely to exit relative to government VCs when the invested firm is more productive, which proxies for profitability ($p < 0.05$). The overall evidence is consistent with private VCs allocating capital for foreseeable immediate returns, and not staying to participate in firm governance for the long term. They sell when holdings turn unprofitable, or once the firm is listed and shares become liquid. This is a consequence of private VC having the freedom to reallocate capital across sectors and regions. Government VCs, on the other hand, are mandated to stay invested in strategic sectors regardless of the firm's current profitability, especially when the investing VC is funded by the local government interested in boosting semiconductor production in the locality.

6.3 Decomposing Local VC Productivity Effects

To understand the extent to which VCs' engagement with corporate governance accounts for post-investment productivity growth, I conduct a decomposition exercise quantifying how observed productivity effects could be attributed to various mediating channels. The exercise is similar to the decompositions in Gelbach (2016), Heckman et al. (2013), and Barwick et al. (2026) that account for the mediators' contribution to the estimated treatment effect by combining (1) the treatment's effect on the mediators and (2) the mediators' conditional association with the outcome. I describe the procedure in detail in Appendix Section G.1.

I focus on decomposing event time effects after three years of investment as I model the mediators to have a lagged rather than immediate impact on firm productivity. Table 4 shows that the number of directors with technical, foreign, or finance backgrounds, together with board size and turnover, accounts for 26.4% of the local government VC effect on productivity and 44% of the local-central gap, averaged across event times 3, 4, and 5. As shares of the local effect, paid-in capital accounts for 8.4%, non-equity subsidies 12.5%, and intellectual property 12.9%, while procurement accounts for almost none, consistent with the fact that local government-invested firms did not differentially see an increase in procurement contracts. As shares of the gap, the same channels account for -3.3%, 9.9%, 3.0%, and 8.2%. Together, these channels account for 60.1% of

the local government VC effect and 61.6% of the local-central gap. This suggests that management and observable resource inputs are correlated with and explain a substantial portion of observed productivity growth, but they don't fully explain how local government-invested firms grow.

Table 4: Mediators' Contributions to Productivity Effects

Channel	Local effect $\widehat{\overline{\theta}}_{\mathrm{L}} = 0.324$	Local–Central gap $\widehat{\Delta}_{\mathrm{LC}} = 0.350$
Board and management	0.086 (26.4%)	0.153 (43.7%)
Shareholder paid-in capital	0.027 (8.4%)	−0.011 (−3.3%)
Procurement	≈ 0 ($\approx 0\%$)	0.029 (8.2%)
Non-equity subsidy	0.041 (12.5%)	0.035 (9.9%)
Patents / intellectual property	0.042 (12.9%)	0.011 (3.0%)
All recorded channels	0.195 (60.1%)	0.215 (61.6%)
Residual	0.129 (39.9%)	0.134 (38.4%)

Notes. Contributions sum products of mediator DiDs and jointly estimated productivity–mediator slopes, averaged over $\tau = 3, 4, 5$. Board and management combines personnel composition, board size, and personnel joining and departing. Parentheses report shares calculated from unrounded estimates. The residual is the unallocated difference. These are descriptive accounting quantities.

6.4 Local Information Advantage

Observables such as management or the money invested cannot fully explain observed productivity change, which suggests that other mechanisms are at play. Local government VCs can provide unobserved regulatory favors and other forms of infrastructure support to their invested firms. Another possibility is that local government VCs have more information on a firm's potential quality. As firms are embedded in the local manufacturing ecosystem built by local governments and need to approach local governments for various permits and applications, there are ample opportunities for interaction between local authorities and startups. Equipped with information from such exchanges, local governments could select firms that are poised to grow faster. In other words, local government VCs may possess private information regarding local firms' future productivity growth. Under the alternative interpretation that higher productivity growth after local government investment is driven by local information, delegating industrial policy to local governments may nevertheless provide value. Local governments more informed about local firms' future productivity can provide capital to firms that will be more efficient in the future.

Two pieces of evidence from the regressions on VC selection are consistent with this channel. First, conditioning on rich firm controls, local government VCs are much more likely to invest in firms with board/management members that share alumni and past work ties as shown in Table 1. This suggests that local alumni networks provide an additional source of information, on top of firm characteristics observable by the researcher, that materially influences how local government VCs invest. By contrast, firm connections to any type of VC GPs do not significantly predict central government or private VC investment once controlling for rich firm observables. The alumni net-

works formed through local firms and academic institutions, and possibly the information that flows through such networks, may be a differentiating factor that contributes to local government-invested firms' outperformance.

Second, both central government VCs and private VCs are more likely to invest in firms that had received local government VC investment, while private VC's propensity to follow the central government VC's investment is much more muted. The "Ownership and previous investment" section of Tables E.4 and E.6 presents the estimates. The facts are consistent with a political economy environment in which local governments serve as sponsors of private firms and are able to screen them through local personal and administrative networks. A local government stake then signals both the firm's quality and its access to regulatory and administrative support to later investors (Bai et al., 2020a; Luo et al., 2025). This possibility reinforces the rationale for the central government to delegate investment decisions and resources to local governments, despite apparent static misallocation from local governments investing in unproductive firms. In the next section, I implement separate modeling exercises quantifying the contribution of decentralization to the size and productivity of China's semiconductor industry under two separate assumptions: that local governments upgrade firm productivity and that local governments have superior information and select on future firm growth.

7 Model and Counterfactual

This section introduces a model that features (1) endogenous government and private venture capital investments that affect both firm productivity and capital as well as (2) firm Cobb-Douglas production under a demand system that treats domestic output and imports as imperfect substitutes. It addresses two questions that the empirical analyses above cannot answer. First, difference-in-differences estimates show only how much invested firms grow relative to non-invested controls, and inform less on how the actual government target, the industry size, evolves as a consequence of the government VC investments. The higher sales of government-invested firms may largely come at the expense of non-invested private firms via business stealing. Thus, naively adding up partial revenue responses will overstate the gains government VC investment brought to the industry. Through the demand system, the model decomposes relative firm revenue gains from government investment into a within-domestic business stealing component and an import substitution component. Only the latter contributes to national industry sales growth.

Second, there is a tradeoff between local governments' potential advantage in improving firm productivity versus the misallocation arising from local governments investing in initially less productive firms. Even if central government and private VCs do not increase firm productivity, they allocate capital to productive firms. Thus, the increase in national sales due to local governments' productivity effect on initially weaker firms may still be outweighed by the central government or private VC provision of capital to more productive firms at the baseline. By modeling local government, central government, and private VC selection, the model predicts counterfactual investment allocations under different counterfactual regimes: the "no government VC" regime with

only private VC, the "centralized" regime where the central VC allocates the sum of resources across central and local funds, and an optimal allocation in which a planner maximizing national industry revenue decides, year by year, whether government investments go to the central fund or to local funds. These counterfactuals highlight and quantify the core tradeoff identified in this paper on the static misallocation versus dynamic treatment advantage of decentralization.

7.1 Model Overview and Timing

The model has two blocks. In the *VC selection block*, each VC in each year $t = 2014, 2015, \ldots, 2023$ simultaneously makes a given number of new investments in firms, choosing firms based on firm characteristics observed at the end of t-1, as well as the anticipated probabilities of other VC types investing in the firm. The block is a reduced form representation of the likelihood that an equity investment deal will be made between VC k and the firm based on firm observables.

In the *firm block*, a representative downstream sector allocates fixed expenditures between domestic production and imports. Firms engage in monopolistic competition and produce with flexible labor under Cobb-Douglas technology. VC investment shifts firms' productivity and capital along paths calibrated to the event studies.

Figure 12 depicts the timing of the model within a year. VC investors invest based on the state at the end of the previous year, $\mathcal{F}_{t-1}$, which contains every firm's productivity, capital, investment history, and characteristics. VCs also know each other's *budgets*—the number of investment deals they can make this year. Firms take the year's VC investments and productivity draw as given and choose labor to maximize static profit. Firms then make capital investment based on current year productivity, capital, and VC investment status. Firm entry and exit are held fixed from the data, which is a limitation but should not affect the aggregate results too much as entering and exiting firms are small relative to incumbents.

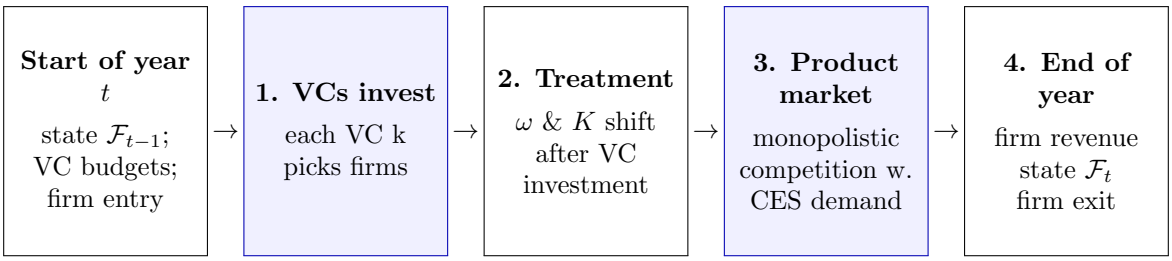


Figure 12: Timing Within a Year

Notes. Shaded boxes mark the two equilibria.

7.2 VC Block: Budgets, Preferences and Selection

The VC block borrows three principal features from empirical models of VC-firm matches in the literature (Sørensen, 2007; Fox et al., 2018; Zhang et al., 2024; Colonnelli et al., 2024). First, VCs are assumed to invest in a fixed number of firms. The count budget reflects the time and effort costs of search, due diligence, and negotiations involved in closing a deal with each firm. Second, the

likelihood of a deal between a VC and a firm depends on firm and VC characteristics, interpreted as the surplus generated from the match. In particular, shifters such as VC-firm distance and, in my application, VC-firm alumni ties, differentially shape the likelihood that a VC invests in a firm. Finally, characteristics of other firms in each VC's choice set and the count budget jointly determine which firms each VC will invest in.

Investors and budgets. The VCs making investments are the central government fund C, the representative private VC sector P, and the local government funds L_r of each province $r \in \mathcal{R}$. Let $k \in \mathcal{K} \equiv \{\mathrm{C}, \mathrm{P}\} \cup \{\mathrm{L}_r\}_{r\in\mathcal{R}}$ index a particular VC. In year t, for each sector s the investor k has a budget of N_{kst} firms it can invest in. It chooses N_{kst} firms to invest in from $\mathcal{E}_{kst}$, the set of sector s firms in year t which it has not yet invested in. The "budget" is modeled as a discrete number of firms rather than an actual monetary budget, consistent with the literature on VC selection. It reflects the fixed costs spent by VCs on investment research, due diligence, and negotiation with the firm's founders, original shareholders, and other syndicated VCs on the deal terms.

VC Investment Propensity: Observables. At the start of year t, investor k's propensity to invest in firm $i \in \mathcal{E}_{kst}$ is summarized by the linear index

$$u_{kit} = \underbrace{\mathbf{x}'_{ki,t-1}\boldsymbol{\gamma}_k}_{\text{firm characteristics}} + \underbrace{\mathbf{conn}'_{ki,t-1}\boldsymbol{\kappa}_k}_{\text{firm connection w. VC k}} + \underbrace{\sum_{k'\neq k} \psi_{k\leftarrow k'}\, \mathbb{1}\{G_{k'i} \leq t-1\}}_{\text{following VC k'}} + \underbrace{\sum_{k'\neq k} \phi_{k\leftarrow k'}\, \pi_{k'it}}_{\text{coordination w. VC k'}} . \quad (2)$$

The vector $\mathbf{x}_{ki,t-1}$ contains firm characteristics such as relative productivity, size, age, innovation, policy support, and board composition. $\mathbf{conn}_{ki,t-1}$ represents the number of main personnel of the firm who share a previous employer or school with a main personnel of a GP firm of VC k (Section 3).

The last two terms capture the interaction between VC types documented in Section 4.3. $\psi_{k\leftarrow k'}$ is the term that captures VC k's propensity to *follow* a distinct VC type k''s investments. Let $G_{k'i}$ be the year in which k' first invested in i, so $\psi_{k\leftarrow k'}$ is k's response to k' already investing in the firm, represented by the indicator $\mathbb{1}\{G_{k'i} \leq t-1\}$. $\sum_{k'\neq k} \phi_{k\leftarrow k'}\, \pi_{k'it}$ describes the part on within-year *coordination*: $\pi_{k'it}$ is the equilibrium probability that k' invests in i in the same year, so $\phi_{k\leftarrow k'}$ is k's response to k''s expected entry. When two or more investor types first invest in a firm in the same year, Appendix Figure E.4 shows that all of the same-year entrants are registered as shareholders on the same day in 73% of cases, so most investments made by different VC types within the same year are one joint round of syndicated investments.

The coordination coefficients are identified by factors that affect other VCs' entry probabilities more strongly, such as ties to the VC's own GP partners and the attractiveness of each VC type's choice set relative to their exogenous count budgets or fixed costs. Following the VC selection literature, I interpret u_{kit} as the predictable part of the joint *surplus* shared between firm i and VC k in year t if k invested in i. A higher predicted surplus increases the likelihood that an investment deal will be reached between VC k and firm i.

VC Investment Propensity: Unobservables. I assume an idiosyncratic logistic shock ξ_{kit} is drawn also for each pair of VC k and firm i, which captures the benefits net of costs of the deal that the econometrician does not observe. VC k invests in firm i in sector s if and only if $u_{kit} + \xi_{kit} \geq \lambda_{kst}$, where the per-deal cost λ_{kst} is set so that its number of investments in sector s equals its budget in expectation:

$$\pi_{kit} \equiv \mathbb{P}\big(k \text{ invests in } i \mid \mathcal{F}_{t-1}, N_{kst}\big) = \Lambda\big(u_{kit} - \lambda_{kst}\big), \qquad \sum_{i \in \mathcal{E}_{kst}} \pi_{kit} = N_{kst}, \tag{3}$$

with the logit function $\Lambda(z) \equiv e^z/(1+e^z)$. The cost is interpreted as the fixed cost of making a deal, which involves the administrative resources and attention of the VC team. A lower λ_{kst} allows VC k to invest in more sector-s firms in the same year.

Equilibrium. VCs observe the state $\mathcal{F}_{t-1}$ and each other's budgets N_{kst} and investment costs λ_{kst}, but not each other's match-specific shocks ξ_{kit}. VCs and firms then choose to form deals simultaneously. A Bayesian Nash equilibrium in year t is a matrix of investment probabilities $\boldsymbol{\pi}_t = [\pi_{kit}]$ such that, when every VC k and firm i evaluates the VC-firm surplus (2) under the beliefs $\boldsymbol{\pi}_t$, its resulting investment probabilities (3) are consistent with $\boldsymbol{\pi}_t$: $\boldsymbol{\pi}_t = \Psi(\boldsymbol{\pi}_t; \mathcal{F}_{t-1}, \mathbf{N}_t)$, where $\mathbf{N}_t \equiv [N_{kst}]_{k,s}$ collects the year's budgets.

An equilibrium exists because Ψ maps a product of $[0,1]$ intervals continuously into itself. Uniqueness is not automatic when investors respond to each other's expected probabilities of investment. Appendix Proposition 1 provides a sufficient condition on the within-year coordination coefficients $\phi_{k \leftarrow k'}$ that guarantees uniqueness, and shows that the estimates satisfy the Proposition's conditions.

Estimation. I estimate the choice parameters on 2007–2024 and simulate the model over 2014–2023. Given parameters $\Theta = (\boldsymbol{\gamma}, \boldsymbol{\kappa}, \boldsymbol{\psi}, \boldsymbol{\phi})$ and beliefs $\boldsymbol{\pi}$, the log-likelihood of the observed first investments, $G_{ki} = t$, is

$$\ell(\Theta, \boldsymbol{\pi}) = \sum_t \sum_s \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{E}_{kst}} \Big[\mathbb{1}\{G_{ki} = t\} \log \pi_{kit}(\Theta, \boldsymbol{\pi}) + \big(1 - \mathbb{1}\{G_{ki} = t\}\big) \log\big(1 - \pi_{kit}(\Theta, \boldsymbol{\pi})\big) \Big]. \tag{4}$$

The fixed costs λ_{kst} enter as VC-specific industry-year intercepts, and their first-order conditions are the budget conditions in (3), with N_{kst} equal to the observed number of k's first entries in sector s and year t. I estimate Θ with the nested pseudo-likelihood algorithm of Aguirregabiria and Mira (2007). Starting from beliefs $\boldsymbol{\pi}(\Theta^{(0)})$ given by reduced-form logit parameters $\Theta^{(0)}$ of each investor k's first investment entries, I maximize (4) holding the beliefs fixed, solve for the equilibrium beliefs $\boldsymbol{\pi}(\Theta^{(n)})$ at the new estimates, and iterate

$$\Theta^{(n+1)} = \arg\max_{\Theta} \; \ell\big(\Theta, \boldsymbol{\pi}(\Theta^{(n)})\big)$$

until the parameters converge. At the fixed point, VCs' beliefs about each other's entry probabilities $\boldsymbol{\pi}(\hat{\Theta})$ are the equilibrium entry probabilities implied by the estimates $\hat{\Theta}$.

Estimates. Appendix Table I.1 reports the selection coefficients $(\boldsymbol{\gamma}, \boldsymbol{\kappa}, \boldsymbol{\psi}, \boldsymbol{\phi})$ alongside the analogous conditional logit specification without the same year coordination terms. The estimates for $\boldsymbol{\gamma}, \boldsymbol{\kappa}, \boldsymbol{\psi}$, the coefficients on the observables of the firm in $t-1$, do not show a significant change between the two specifications. A firm in which private VC already invests is much more likely to receive both local and central government VC investment. A firm that local government VC has invested in is more likely to receive both central government and private VC investments. Past central government VC investment mildly increases the likelihood of local government investment but not private VC investment.

For the same-year coordination variables, the estimates suggest that local government VCs invest where private VC is likely to invest too within the same year ($\phi_{\mathrm{L}\leftarrow\mathrm{P}} = 10.27$, s.e. 3.37). Private VCs instead avoid firms where local government VCs are expected to enter ($\phi_{\mathrm{P}\leftarrow\mathrm{L}} = -3.70$, s.e. 2.03) but do not respond to expected central entry ($\phi_{\mathrm{P}\leftarrow\mathrm{C}} = 0.40$, s.e. 2.27). Central government VCs weakly prefer firms where either local or private VC is expected to enter ($\phi_{\mathrm{C}\leftarrow\mathrm{L}} = 3.07$, s.e. 2.16; $\phi_{\mathrm{C}\leftarrow\mathrm{P}} = 3.23$, s.e. 2.19). At these estimates, the condition of Appendix Proposition 1 holds, and hence the equilibrium induced by these estimates is unique.

Figure 13 shows that the fitted probabilities predict which firms receive funding. Among firm-years in industry-years where the investor type made at least one first investment, the median firm that the central fund entered had a fitted probability 11 times that of the median firm it did not enter; the ratio is 4 for private VC and 7 for local VCs. Fitted probabilities also match observed VC entry rates: in the top decile of fitted probabilities, the mean fitted and observed entry rates are 8.8% and 9.1% for the central fund, 9.9% and 10.0% for private VC, and 11.7% and 11.2% for local VC funds (Appendix Figure I.4).

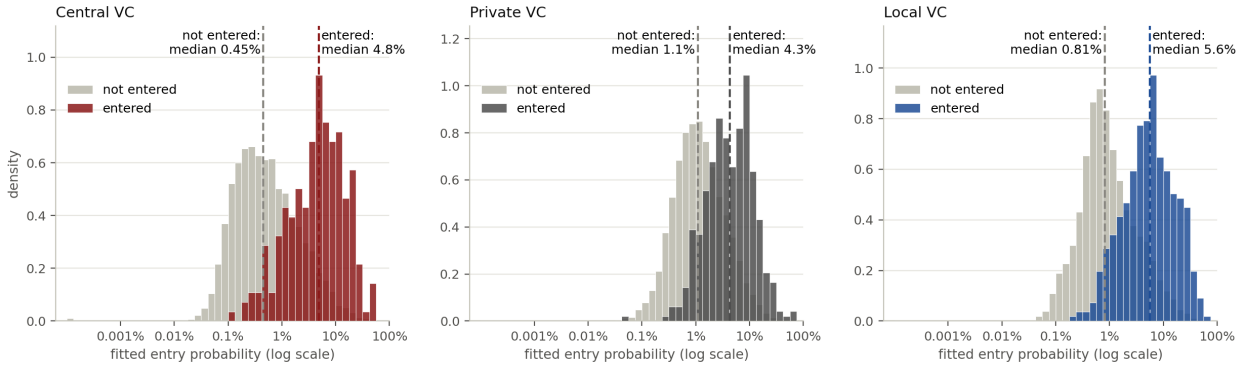


Figure 13: Fitted Investment Probabilities of Invested and Not Invested Firms

Notes. Fitted probabilities at the equilibrium beliefs for all firm-years not yet invested by the corresponding VC, 2007–2024, split into two groups: the pale probability distribution comes from firm-years that did not receive the said VC type's investment next year, while the colored distribution is from firm-years that actually received investments. That the colored distribution is to the right of the pale distribution suggests that the model can predict which firms will receive investment. Dashed lines mark within-group medians.

7.3 Firm Block I: Demand

Revenue Gains from Government Investment Can Come from Imports. I now describe the firm block by starting first with demand. Motivated by the fact that Chinese domestic firms are mostly competing against imports, I model demand for semiconductors as coming from a representative downstream sector allocating expenditures between domestic production and imports. Integrated circuits are China's largest import by value in 2025: 424.3 billion US dollars, against 296.5 billion for crude petroleum.[6] This mitigates the concern that relative gains from government investment come primarily from domestic business stealing. A large part of the increase in the sales of a government-invested firm should come at the expense of imports, and the equilibrium impact of government support on the size of the domestic industry would be stronger (Rotemberg, 2019).

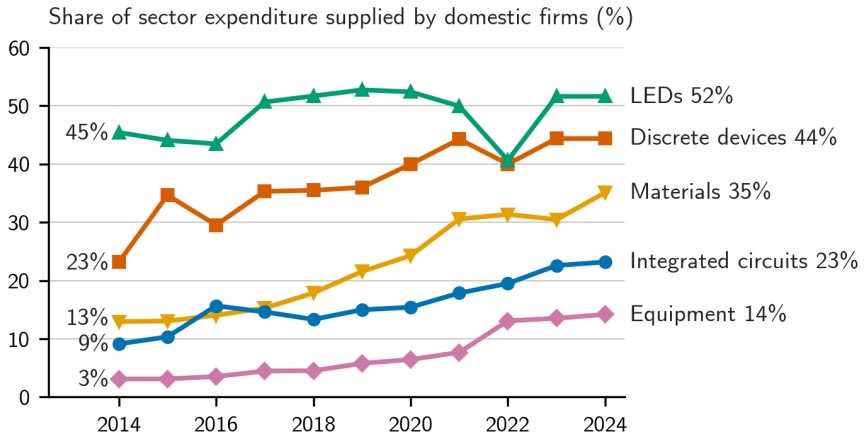


Figure 14: Domestic Expenditure Shares by Sector, 2014–2024

Notes. Sales of domestic-owned firms (foreign ownership below 50%) from the firm panel; imports and general-trade exports from UN Comtrade and China Customs. Integrated circuits pool value-added of integrated circuits design, manufacturing, and assembly and testing to avoid double counting. For equipment and materials the denominator is SEMI's equipment and materials market billings in China; LEDs use LED chip and package makers and the LED HS codes. Appendix subsection I.1 discusses the details.

Using UN Comtrade and SEMI equipment and materials billings data, I measure the domestic expenditure share of sector s in year t as

$$s_{st}^{D,0} = \frac{R_{st} - EX_{st}}{R_{st} + IM_{st} - EX_{st}}, \tag{5}$$

where R_{st} is the revenue of domestic-owned firms in the firm panel of Section 3, and IM_{st} and EX_{st} are China's imports and exports of the sector's products, reported by China at the six-digit level of the Harmonized System (HS). The numerator is what domestic firms sell in China, while the denominator is domestic absorption. Figure 14 shows that domestic expenditure shares are generally low but rising after China's 2014 National Integrated Circuit Industry Development Promotion Guidelines. Domestic firms supplied 9% of China's expenditure on integrated circuits in 2014 and 23% in 2024. Over the same years, their share rose from 3% to 14% in equipment

[6] "China's Major Imports by Quantity and Value, Dec 2025 (in USD)". China Customs. http://english.customs.gov.cn/Statics/83fb6750-e095-47c6-9890-14979f5a22e8.html.

and from 13% to 35% in materials. Shares are higher for more mature products: 44% for discrete semiconductors and 52% for LED devices in 2024.

Demand for Domestic Output & Imports. For each sector s in year t, I assume a downstream sector spends $\mathcal{X}_{st}$ on the sector's output that is exogenous to the Chinese domestic sector. For semiconductor producing sectors, Appendix H.1 derives $\mathcal{X}_{st}$ as an exogenous Markov process arising from exogenous household demand for electronics, the electronics sector's productivity, and prices of other electronics inputs. Appendix H.2 then readily extends the result to cover materials and equipment, the sectors upstream of semiconductor producers. Chinese firms in the data are generally too small to affect electronics demand through producing cheaper semiconductors: the largest Chinese firm's sales are 1.3 to 5.7% of its sector's imports in 2023, apart from optoelectronics, where the share is 10.6% (Appendix Figures I.1 and I.2).

With budget $\mathcal{X}_{st}$, the downstream sector demands semiconductors of effective quantity $\mathcal{Q}_{st}$, which combines a domestic composite Q^D_{st} with imports Q^F_{st},

$$\begin{aligned} \mathcal{Q}_{st} &= \left[(Q^D_{st})^{\frac{\zeta-1}{\zeta}} + (Q^F_{st})^{\frac{\zeta-1}{\zeta}} \right]^{\frac{\zeta}{\zeta-1}}, \\ Q^D_{st} &= \Big(\sum_{i \in \mathcal{J}_{st}} q_{it}^{\frac{\sigma-1}{\sigma}} \Big)^{\frac{\sigma}{\sigma-1}}, \end{aligned} \tag{6}$$

where $\mathcal{J}_{st}$ is the set of domestic firms and $\sigma > \zeta > 1$: domestic varieties substitute more easily for one another than for imports. Imports are supplied by a competitive foreign sector at the world price P^F_{st}. With the domestic price index $P^D_{st} = (\sum_{i \in \mathcal{J}_{st}} p_{it}^{1-\sigma})^{1/(1-\sigma)}$, cost minimization gives the domestic expenditure share s^D_{st}:

$$s^D_{st} \equiv \frac{P^D_{st} Q^D_{st}}{\mathcal{X}_{st}} = \frac{(P^D_{st})^{1-\zeta}}{(P^D_{st})^{1-\zeta} + (P^F_{st})^{1-\zeta}}, \tag{7}$$

the demand for the domestic composite $Q^D_{st} = \frac{s^D_{st} \mathcal{X}_{st}}{P^D_{st}}$, and the demand for each firm's variety $q_{it} = Q^D_{st} \left(\frac{p_{it}}{P^D_{st}} \right)^{-\sigma}$. I denote the observed value of the share by $s^{D,0}_{st}$, which is the plotted share in Figure 14. The price elasticity of demand for the domestic composite, holding the downstream sector's expenditures $\mathcal{X}_{st}$ and foreign prices P^F_{st} fixed, is

$$\eta^D_{st} \equiv -\frac{\partial \log Q^D_{st}}{\partial \log P^D_{st}} \bigg|_{\mathcal{X}_{st}, P^F_{st}} = 1 + (\zeta - 1)(1 - s^D_{st}). \tag{8}$$

The elasticity is greater if the domestic expenditure share s^D_{st} is lower. For a higher baseline domestic market share, there are fewer imports left to displace, and domestic quantity Q^D_{st} rises less from the same percentage change in the domestic price P^D_{st}.

7.4 Firm Block II: Revenue, Markups, Productivity and Capital

Revenue. Firm i produces $q_{it} = A_{it}K_{it}^{\alpha_K}L_{it}^{\alpha_L}$ with physical productivity A_{it}. Sector subscripts on the elasticities are suppressed for notational convenience. Inverting each firm's demand curve, $p_{it} = P_{st}^D(Q_{st}^D/q_{it})^{1/\sigma}$, so its revenue is $R_{it} \equiv p_{it}q_{it} = P_{st}^D(Q_{st}^D)^{1/\sigma}q_{it}^{\rho}$ with $\rho \equiv (\sigma-1)/\sigma$, and hence

$$\log R_{it} = \omega_{it} + \beta_K \log K_{it} + \beta_L \log L_{it}, \qquad \omega_{it} \equiv \underbrace{\log P_{st}^D + \sigma^{-1}\log Q_{st}^D}_{\text{common sector demand}} + \rho \log A_{it}, \tag{9}$$

with $\beta_K \equiv \rho\alpha_K$ and $\beta_L \equiv \rho\alpha_L$. Revenue productivity combines a demand component common to all domestic firms in sector s with the firm's own physical productivity.

Markups. Firms engage in monopolistic competition: each firm is small relative to the domestic industry and sets its price taking the domestic price index P_{st}^D and the domestic composite Q_{st}^D as given. Its perceived demand elasticity is therefore the within-domestic demand elasticity σ. Firms charge a constant markup over marginal cost: $\mu \equiv \frac{p_{it}}{MC_{it}} = \frac{\sigma}{\sigma-1} = \frac{1}{\rho}$. Appendix I.4 presents a variant of the model with variable markups derived by Atkeson and Burstein (2008). The results do not change much under alternative conduct assumptions because the concentration of sales is not too high within each 4-digit sector.

Labor and optimized revenue. Given its capital, which is decided before year t begins, the firm hires labor at the common sector wage w_{st}. The first-order condition sets the wage bill to be a constant share of revenue, $w_{st}L_{it}^* = (\alpha_L/\mu)R_{it}^* = \beta_L R_{it}^*$. Substituting optimal labor into (9) gives the optimal sales

$$\log R_{it}^* = \frac{\omega_{it} + \beta_K \log K_{it} + \beta_L \log\left(\beta_L/w_{st}\right)}{1-\beta_L}. \tag{10}$$

Optimized revenue rises with revenue productivity and capital, amplified by labor through the factor $\frac{1}{1-\beta_L}$. The markup is common to all firms and enters only through $\beta_L = \alpha_L/\mu$, so it scales every firm's labor and sales in the same proportion.

VC effects on productivity and capital. Let $\tau_{kit} \in \{0, 1, \ldots, 4, 5+\}$ be the number of years since investor type $k \in \{\mathrm{C}, \mathrm{L}, \mathrm{P}\}$ first invested in firm i, with $\tau_{kit} = \emptyset$ indicating that k has not yet invested in i. Investment shifts the levels of physical productivity relative to the counterfactual, and the effects of different investor types are additive:

$$\rho \log A_{it} = \rho \log A_{it}(\emptyset) + \sum_k \theta_k^{\omega}(\tau_{kit}) \tag{11}$$

with $\theta_k^{\omega}(\emptyset) = 0$. Without investment, productivity follows a first-order Markov process

$$\log A_{i,t+1} = f_A(\log A_{it}) + \epsilon_{i,t+1}^A \tag{12}$$

Capital follows a flexibly estimated investment policy

$$\log K_{it} = f_K(\log K_{i,t-1}, \omega_{i,t-1}, \mathbf{x}_{i,t-1}, \{\tau_{kit}\}_{k\in\{\mathrm{C,L,P}\}}) \tag{13}$$

where $\mathbf{x}_{i,t-1}$ includes characteristics such as firm age, sector indicator, foreign, and SOE status.

Note that (9) and (11) imply

$$\begin{aligned}\omega_{it} &= \log P_{st}^D + \sigma^{-1}\log Q_{st}^D + \rho \log A_{it} \\ &= \log P_{st}^D + \sigma^{-1}\log Q_{st}^D + \rho \log A_{it}(\emptyset) + \sum_k \theta_k^\omega(\tau_{kit}).\end{aligned} \tag{14}$$

Because treated and control firms in a sector-year share P_{st}^D and Q_{st}^D, event-study comparisons of ω_{it} difference out sector demand.

7.5 Product Market Equilibrium

Counterfactual firm sales. Define an investment history $\mathbf{G} \equiv \{G_{\mathrm{C}i}, G_{\mathrm{L}i}, G_{\mathrm{P}i}\}_i$, which is a collection of years in which each investor C, L, P first invested in each firm i, possibly never. For any variable X, let $d\log X \equiv \log X(\mathbf{G}) - \log X(\mathbf{G}^0)$ be its log change from the factual history $\mathbf{G}^0$ to some counterfactual $\mathbf{G}$. The new history shifts firm i's revenue productivity and capital by

$$\begin{aligned}\Delta_{it}^\omega &\equiv \sum_k \Big[\theta_k^\omega\big(\tau_{kit}(\mathbf{G})\big) - \theta_k^\omega\big(\tau_{kit}(\mathbf{G}^0)\big)\Big], \\ \Delta_{it}^K &\equiv d\log K_{it} = \log K_{it}(\mathbf{G}) - \log K_{it}(\mathbf{G}^0).\end{aligned}$$

Define domestic sales $R_{st}^D \equiv P_{st}^D Q_{st}^D$. Differencing (10) with the wage fixed, noting (9), gives

$$d\log R_{it}^* = \underbrace{\frac{\Delta_{it}^\omega + \beta_K \Delta_{it}^K}{1-\beta_L}}_{\text{direct treatment}} + \underbrace{\frac{\rho\, d\log P_{st}^D + \sigma^{-1} d\log R_{st}^D}{1-\beta_L}}_{\text{sector demand}} \tag{15}$$

The first term is how differences in VC allocation affect counterfactual firm sales via productivity and capital response. The second term is common to every domestic firm in the sector and depends on counterfactual domestic sales and the domestic price index it implies. Because $\sigma > \zeta$, this term is negative whenever domestic sales rise, as higher domestic sales reduce the domestic price index. Thus, firms without VC investment will lose sales, but they lose less when the domestic expenditure share is lower, consistent with Rotemberg (2019).

Closing the model. Given the status quo history $\mathbf{G}^0$ and a counterfactual history $\mathbf{G}$, the change in equilibrium is defined by the objects $\{d\log R_{st}^D, d\log P_{st}^D, \{d\log R_{it}^*\}_i\}$, which are the equilibrium change in total domestic sector sales, the change in the sector price index, and the change in each firm's sales respectively. The equilibrium condition requires the change in firm sales to add up to the change in domestic sector sales:

$$d\log R_{st}^D = \log \sum_{i \in \mathcal{J}_{st}} h_{it}^0 \exp\big(d\log R_{it}^*\big), \tag{16}$$

where h_{it}^0 is the firm's share of domestic sales under $\mathbf{G}^0$. I apply exact hat algebra (Dekle et al., 2008; Costinot and Rodríguez-Clare, 2014) to solve the counterfactual equilibrium, which requires only observed trade shares $s_{st}^{D,0}$ and h_{it}^0, treatment paths θ^ω and the capital policy f_K, and calibrated trade elasticities σ, ζ, but does not require prices or quantity demanded to be observed. Appendix Section I.5 discusses the details and the uniqueness of the equilibrium.

7.6 Calibration

Table 5 lists the model's essential ingredients. The two demand elasticities are taken from the literature: $\zeta = 3$ between domestic goods and imports, and $\sigma = 5$ among domestic varieties. I also test the sensitivity of the results to calibrated elasticities by using the top and bottom of the values in the literature's range, i.e. $[4.57, 5.48]$ for σ and $[2.40, 3.48]$ for ζ (Appendix Figure I.7 and Table I.3).

I discuss in detail the estimation of within-model productivity treatment effect parameters $\theta_k^\omega(\tau)$ and the capital process (13) in Appendix I.6. I jointly estimate $\theta_k^\omega(\tau)$ and (13) by minimizing the distance between model-implied and empirical difference-in-differences ATTs on ω_{it} and $\ln K_{it}$. For candidate parameters, I simulate model-implied outcomes on observed VC allocations and run difference-in-differences estimates. I minimize the mean-squared error between the generated estimates and the corresponding empirical estimates from the data.

Table 5: Calibration and Estimation

Block	Object	Value	Source
VC selection	$\boldsymbol{\gamma}_k$, $\boldsymbol{\kappa}_k$, $\psi_{k\leftarrow k'}$, $\phi_{k\leftarrow k'}$	estimated	nested pseudo-likelihood, Table I.1
Treatment	$\theta_k^\omega(\tau)$	estimated	matched to productivity event study, Table I.2
	f_K	estimated	flexible capital prediction, Appendix Section I.6
Production	β_K, β_L by sector	estimated	Ackerberg et al. (2015), Appendix Section C
Demand	$s_{st}^{D,0}$	data	Figure 14
	ζ	3 [2.40, 3.48]	home–import elasticity of U.S. electronics, 2.40–3.48 (Feenstra et al., 2018)
	σ	5 [4.57, 5.48]	demand for Chinese exports: median 4.57 (Amiti et al., 2020); 4.82 and 5.48 in the calibrations of Fan et al. (2020)
Held fixed	w_{st}, $\mathcal{X}_{st}$	data	median wage & trade data

Notes. $\boldsymbol{\gamma}_k$, $\boldsymbol{\kappa}_k$: weights of firm characteristics and director ties in investor k's selection index; $\psi_{k\leftarrow k'}$, $\phi_{k\leftarrow k'}$: responses to investor k' already owning the firm and to its expected same-year entry; $\theta_k^\omega(\tau)$: productivity effect τ years after k's first investment; f_K: capital law of motion; $s_{st}^{D,0}$: observed domestic expenditure share; ζ, σ: elasticities between domestic goods and imports and among domestic varieties; w_{st}, $\mathcal{X}_{st}$: sector wage and downstream expenditure.

7.7 Counterfactual Allocations

Counterfactuals. Over 2014–2023, central government VCs invested in 1,674 firms, local government VCs invested in 3,985 firms, and private VC made 4,684 investments. I compare this observed VC allocation with three counterfactuals that reallocate the investments across VC types,

keeping the total number of investments in each sector and year, $\sum_{k\in\mathcal{K}} N_{kst}$, fixed at the observed level (Appendix Figure I.5):

(1) *No government VC*: every central and local investment slot goes to private VC. Private VCs now invest in $N^{cf}_{\mathrm{P}st} = \sum_{k\in\mathcal{K}} N_{kst}$ firms in each sector and each year. Government VCs do not invest. This counterfactual assumes that government VCs had crowded out private VC investments in the extreme form by taking every opportunity private VCs would otherwise have taken. The empirical evidence instead suggests that across countries, government VC appears to induce private VC rather than replace it (Brander et al., 2015; Cheng et al., 2026; Bai et al., 2021).

(2) *Centralization*: every local government VC's investment slot goes to the central VC fund. The central government VC invests in $N^{cf}_{\mathrm{C}st} = N_{\mathrm{C}st} + \sum_{r\in\mathcal{R}} N_{\mathrm{L}_r st}$ firms in each sector-year. Local government VCs do not invest, and private VC keeps $N_{\mathrm{P}st}$.

(3) *Optimal allocation*: the total government investment slots of each year are divided among the central government VC and local government VCs to maximize expected 2023 domestic sales, taking into account different governments' selection preferences and treatment technology. The annual counts of government and private investments are fixed at their observed levels.

Appendix Figure I.5 plots each investor's annual number of first investments, $N_{kt} \equiv \sum_s N_{kst}$, under the status quo and each counterfactual allocation. Investors keep their estimated preferences and treatment technology, and only their budgets change: in each simulated year, the per-deal costs λ_{kst} are re-solved from the budget conditions (3) at the counterfactual budgets N^{cf}_{kst}.

Simulation. I simulate each allocation forward from 2014 and average over 100 simulated histories. In each year of each simulation, given the counterfactual budgets, I draw investments predicted by the selection model given the simulated investment histories through $t-1$, update every firm's implied capital and productivity changes from VC treatments, and solve the product-market equilibrium of every sector.

Results. Figure 15 reports the simulated counterfactuals. Relative to the status quo decentralized government investment regime, giving government investment slots to private VC lowers the domestic industry's sales in every year from 2015, reaching 11.6% in 2023. In the centralization counterfactual, reallocating local investments to the central fund lowers 2023 sales by 4.0%. Centralization raises sales slightly in the first six years (by at most 1.2% in 2018), but the decentralized status quo outperforms it in every year from 2020 and the gap widens to 4.0% by 2023.

The optimal allocation, shown in Appendix Figure I.5, moves all central government investments to local funds in 2014–2019 and all local government investments to the central fund in 2020–2023. Sales under the optimal allocation are below the status quo through 2021 but 2.1% higher by 2023. Appendix Figure I.6 shows sales-weighted productivity: the optimal allocation raises it in every year from 2016 (2.6% by 2023), while the no-government-VC and centralization counterfactuals lower it by 2.2% and 2.4% in 2023.

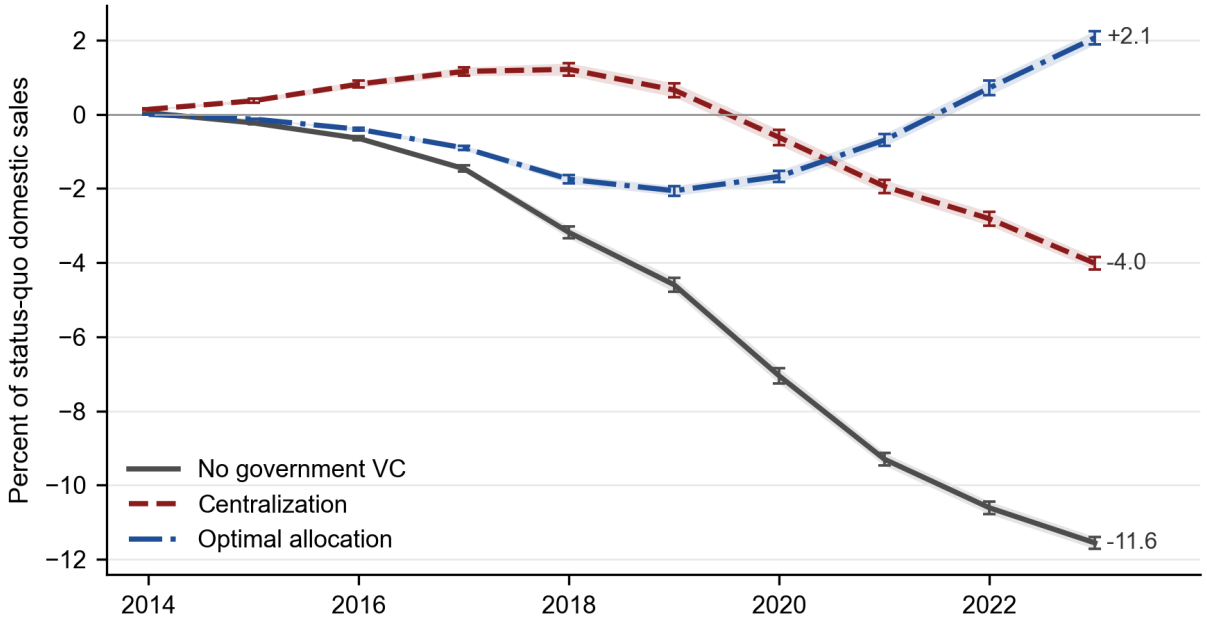


Figure 15: Total Industry Sales Relative to Decentralized Status Quo, Local Government Treatment

Notes. Counterfactual industry sales minus status quo sales in the same year, expressed as a percentage of status quo sales. Results average over 100 simulated histories, holding firm entry and exit fixed. Counterfactuals under constant markups and elasticities $(\zeta, \sigma) = (3, 5)$.

Local Information vs. Treatment. The estimated increase in productivity following local government investment may come from local governments' differential access to information on firms' future productivity. As argued in Section 6.4, under the extreme assumption that all the estimated productivity growth after local government investment comes from superior local information rather than treatment, delegating industrial policy to local governments may nevertheless provide value. In a separate exercise, I quantify the value of local governments' information on future winners by setting all VC types' treatment effect on productivity to be zero, and VC investments only provide capital. Instead, local government VCs observe a noisy signal of the future productivity shock of firms in their province. I estimate local governments' selection on this signal to match observed event study coefficients, the details of which I discuss in Appendix Section I.7. Appendix Figure I.3 shows that centralization nevertheless results in lower industry sales by a more moderate 1.1% by 2023. Centralization would result in higher domestic sales from 2014 to 2019 due to superior central government allocation to more productive firms, but local governments' ability to select firms that become efficient in the future eventually outweighs the static gains from centralized allocation.

8 Conclusion

This paper studies how different levels of government affect the implementation and outcomes of industrial policy. Given the long record of failed industrial policy and underperforming state-owned firms, it is surprising that in Chinese semiconductors, local government VCs, which do not target obvious winners, have seen their invested firms grow more productive. Micro-evidence on the

characteristics of the personnel running the firms and the government investment funds generates further insights on the nature of Chinese state capitalism in the Xi Jinping era: professional state venture capitalists target promising private firms, and help firms in their portfolio grow more by actively intervening in firm management. In particular, local governments play an essential role in the process via their proximity and information advantage, as well as their strong political incentives to improve local economic and technological performance.

Via a parsimonious model that preserves both the documented selection incentives and treatment advantages of local governments vis-à-vis those of the central government and private VCs, I quantify the gains from decentralization relative to scenarios with only private venture capital or fully centralized allocation of government capital. The decentralized status quo generates higher domestic sales only because of the assumed significant local government VC treatment advantage on productivity. Some part of the estimated effects may be driven by local government VCs' information advantage in knowing local firms' future growth, but this also suggests that local governments are allocating capital to firms able to utilize it more efficiently in the future. For the central government interested in maximizing domestic industry sales growth, my exercises show that decentralization may nevertheless be advantageous.

The paper's results qualify the common policy concern in China that decentralized industrial policy simply dissipates resources across local firms without corresponding productivity growth (Young, 2000; Fang et al., 2022; Barwick et al., 2021). Local governments do appear to support firms that are weaker initially, but they can create dynamic gains in productivity through active monitoring and participation in management. The findings point towards a fruitful research agenda: how institutions could be designed to preserve the information and implementation advantages of local discretion while limiting local protectionism and allocation to politically connected beneficiaries.

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A Measurement of Production Function Inputs

Reconciling Multiple Series. To measure sales, I use operating revenue from Orbis and main-business revenue from ASIF. For capital, I use noncurrent assets from Orbis and the equivalent measure from ASIF, which is total minus current assets. I use Orbis' cost of goods sold and the ASIF's main-business cost as the measure of cost of goods sold. For firm-years where the measure from Orbis is missing prior to 2013, I use ASIF's reported measure if available. For the number of employees, I combine both Orbis' and ASIF's measure as well as the number of employees enrolled in social insurance reported on Qichacha from 2016–24, as the coverage of Orbis on employees is less complete. Orbis reports employment for 83% of firm-years with revenue in 2016–2024, adding Qichacha raises coverage to 94%.

Following Banares-Sanchez et al. (2026)'s work on the same datasets on solar manufacturers, I compare Orbis and ASIF where they overlap on the same firm and year (Table A.1 and Figure A.1). The series is strongly correlated across all measures: the slopes are 0.98–1.00, R^2 is 0.85–0.93, and the median Orbis-to-ASIF ratio is within 3 percent of one. Employment fits less well (R^2 0.57).

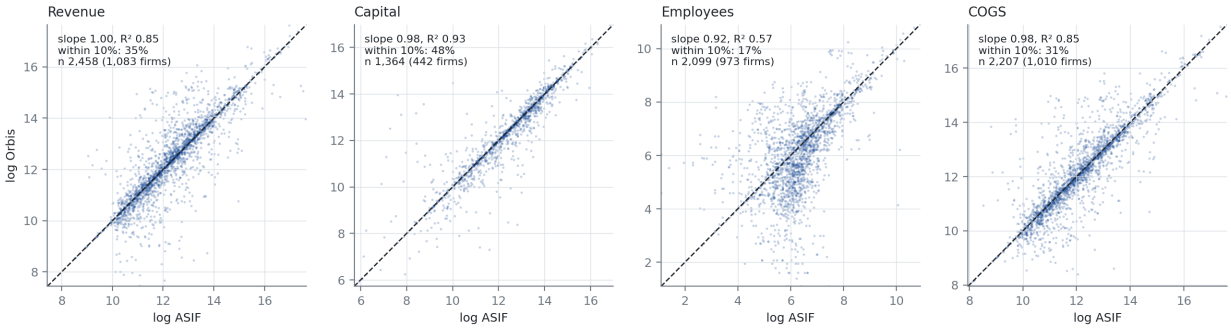


Figure A.1: Orbis and ASIF on the Same Firm-Years: Levels

Notes. Log Orbis against log ASIF, one point per firm-year, with the 45-degree line, as in Figure B.4 of Banares-Sanchez et al. (2026). The sample is that of Table A.1.

The ASIF and Orbis disagree from year to year rather than by a stable gap for each firm. Rescaling the ASIF series by the firm's median Orbis-ASIF ratio in its other shared years predicts a held-out shared year worse than the reported ASIF value. For revenue, rescaling ASIF results in 44 percent of shared firm-years within 10 percent of Orbis', while the corresponding figure for the ASIF as reported is 51 percent. The performance of rescaling is 37 against 52 percent for capital (Table A.1, Panel C). Switches between sources also show little level break. The median change is 0.05 for revenue and 0.04 for capital when the series leaves the ASIF, against 0.14 and 0.07 in years without a switch.

Table A.1: Orbis and ASIF: Fit and Source Switches

	Revenue (Y)	Capital ($\tilde{K}$)	Employees (L)	COGS	Total assets (benchmark)
A. Levels, same firm and year					
Firm-years	2,458	1,364	2,099	2,207	1,945
Firms	1,083	442	973	1,010	791
Slope of ln Orbis on ln ASIF	1.00	0.98	0.92	0.98	1.01
	(0.011)	(0.009)	(0.028)	(0.012)	(0.007)
R^2	0.85	0.93	0.57	0.85	0.95
Median Orbis / ASIF	1.00	1.00	0.90	0.98	1.00
Share within 10%	35%	48%	17%	31%	53%
More than 10× apart (dropped)	3%	2%	9%	3%	1%
B. Changes within firm					
Slope with firm effects	0.93	0.91	0.49	0.92	0.96
Correlation of annual growth	0.35	0.54	0.09	0.44	0.71
Transitory noise s.d., ASIF	0.16	0.36	0.16	0.17	0.07
Transitory noise s.d., Orbis	0.06	0.14	0.18	0.07	0.00
Orbis $\lvert\Delta \ln\rvert$ gap at ASIF entry/exit	0.012	0.013	0.014	−0.019	−0.004
	(0.011)	(0.010)	(0.013)	(0.010)	(0.009)
C. Switching out of the ASIF					
Firm-years switching	1,304	1,105	1,336	1,316	
Median $\Delta \ln$ at the switch	0.05	0.04	−0.06	0.06	
Median $\Delta \ln$ without a switch	0.14	0.07	0.00	0.14	
Held-out within 10%: as reported	51%	52%	21%		
Held-out within 10%: rescaled	44%	37%	24%		

Notes. Firm-years in which both Orbis and the ASIF report a positive value, 1998–2015 excluding 2011 (ASIF 2011 records are inconsistent with the same firms in 2010 and 2012). Orbis operating revenue vs. ASIF main-business revenue; Orbis noncurrent assets vs. ASIF total minus current assets; employees; Orbis COGS vs. ASIF main-business cost; total assets from both, the variable compared by Banares-Sanchez et al. (2026) (their Figure B.4: slope 1.01, R^2 0.97). Panel A: OLS of log Orbis on log ASIF with standard errors clustered by firm. Panel B: the two series' growth correlation over consecutive overlap years. Transitory noise of growth g_t is measured as $\sqrt{-\text{cov}(g_t, g_{t-1})}$ of each source on the same firm-years with three consecutive years in both; the last row is the difference in absolute Orbis growth between years in which the firm enters or leaves the ASIF and other years (year means removed, firm-clustered s.e.), the analogue of footnote 55 in Banares-Sanchez et al. (2026). Panel C: a switch is a consecutive year in which the series moves from the ASIF to another source such as Orbis or social insurance; "without a switch" is consecutive years from the same source. Held-out: for firms with at least two years shared between the ASIF and Orbis, for each shared year, I compare how well Orbis' value can be predicted by ASIF's value as reported versus ASIF's value rescaled by the firm's median Orbis/ASIF ratio in the other shared years. Rescaling ASIF's value with Orbis/ASIF ratio does not improve the fit for revenue and capital, so I did not rescale when joining ASIF to Orbis.

Capital. For firms in the IC Manufacturing, Discrete Semiconductor Manufacturing, and Optoelectronics sectors covered by the SEMI data, I aggregate SEMI's plant-level quarterly equipment

and construction investment to the firm-year as total capital investment by the firm. From yearly fixed capital investment I_{it} of firm i in year t, I construct capital stock by the perpetual inventory method $K_{it+1} = (1-\delta)K_{it} + I_{it}$, depreciating lagged capital stock at a rate of $\delta = 0.09$ following Brandt et al. (2012). For firms in the Design, Equipment, and Materials sectors not covered by the SEMI plant-level data, the raw data of capital uses noncurrent assets (fixed assets) from Orbis for non-listed firms and Wind for listed firms.

For these sectors, I only observe the book value of noncurrent assets $\tilde{K}$. I construct my measure of capital as follows: for the first observed value $\tilde{K}_{it}$ for each firm i in year t, deflate it by the Chinese National Bureau of Statistics' special machinery and equipment producer price index (2023 = 100) and treat it as initial capital $K_{it} \equiv \frac{\tilde{K}_{it}}{P_t^K} \times 100$. Then for each firm that reports accounting depreciation expense $\tilde{D}_{it+1}$ in year $t+1$, nominal investment $\tilde{I}_{it}$ is constructed to be $\tilde{K}_{it+1} - \tilde{K}_{it} + \tilde{D}_{it+1}$. Real investment I_{it} is then $\frac{\tilde{I}_{it}}{P_t^K} \times 100$.

For non-listed firms that do not report $\tilde{D}_{it+1}$, I impute the firm's accounting depreciation $\tilde{D}_{it+1}$ to be $\tilde{K}_{it}$ multiplied by the within-sector-year median depreciation rate $d_{st} \equiv \underset{i':s(i')=s(i),\tilde{D}_{i',t+1}>0}{\text{median}} \frac{\tilde{D}_{i',t+1}}{\tilde{K}_{i't}}$ of firms i' in i's sector s that reported $\tilde{D}_{i',t+1}$, and thus for these firms the imputed investment $\tilde{I}_{it} = \tilde{K}_{it+1} - \tilde{K}_{it} + d_{st}\tilde{K}_{it}$. I then reconstruct capital recursively via the perpetual inventory method as $K_{it+1} = (1-\delta)K_{it} + I_{it}$, with $\delta = 0.09$. The median accounting depreciation is close to the $\delta = 0.09$ recommended by Brandt et al. (2012).

Table A.2: Imputed Depreciation Rates d_{st}: within-sector-year medians of reported accounting depreciation over lagged capital

	Sector-year medians d_{st}			Pooled		
Sector	Min	Median	Max	N	d_s	Cells
Assembly & Testing	0.070	0.116	0.163	1,176	0.111	26
Design	0.069	0.097	0.132	1,776	0.100	26
IC Manufacturing	0.072	0.101	0.149	856	0.096	26
Optoelectronics	0.071	0.099	0.137	1,512	0.097	26
Equipment	0.056	0.091	0.117	1,350	0.090	26
Electronics	0.066	0.089	0.115	4,144	0.091	26
Discrete	0.051	0.088	0.126	2,422	0.088	26
Materials	0.051	0.087	0.126	3,412	0.087	26
All sectors	0.067	**0.093**	0.129	16,648	0.093	208

Notes. d_{st} is the median of $\tilde{D}_{i',t+1}/\tilde{K}_{i't}$ across firms i' in sector s reporting positive depreciation in $t+1$, computed separately for each of the 26 year cells per sector. Min/Median/Max summarize the distribution of those sector-year medians; "All sectors" Min and Max are the range of the pooled annual median across years. Depreciation is reported for roughly 15% of firm-years (sources: current-year depreciation, Wind, tax filings, Orbis); the remainder receive $d_{st}\tilde{K}_{it}$.

Materials. The preferred measure of materials is cost of goods sold (COGS) from the NBS panel for pre-2013 observations, Orbis for non-listed firms, and Wind for listed firms. Although COGS includes components of fixed costs such as depreciation expenses (Syverson, 2019), the lack of a consistently defined materials measure across years and sources in my data compels me to adopt this measure, which is well-defined and consistent across firms and accounting years.

B Other Data Sources

SEMI data. SEMI's global semiconductor plant-level data on capacity, investment, product & process technologies (1996–2024) has quarterly estimates of each known semiconductor wafer plant's capacity and investment ($ US million) in equipment and construction, as well as the plant's product offerings and technology process node each quarter. According to SEMI, the capacity and spending estimates are from company contacts as well as various industry sources such as "news articles, capital spending plans, earning reports, SEC filings, presentations, announced fab plans, ramp schedules, and technology roadmaps." It also utilizes its network of equipment suppliers and uses its billing information to update and adjust quarterly data.

A firm's technology process node (measured in units of microns or 1000 nanometers) is measured by the most advanced process node the firm can produce in the year across its fabs. A smaller process node indicates that the firm's manufacturing process can fit more components on a given area of semiconductor material and hence is more advanced. I link data across the datasets via firm name, past firm names, and the firms' Social Credit Identifiers.

Grants and subsidy data. To paint a fuller picture of the fiscal incentives provided to Chinese semiconductor firms, I build data on government grants and awards received by firms from various sources. The ASIF has total firm-level government subsidies. Publicly listed firms also report the subsidies they received from the government, which I obtain from Wind, a China-focused financial database (Branstetter et al., 2023). Corporate information platforms including Baidu's Aiqicha and Qizhidao list publicly announced government grants and recognitions received by firms collected from government websites. The data includes details on the level of government that issued the grant and the subsidy type, categorized by whether the grant subsidizes R&D, fixed assets, tax, loans, labor talent, or incentives for performance. Firms could also be designated by government ministries as a "High-Tech Enterprise", "Little Giant", or "Specialized & Innovative Small & Medium Enterprise" that come with tax incentives and one-time grants. I harmonize the ASIF, Aiqicha, and Wind data to construct a firm-level measure of subsidies it receives every year.

C Production Function Estimation

C.1 Productivity Estimation

Revenue productivity (TFPR) is my core measure of firm performance. I observe operating revenue, capital, and labor for 49,823 firm-year observations; 26,314 of these also record cost of goods sold, which I take as my measure of intermediate inputs. Due to the lack of comprehensive coverage of

materials in the data, my primary measure of firm productivity is the residual of operating revenue to capital and labor. Specifically, I estimate a Cobb-Douglas production function separately by each 4-digit semiconductor subsector:

$$\ln R_{it} = \omega_{it}^R + \tilde{\beta}_K \ln K_{it} + \tilde{\beta}_L \ln L_{it} + \epsilon_{it}^R,$$

where R is deflated revenue, K is capital, L is the number of employees, ω_{it}^R is persistent revenue productivity that follows a first-order Markov process, and ϵ_{it}^R is an unanticipated mean zero iid shock to the firm's revenue after it made its input decisions. I use the control-function approach of Ackerberg et al. (2015) with firm investment I_{it} as the proxy variable.

I discuss the interpretation of the productivity residual ω_{it}^R in Appendix Section C.2. I show that ω_{it}^R is a function of physical productivity as well as the markup and materials prices. The lack of materials does not defeat my purpose if the government's goal is to maximize its firms' sales given inflexible capital and labor inputs. An increase in a firm's revenue efficiency coming from any of physical productivity, higher capacity utilization and materials use, or quality improvement that leads to higher markups is consistent with the government's objectives.

Nevertheless, to ensure the robustness of my results, I further estimate a value-added production function on the sample for which I observe cost of goods sold. I construct value-added VA as revenue minus cost of goods sold, and estimate the following with Ackerberg et al. (2015) using investment as the proxy variable:

$$\ln VA_{it} = \omega_{it}^{VA} + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \epsilon_{it}^{VA},$$

As my primary outcome of interest is private firms' productivity before and after government acquisition, I also estimate the production function on the not-yet-invested domestic firm sample. This includes never-invested firms, and eventually-invested firms in years before any government investment occurs. Firms that are fully state-owned or foreign-owned may operate with different input intensities than private domestic firms in China. The recovered production parameters on the sample restricted to private domestic firms characterize input elasticities for domestic firms operating without direct government ownership, which may well differ from those of state-owned firms or foreign subsidiaries.

Appendix Table C.1 reports the estimated factor elasticities β_K, β_L across semiconductor subsectors with two different specifications: elasticities estimated on the full sample with the first stage using capital, labor, and investment; and estimates from the sample of private domestic firms. The estimates are broadly similar and suggest that firms exhibit roughly constant returns to scale. Appendix Table C.2 reports estimates from the value-added specification. To probe the robustness of this measure, I plot the correlation of estimated revenue productivity ω_{it}^R against value-added productivity ω_{it}^{VA} in Appendix Figure C.1. Reassuringly, these two measures are highly correlated across estimates, with a correlation of 0.73–0.75 across specifications.

C.2 Structural Interpretation of the Capital-Labor Residual

The estimation in Section C.1 projects log revenue on capital and labor alone and interprets the residual as a productivity index ω_{it}^R. However, firms buy materials such as chemicals, gases, silicon wafers, and photoresist, which are included in the productivity residual. The practical issue the paper faces is that cost of goods sold, a proxy for materials use, is observed for only 26,314 of 49,823 firm-years. This subsection adds a flexibly chosen materials input M to the firm problem and shows that the residual identifies a Domar-scaled (its capital and labor elasticities inflated by $1/(1-\beta_M)$) revenue-generating productivity measure.

The firm problem with materials. Suppose a firm combines capital, labor, and a flexible materials composite M_{it} bought at a common sector-year price P_{st}^M:

$$q_{it} = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M} \epsilon_{it}, \qquad \ln R_{it} = \omega_{it} + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_M \ln M_{it} + \rho \ln \epsilon_{it},$$

with $\beta_M \equiv \rho \alpha_M$ and ω_{it} revenue productivity. Following Ackerberg et al. (2015), where labor is treated as a less flexible input than materials, labor is chosen before materials at some time $t+b-1$ between the end of $t-1$ and the start of time t. This is after the firm observes $\omega_{i,t+b-1}$, a Markovian update from $\omega_{i,t-1}$, and government investment $x_{i,t-1}^{\mathrm{L}}$, $x_{i,t-1}^{\mathrm{C}}$. The firm observes another updated productivity $\omega_{i,t}$ at time t and materials prices P_{st}^M before choosing materials inputs M_{it}. It then produces and receives an iid mean zero disturbance ϵ_{it}.

Step 1: the materials FOC and the constant revenue share. Materials enter revenue with a constant elasticity β_M, so the firm maximizes $\theta_{it}^y \exp(\omega_{it}) K_{it}^{\beta_K} L_{it}^{\beta_L} M_{it}^{\beta_M} \mathbb{E}(\epsilon_{it}^{\rho}) - P_{st}^M M_{it}$ over M_{it}. The static first-order condition equates the wedge-adjusted expected marginal revenue product of materials to their price, so the planned materials bill is a constant fraction of expected sales,

$$s_{it}^M \;\equiv\; \frac{P_{st}^M M_{it}}{\mathbb{E}_t\, R_{it}(K_{it}, L_{it}, \omega_{it})} \;=\; \beta_M\, \theta_{it}^y, \tag{C.1}$$

where firm materials spending is $\beta_M \theta_i^y \,\mathbb{E}\, R_i$. The *observed share* s_{it}^M equals the *revenue elasticity* of materials β_M only when the output wedge is slack ($\theta_{it}^y = 1$). Inverting (C.1) gives the materials demand

$$\ln M_{it} = \frac{1}{1-\beta_M}\Big[\omega_{it} + \beta_K \ln K_{it} + \beta_L \ln L_{it} - \ln P_{st}^M\Big] + c(\theta_{it}^y), \tag{C.2}$$

where $c(\theta_{it}^y) \equiv \frac{1}{1-\beta_M} \ln\big(\beta_M \theta_{it}^y \,\mathbb{E}(\epsilon_{it}^{\rho})\big)$ collects the wedge and firm-invariant constants.

Step 2: substitute in materials. Substituting the materials demand (C.2) back into the gross-output revenue function eliminates $\ln M_{it}$ and leaves revenue as a function of the two observed

inputs:

$$\ln R_{it} = \underbrace{\frac{\beta_K}{1-\beta_M}}_{\equiv\tilde{\beta}_K} \ln K_{it} + \underbrace{\frac{\beta_L}{1-\beta_M}}_{\equiv\tilde{\beta}_L} \ln L_{it} + \underbrace{\frac{1}{1-\beta_M}\omega_{it} - \frac{\beta_M}{1-\beta_M} \ln P^M_{st}}_{\omega^R_{it}} + \rho \ln \epsilon_{it} + \text{const.} \tag{C.3}$$

This is the "value-added" revenue function. Omitting an unobserved flexible materials input results in capital and labor elasticities inflated by the Domar factor $1/(1-\beta_M)$, the reciprocal of one minus the materials' *revenue elasticity*.

Step 3: the revenue productivity measure. The residual of revenue on capital and labor in (C.3) is:

$$\omega^R_{it} \equiv \frac{1}{1-\beta_M}\omega_{it} - \frac{\beta_M}{1-\beta_M} \ln P^M_{st} = \frac{1}{1-\beta_M}\Big[\ln P^D_{st} + \tfrac{1}{\sigma} \ln Q^D_{st} + \rho \ln A_{it}\Big] - \frac{\beta_M}{1-\beta_M} \ln P^M_{st}. \tag{C.4}$$

It is composed of markup-scaled physical productivity $\rho \ln A_{it}$, residual demand Q^D_{st}, and the domestic price index P^D_{st}, net of the materials price P^M_{st}, with all terms rescaled by the Domar factor. As ω^R_{it} measures the firm's idiosyncratic and persistent capability to generate revenue from fixed capital and labor inputs, government policies that maximize industry revenue should target firms with higher ω^R_{it} and / or increase invested firms' ω^R_{it}. Under the additional assumption that firms in sector s face a common materials price index P^M_{st}, total demand Q^D_{st}, and output price index P^D_{st}, within sector-year variation in ω^R_{it} identifies physical productivity $\ln A_{it}$ up to a sector-year specific intercept. As firms in my setting mostly rely on imported materials inputs competitively priced and sold globally, it is a reasonable assumption. I could further relax this assumption by assuming that firms' materials prices are strictly monotone in observed government fund investment status and subsidies.

Assumption 1 (Single index and control function)**.** *Within sector s and year t: (i) the sector price index and market demand (P^D_{st}, Q^D_{st}) are common to all firms; (ii) firm input prices, including the cost of capital $(1+\tau^k)r$, wage w, and materials prices P^M, are strictly decreasing in local and central government investment $x^{\mathrm{L}}_{it}, x^{\mathrm{C}}_{it}$ and non-equity subsidies x^{S}_{it}, which lower a subsidized firm's effective materials price and cost of capital; (iii) capital is predetermined, $K_{it} = (1-\delta)K_{i,t-1} + I_{i,t-1}$, the firm observes $\omega_{i,t+b-1}$ before choosing labor and ω_{it} before choosing materials, and revenue productivity follows a controlled first-order Markov process.*

Part (i) follows from the fact that firms charge a fixed markup under monopolistic competition and that they are sufficiently small in both international and domestic markets to take domestic goods demand Q^D_{st} and the domestic price index P^D_{st} as given. Then (P^D_{st}, Q^D_{st}) are common to all firms within a sector-year and are absorbed by sector-year fixed effects. Part (ii) addresses unobserved firm heterogeneity in input prices. The assumption is that observed government investment and subsidies are sufficient to pin down input price heterogeneity across firms. This is plausible as most upstream materials and equipment for Chinese domestic semiconductor manufacturers are supplied by international firms that are unlikely to charge different prices to relatively small Chinese customers. Cost differences across firms instead come from differential government

support, which I assume my measure of subsidies and investment captures. Thus conditioning the first-stage sector-year-specific "planned output" function on government investment and subsidies restores invertibility: holding $\mathbf{x}_{it}^G \equiv (x_{it}^{\mathrm{L}}, x_{it}^{\mathrm{C}}, x_{it}^{\mathrm{S}})$ fixed, the only firm-specific unobservable left in ω_{it}^R is physical productivity $\rho \ln A_{it}$.

Under Assumption 1 and investment monotonicity, optimal investment $I_{it}^*(\omega_{it}, K_{it}, \mathbf{x}_{it}^G)$ is strictly increasing in ω_{it} given capital and government investment status. Thus I could identify the value-added coefficients $(\tilde{\beta}_K, \tilde{\beta}_L)$ by Ackerberg et al. (2015).

C.3 Estimation Details

1. For each sector s and year t, regress observed revenue R_{it} or value-added VA_{it} on a flexible third-order polynomial function of inputs $\ln K_{it}$, $\ln L_{it}$, government support $\mathbf{x}_{it}^G$, and the proxy variable investment $\ln I_{it}$, which is assumed to be strictly increasing in productivity conditioning on the other variables. With the resulting function $\Phi_{st}(K, L, I, \mathbf{x}^G)$ that predicts output, termed by De Loecker and Syverson (2021) as the firm's "planned output" when it makes input decisions, I can then estimate mean-zero shocks $\ln \epsilon_{it} = \ln R_{it} - \Phi_{st}(K, L, I, \mathbf{x}^G)$ which are estimated shocks to the firm's output that are assumed to be independent from firms' lagged input decisions.

2. Utilizing the assumption that productivity follows a Markov process, let $\hat{f}_\omega$ be a flexible 3rd degree polynomial function approximating $\mathbb{E}(\omega_{it}|\omega_{i,t-1}) = f_\omega(\omega_{i,t-1})$. For candidate β_K, β_L, the productivity residual is $\hat{\omega}_{it}(\beta_K, \beta_L) = \Phi_{st}(K_{it}, L_{it}, I_{it}, \mathbf{x}_{it}^G) - \beta_K \ln K_{it} - \beta_L \ln L_{it}$. The productivity shock $\hat{\epsilon}_{it}^{\omega}(\beta_K, \beta_L) = \hat{\omega}_{it}(\beta_K, \beta_L) - \hat{f}_\omega(\hat{\omega}_{i,t-1}(\beta_K, \beta_L))$ is also independent of the firm's input choices. Thus I can utilize the moment

$$\mathbb{E}[\ln R_{it} - \beta_K \ln K_{it} - \beta_L \ln L_{it} - \hat{f}_\omega(\hat{\omega}_{i,t-1}(\beta_K, \beta_L))|K_{it-1}, L_{it-1}, I_{it-1}] \tag{C.5}$$

   to form the moment conditions to estimate (β_K, β_L) by the generalized method of moments.

C.4 Production Function Estimates

Table C.1: Revenue Production Function Estimates (Ackerberg et al., 2015)

ACF Gross Output Estimates

	Full				Private Only			
Sector	β_K	β_L	RTS	Obs.	β_K	β_L	RTS	Obs.
Assembly & Testing	0.338	0.754	1.091	2039	0.318	0.722	1.040	1109
	(0.037)	(0.049)	(0.018)		(0.059)	(0.084)	(0.037)	
Design	0.293	0.759	1.052	5222	0.249	0.778	1.026	2609
	(0.013)	(0.017)	(0.010)		(0.017)	(0.022)	(0.015)	
Discrete	0.307	0.638	0.945	5604	0.288	0.587	0.876	3381
	(0.017)	(0.019)	(0.008)		(0.021)	(0.020)	(0.012)	
Equipment	0.335	0.725	1.059	3408	0.322	0.673	0.995	1884
	(0.015)	(0.019)	(0.008)		(0.024)	(0.028)	(0.015)	
IC Manufacturing	0.227	0.852	1.079	1470	0.245	0.760	1.005	590
	(0.047)	(0.078)	(0.040)		(0.051)	(0.073)	(0.043)	
Materials	0.321	0.704	1.025	5565	0.356	0.648	1.003	3679
	(0.011)	(0.015)	(0.007)		(0.017)	(0.021)	(0.010)	
Optoelectronics	0.307	0.724	1.031	2532	0.229	0.784	1.014	1490
	(0.019)	(0.024)	(0.011)		(0.036)	(0.045)	(0.025)	

Notes. "Full" and "Private Only" report ACF elasticities of gross output with respect to K and L, estimated with the baseline (unconditioned) first stage on the whole sample and on the sample of private domestic firm-years (pre-investment). RTS is the returns to scale, $\beta_K + \beta_L$; its standard error accounts for the estimated covariance between $\hat{\beta}_K$ and $\hat{\beta}_L$. Standard errors in parentheses. Capital is rebuilt at a uniform 9 per cent depreciation rate.

Table C.2: Value-Added Production Function Estimates (Ackerberg et al., 2015)

ACF Value-Added Estimates

	Full				Private Only			
Sector	β_K	β_L	RTS	Obs.	β_K	β_L	RTS	Obs.
Assembly & Testing	0.416	0.610	1.026	1664	0.367	0.547	0.915	880
	(0.046)	(0.053)	(0.032)		(0.042)	(0.053)	(0.028)	
Design	0.217	0.783	0.999	3346	0.225	0.729	0.954	1746
	(0.020)	(0.037)	(0.028)		(0.019)	(0.040)	(0.033)	
Discrete	0.262	0.643	0.905	4321	0.323	0.455	0.778	2601
	(0.023)	(0.037)	(0.027)		(0.020)	(0.031)	(0.024)	
Equipment	0.268	0.764	1.031	2338	0.306	0.578	0.883	1283
	(0.032)	(0.052)	(0.031)		(0.026)	(0.049)	(0.038)	
IC Manufacturing	0.450	0.438	0.888	1210	0.249	0.665	0.914	559
	(0.050)	(0.096)	(0.064)		(0.090)	(0.164)	(0.097)	
Materials	0.427	0.578	1.005	4819	0.504	0.390	0.894	3291
	(0.020)	(0.032)	(0.020)		(0.020)	(0.032)	(0.021)	
Optoelectronics	0.363	0.626	0.989	2133	0.367	0.579	0.946	1287
	(0.033)	(0.052)	(0.030)		(0.039)	(0.071)	(0.041)	

Notes. "Full" and "Private Only" report ACF elasticities of value-added with respect to K and L, estimated with the baseline (unconditioned) first stage on the whole sample and on the sample of private domestic firm-years (pre-investment). RTS is the returns to scale, $\beta_K + \beta_L$; its standard error accounts for the estimated covariance between $\hat{\beta}_K$ and $\hat{\beta}_L$. Standard errors in parentheses. Capital is rebuilt at a uniform 9 per cent depreciation rate.

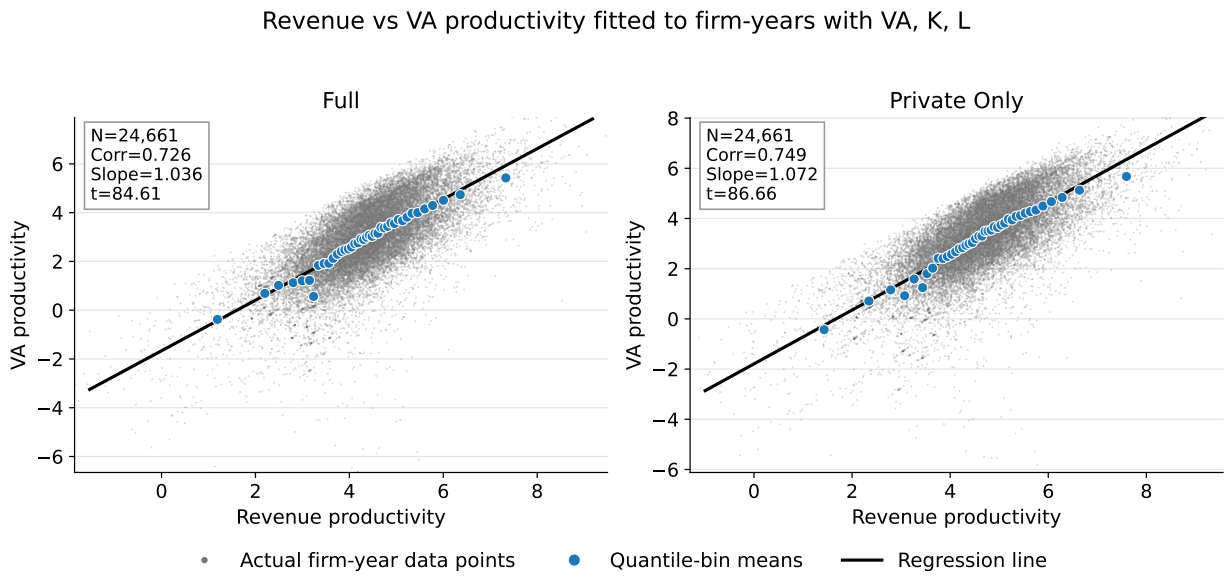


Figure C.1: Correlation of ω_{it}^{R} and ω_{it}^{VA}

Notes. Correlation of the productivities estimated in Table C.1 and Table C.2, on the sample with cost of goods sold records so that value-added productivity can be estimated. Each panel plots the raw data points, the binned scatter, and the fitted regression line correlating value-added productivity ω^{VA} with revenue productivity ω^{R} estimated off the full sample and the private-only sample.

C.5 Local Government Policy Targets

The following lists a few examples of local governments targeting semiconductor industry revenue or productivity in their policies: Shenzhen, South China's flagship technology hub, resolved in its 2019 semiconductor action plan to lift its entire local integrated-circuit industry's sales revenue past 200 billion yuan (roughly US$30 billion) by 2023.[7] Hangzhou, a major city in the Yangtze River Delta, targets a local chip industry of 80–100 billion yuan by 2025 with a growth rate of 20% per year in its 2022 implementation guidelines.[8] The same template recurs in smaller cities, both on the coast and inland. Changzhou, a mid-sized manufacturing city in Jiangsu, set a target in 2020 of 50 billion yuan of local industry revenue by 2025.[9] Nanyang, an inland prefecture in Henan that did not have a significant semiconductor industry base, nonetheless committed in 2022 to a 10-billion-yuan local industry by 2025 and 50 billion by 2035.[10] These examples suggest that each jurisdiction seeks to maximize the aggregate revenue of the semiconductor industry located within its own borders. Local governments do not target only the scale of their semiconductor industries; many also write

[7] Shenzhen Municipal People's Government, *Action Plan for Further Promoting the Development of the Integrated Circuit Industry (2019–2023)*, Shen Fu [2019] No. 28, 23 April 2019. https://www.sz.gov.cn/zfgb/2019/gb1100/content/post_5017853.html

[8] General Office of the Hangzhou Municipal People's Government, *Implementation Opinions on Promoting the High-Quality Development of the Integrated Circuit Industry*, Hang Zheng Ban [2022] No. 1, 8 July 2022. https://www.hangzhou.gov.cn/art/2022/7/15/art_1229063382_1822591.html

[9] Changzhou Municipal People's Government, *Opinions on Accelerating the Development of the Integrated Circuit Industry*, Chang Zheng Fa [2020] No. 103, 10 October 2020. https://www.changzhou.gov.cn/gi_news/971603701231188

[10] General Office of the Nanyang Municipal People's Government, *Opinions on Accelerating the Development of the Integrated Circuit Industry*, Wan Zheng Ban [2022] No. 47, July 2022. https://www.nanyang.gov.cn/2022/07-29/312203.html

productivity upgrading directly into their policy goals. Shanghai's Qingpu district, in its 2023 integrated-circuit action plan, explicitly encourages local firms "through technical transformation, to raise production efficiency and expand production scale."[11]

D Implementation of de Chaisemartin and D'Haultfœuille (2023)

Let G_{ki} be firm i's year of receiving investor type k's investment, and denote $G_{ki} = \infty$ if i is never invested by k in the sample. Denote $\mathbf{G}_i^{-k}(t) = (G_{k'i}(t))_{k' \neq k}$ to be the vector of i's years of receiving the two other VC types' investments *observed at year t*. For each VC type k', define

$$G_{k'i}(t) = \begin{cases} G_{k'i}, & \text{if } G_{k'i} \leq t, \\ \infty, & \text{if } G_{k'i} > t. \end{cases}$$

That is, if by year t i has already received k''s investment in year $G_{k'i} \leq t$, $G_{k'i}(t)$ records k''s investment year $G_{k'i}$, else if by year t k' has not yet invested, $G_{k'i}(t)$ records ∞, i.e., the not yet invested status. The detailed implementation is as follows:

Step 1: Primitive Effect $ATT_{k,s}(g, \tau|\mathbf{g}^-)$. I first estimate the average treatment effect $ATT_{k,s}(g, \tau|\mathbf{g}^-)$ of VC k's investment in industry s in year $g \in \{2003, 2004, \ldots, 2023\}$ on outcomes τ years later, in year $g + \tau$, *conditioning* on the firm's year of treatment by other VC types observed in treatment year g, $\mathbf{G^{-k}}(g) = \mathbf{g}^-$. Specifically, define the treated group of $ATT_{k,s}(g, \tau|\mathbf{g}^-)$ as

$$\mathcal{T}_{k,s}(g, \mathbf{g}^-, \tau) = \{i : \ G_{ki} = g, \ \mathbf{G}^{-k}(g) = \mathbf{g}^-, \ s(i) = s, \ G_{k'i} \notin (g, \ g + \tau] \ \forall k' \neq k\},$$

and the control group is

$$\mathcal{C}_{k,s}(g, \mathbf{g}^-, \tau) = \{i : \ G_{ki} > g + \tau \text{ or } G_{ki} = \infty, \ \mathbf{G}^{-k}(g) = \mathbf{g}^-, \ s(i) = s, \ G_{k'i} \notin (g, \ g + \tau] \ \forall k' \neq k\}.$$

That is, both treated and control firms are in the same sector s and share the same treatment history of other VCs prior to year g: $\mathbf{G}^{-k}(g) = \mathbf{g}^-$. Furthermore, no other investors had entered between year g and year $g + \tau$ (either $G_{k'i} < g$ or $G_{k'i} > g + \tau$).

Let $Y_{i,t}(g, \mathbf{g}^-)$ be unit i's potential outcome in year t when its year of treatment is $(G_{ki}, \mathbf{G}_i^{-k}) = (g, \mathbf{g}^-)$. The primitive average treatment effect on the treated is

$$\begin{aligned} ATT_{k,s}(g, \tau|\mathbf{g}^-) = & E[Y_{i,g+\tau}(g, \mathbf{g}^-) - Y_{i,g-1}(g, \mathbf{g}^-) \mid i \in \mathcal{T}_{k,s}(g, \mathbf{g}^-, \tau)] \\ & - E[Y_{i,g+\tau}(\cdot, \mathbf{g}^-) - Y_{i,g-1}(\cdot, \mathbf{g}^-) \mid i \in \mathcal{C}_{k,s}(g, \mathbf{g}^-, \tau)] \end{aligned}$$

[11] General Office of the Qingpu District People's Government, Shanghai, *Action Plan for Promoting the High-Quality Development of the Integrated Circuit Industry in Qingpu District (2023–2025)*, Qing Fu Ban Fa [2023] No. 25, 27 April 2023, Box 1, item (3). https://www.shqp.gov.cn/shqp/zwgk/zcwj/20231020/1143224.html

which is estimated by the sample analog $\widehat{ATT}_{k,s}(g,\tau|\mathbf{g}^-)$.

$$\widehat{ATT}_{k,s}(g,\tau|\mathbf{g}^-) = \left[\bar{Y}_{g+\tau}(\mathcal{T}_{k,s}(g,\mathbf{g}^-,\tau)) - \bar{Y}_{g-1}(\mathcal{T}_{k,s}(g,\mathbf{g}^-,\tau))\right] - \left[\bar{Y}_{g+\tau}(\mathcal{C}_{k,s}(g,\mathbf{g}^-,\tau)) - \bar{Y}_{g-1}(\mathcal{C}_{k,s}(g,\mathbf{g}^-,\tau))\right],$$

where $\bar{Y}_t(A)$ is the sample average of Y in year t for firms in set A. The primitive DiDs condition on $\mathbf{G}_i^{-k}(g)$, the treatment history observed at event time $G_{ki} = g$, rather than the full treatment history $\mathbf{G}_i^{-k}$, because under the no-anticipation assumption, treated or control firms' future VC investment does not affect their current outcomes and thus could be used in primitive comparisons.

Step 2: Aggregation. I aggregate $\widehat{ATT}_{k,s}(g,\tau|\mathbf{g}^-)$ to the reported coefficient $\widehat{\theta}_k(\tau)$ weighting by the number of treated observations in each primitive DiD

$$\widehat{\theta}_k(\tau) = \sum_{(g,\mathbf{g}^-,s)} w_{g,\mathbf{g}^-,s,\tau}\, \widehat{ATT}_{k,s}(g,\tau|\mathbf{g}^-)$$

with weights $w_{g,\mathbf{g}^-,s,\tau}$ equal to the share of treated firms observed in both $g-1$ and $g+\tau$ for each $\widehat{ATT}$ estimated.

Step 3: Inference. Inference is based on a firm-block bootstrap that samples a firm's whole history in the panel. This choice preserves the serial dependence in outcomes, treatment timing, and pre-investment connection within each firm. In each bootstrap draw $b = 1,\ldots,B = 300$, I resample firms with replacement, keep all observations for each selected firm, reestimate the primitive DiD estimands, and then re-aggregate the event-time estimates with weights $w^{(b)}_{g,\mathbf{g}^-,s,\tau}$ based on the drawn observations across ATT cells.

In bootstrap draw b, I recompute the same object:

$$\widehat{\theta}^{(b)}_k(\tau) = \sum_{(g,\mathbf{g}^-,s)} w^{(b)}_{g,\mathbf{g}^-,s,\tau} \widehat{ATT}^{(b)}_{k,s}(g,\tau \mid \mathbf{g}^-).$$

The bootstrap standard error is

$$\widehat{\text{se}}\{\widehat{\theta}_k(\tau)\} = \left[\frac{1}{B-1}\sum_{b=1}^{B}\left(\widehat{\theta}^{(b)}_k(\tau) - \bar{\theta}^*_k(\tau)\right)^2\right]^{1/2},$$

where

$$\bar{\theta}^*_k(\tau) = \frac{1}{B}\sum_{b=1}^{B}\widehat{\theta}^{(b)}_k(\tau).$$

Pointwise confidence intervals use the normal approximation $\widehat{\theta}_k(\tau) \pm 1.96\widehat{\text{se}}\{\widehat{\theta}_k(\tau)\}$, or the empirical bootstrap percentiles.

Poisson outcomes. For count outcomes, I make an analogous Poisson DiD assumption of parallel trends in the growth rate/log of the mean outcome between treated and control firms:

$$\frac{E[Y_{i,g+\tau}(\infty, \mathbf{g}^-) \mid i \in \mathcal{T}_{k,s}(g, \mathbf{g}^-, \tau)]}{E[Y_{i,g-1}(\infty, \mathbf{g}^-) \mid i \in \mathcal{T}_{k,s}(g, \mathbf{g}^-, \tau)]} = \frac{E[Y_{i,g+\tau}(\infty, \mathbf{g}^-) \mid i \in \mathcal{C}_{k,s}(g, \mathbf{g}^-, \tau)]}{E[Y_{i,g-1}(\infty, \mathbf{g}^-) \mid i \in \mathcal{C}_{k,s}(g, \mathbf{g}^-, \tau)]} \quad \forall\ (g, \mathbf{g}^-, \tau)$$

The primitive ATT is then estimated as

$$\widehat{ATT}^{\text{Pois}}_{k,s}(g, \tau \mid \mathbf{g}^-) = \log\left(\frac{\bar{Y}_{g+\tau}(\mathcal{T}_{k,s}(g, \mathbf{g}^-, \tau))/\bar{Y}_{g-1}(\mathcal{T}_{k,s}(g, \mathbf{g}^-, \tau))}{\bar{Y}_{g+\tau}(\mathcal{C}_{k,s}(g, \mathbf{g}^-, \tau))/\bar{Y}_{g-1}(\mathcal{C}_{k,s}(g, \mathbf{g}^-, \tau))}\right),$$

where $\bar{Y}_t(A)$ is, as before, the sample average of Y in year t for firms in set A. The preferred event-time estimand averages these primitive log ratios by the share of observations:

$$\widetilde{\theta}^{\text{Pois}}_k(\tau) = \sum_{(g,\mathbf{g}^-,s)} w_{g,\mathbf{g}^-,s,\tau} \widehat{ATT}^{\text{Pois}}_{k,s}(g, \tau \mid \mathbf{g}^-).$$

which gives the estimand the interpretation of the average multiplicative effect for a treated firm-pair observed τ years from treatment. Inference is done identically.

E Additional Descriptives

E.1 Shareholdings

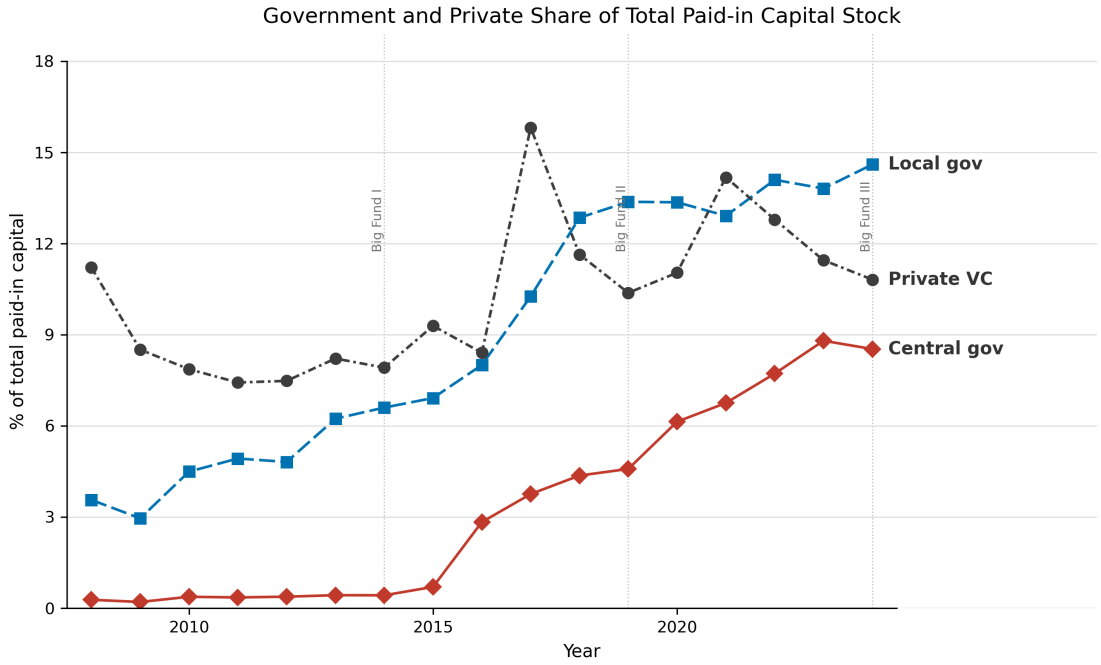


Figure E.1: Government funds' share of total paid-in capital stock

Notes. Paid-in capital held by central government funds, local government funds, and private VC as a percentage of the total registered paid-in capital of firms with at least two years of estimated productivity, by year. Firm-years of the same ultimate owner are averaged before summing across owners. Firm-years whose registered capital is implausibly large relative to revenue, capital stock, and employment are excluded from all series. Private VC excludes corporate parents and insiders. Dotted lines mark the three phases of the Big Fund.

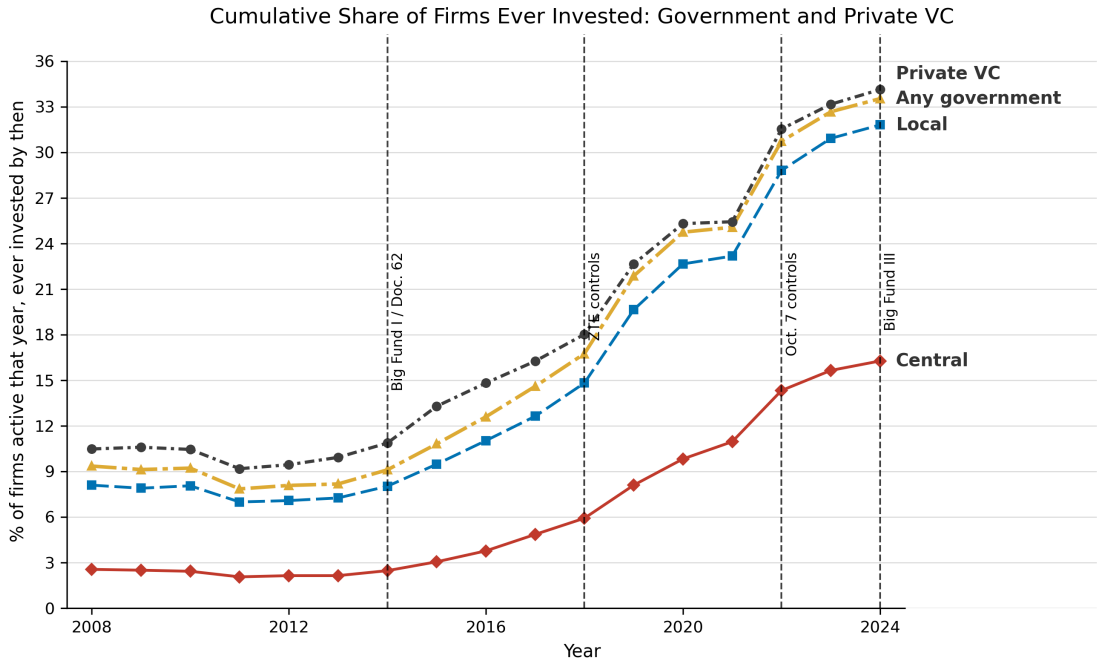


Figure E.2: Government Venture Capital-Invested Firms as a Share of All Firms in the Panel

Notes. Percentage of firms with at least two years of estimated productivity and active in a given year that have received equity investment from each investor type in that year or earlier. "Any government" counts firms invested by a central or a local government fund. Vertical lines mark the Big Fund I and State Council Document No. 62 (2014), US export controls on ZTE (2018), the October 2022 US export controls, and the Big Fund III (2024).

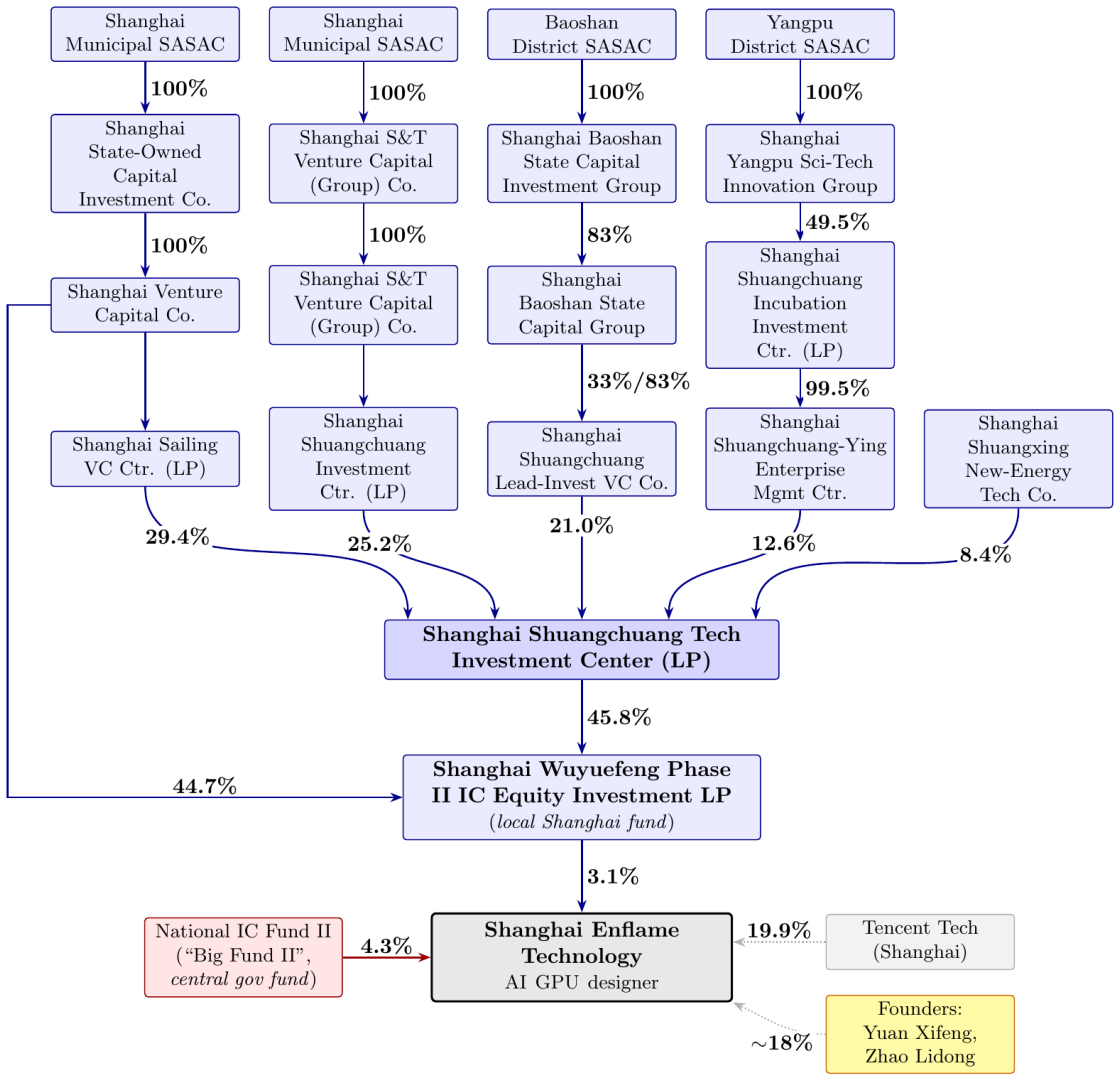


Figure E.3: Shareholders and Shareholder Control Chain of Enflame

Notes. Shareholding chain behind two of Enflame's shareholders, from Qichacha shareholder-registration records. Arrows run from shareholder to investee and are labeled with the equity share. Blue boxes are entities ultimately controlled by Shanghai municipal or district state-asset commissions (SASACs); red is a central government fund; gray and yellow are other private shareholders and founders. Minor residual shareholders are omitted.

E.2 Connection Types

Table E.1: Top 10 institutions linking firm and fund personnel, by fund type

Rank within fund type	Central-government fund			Local-government fund			Private fund		
	Institution	Pairs	Top pair types	Institution	Pairs	Top pair types	Institution	Pairs	Top pair types
1	Tsinghua U	7,276	postgrad-undergrad 31%; postgrad-postgrad 27%; academic-postgrad 26%	Tsinghua U	12,689	postgrad-undergrad 29%; academic-postgrad 24%; postgrad-postgrad 16%	Tsinghua U	7,582	postgrad-undergrad 28%; academic-postgrad 27%; postgrad-postgrad 18%
2	Peking U	2,474	academic-postgrad 30%; postgrad-postgrad 24%; postgrad-undergrad 21%	Fudan U	4,787	academic-postgrad 48%; postgrad-postgrad 16%; postgrad-undergrad 16%	Zhejiang U	2,863	academic-postgrad 46%; academic-undergrad 21%; postgrad-undergrad 15%
3	Renmin U	2,155	postgrad-postgrad 34%; academic-postgrad 27%; postgrad-undergrad 21%	Peking U	4,661	academic-postgrad 32%; postgrad-undergrad 21%; postgrad-postgrad 21%	Peking U	2,719	academic-postgrad 28%; postgrad-undergrad 27%; academic-undergrad 22%
4	Fudan U	1,753	academic-postgrad 33%; academic-undergrad 25%; postgrad-undergrad 18%	Zhejiang U	3,926	academic-postgrad 34%; academic-undergrad 28%; postgrad-undergrad 13%	Fudan U	2,364	academic-postgrad 36%; academic-undergrad 23%; postgrad-postgrad 17%
5	Zhejiang U	1,113	academic-postgrad 42%; academic-undergrad 29%; postgrad-undergrad 13%	SJTU	3,204	academic-postgrad 30%; academic-undergrad 25%; postgrad-undergrad 17%	SJTU	1,885	academic-undergrad 32%; academic-postgrad 25%; postgrad-undergrad 19%
6	SJTU	901	academic-undergrad 40%; academic-postgrad 29%; postgrad-undergrad 14%	SUFE	2,691	academic-postgrad 27%; postgrad-undergrad 27%; postgrad-postgrad 17%	ZTE	1,489	work-work 100%
7	XJTU	763	academic-postgrad 36%; postgrad-undergrad 23%; academic-undergrad 18%	Renmin U	2,011	academic-postgrad 33%; postgrad-postgrad 26%; postgrad-undergrad 18%	Renmin U	1,274	academic-postgrad 31%; postgrad-undergrad 24%; postgrad-postgrad 20%
8	SUFE	732	postgrad-undergrad 25%; undergrad-undergrad 22%; academic-undergrad 20%	XJTU	1,831	academic-postgrad 44%; academic-undergrad 22%; postgrad-undergrad 14%	XJTU	1,149	academic-postgrad 32%; academic-undergrad 23%; postgrad-undergrad 20%
9	Wuhan U	615	academic-postgrad 30%; postgrad-undergrad 26%; postgrad-postgrad 22%	Nanjing U	1,680	academic-postgrad 35%; postgrad-undergrad 20%; postgrad-postgrad 20%	SUFE	879	academic-postgrad 32%; postgrad-undergrad 21%; postgrad-postgrad 17%
10	ZTE	556	work-work 100%	Shenzhen Capital Group	1,616	work-work 100%	HUST	672	academic-postgrad 59%; postgrad-postgrad 19%; academic-academic 8%
	Total pairs	41,925		Total pairs	89,837		Total pairs	56,072	

Notes. A pair is a distinct (firm-person, fund-person) dyad affiliated at some time with the same institution. "Total pairs" is the total number of unique pairs across all institutions across time in the data. Each person's recorded capacity at that institution is denoted as follows: Academic denotes faculty or research employment; postgrad and undergrad denote domestic or foreign study at the corresponding level; and work denotes employment at a private firm, state-owned enterprise, foreign firm, or government body. "Top pair types" lists up to three leading types of the pairs' capacity at that institution, with shares calculated among that institution's tie pair types.

E.3 Correlates of Productivity and Connections

Table E.2: Correlates of Productivity

	(1)	(2)	(3)	(4)
1(local fund invested)	-0.356***	-0.344***	0.038	0.033
	(0.040)	(0.040)	(0.031)	(0.031)
1(central fund invested)	0.058	0.059	0.115***	0.121***
	(0.050)	(0.051)	(0.039)	(0.039)
1(foreign invested)	0.333***	0.326***	0.012	0.020
	(0.040)	(0.041)	(0.050)	(0.050)
1(private VC invested)	-0.012	-0.006	0.046	0.040
	(0.035)	(0.035)	(0.029)	(0.029)
1(SOE invested)	-0.106**	-0.107***	-0.026	-0.015
	(0.041)	(0.042)	(0.042)	(0.042)
firm age	0.013***	0.012***	0.000	0.000
	(0.002)	(0.002)	(.)	(.)
asinh(invention patent stock)	0.028**	0.028**	0.085***	0.093***
	(0.011)	(0.011)	(0.012)	(0.013)
asinh(IC layout stock)	0.094***	0.095***	0.057***	0.060***
	(0.013)	(0.013)	(0.019)	(0.019)
asinh(software stock)	0.023**	0.023**	0.069***	0.070***
	(0.010)	(0.010)	(0.012)	(0.012)
asinh capacity	-0.012*	-0.011*	0.111***	0.109***
	(0.006)	(0.006)	(0.032)	(0.032)
log(capital)	0.011	0.012	-0.055***	-0.055***
	(0.011)	(0.011)	(0.010)	(0.010)
log(employees)	-0.040***	-0.040***	-0.179***	-0.177***
	(0.013)	(0.013)	(0.016)	(0.016)
asinh total grants received	0.025***	0.025***	0.020***	0.021***
	(0.003)	(0.003)	(0.002)	(0.002)
High-Tech Enterprise	0.148***	0.142***	0.131***	0.153***
	(0.027)	(0.029)	(0.021)	(0.021)
Specialized SME (national)	0.176***	0.170***	0.034	0.063**
	(0.036)	(0.036)	(0.027)	(0.027)
Specialized SME (local)	0.038*	0.038*	0.046***	0.059***
	(0.021)	(0.021)	(0.016)	(0.016)
# directors (total)	0.003	0.005	-0.004	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)
# directors w/ finance experience	0.017	0.012	-0.012	-0.009
	(0.020)	(0.023)	(0.017)	(0.020)
# directors w/ masters	0.007	0.015	0.004	-0.008
	(0.013)	(0.016)	(0.013)	(0.016)
# directors w/ foreign edu	0.012	0.024	0.055**	0.054**
	(0.026)	(0.026)	(0.024)	(0.024)
# directors w/ SOE experience	0.024*	0.032**	0.011	-0.000
	(0.014)	(0.015)	(0.016)	(0.017)
# directors w/ local-fund tie	-0.112***	-0.125***	-0.031	-0.041
	(0.031)	(0.032)	(0.027)	(0.027)
# directors w/ central-fund tie	-0.135***	-0.134***	0.014	0.017
	(0.052)	(0.051)	(0.040)	(0.040)
# directors w/ private-fund tie	-0.030	-0.023	-0.047*	-0.040
	(0.023)	(0.025)	(0.025)	(0.025)
Mean Outcome	4.57	4.57	4.57	4.57
N	40482	40482	40194	40194
R-squared	0.11	0.12	0.65	0.65
N clusters (Firms)	5035	5035	4747	4747
Firm FE	N	N	Y	Y
Ind × Year FE	Y	Y	Y	Y
other board person types & connection controls	N	Y	N	Y

Notes. OLS regressions of firm revenue productivity ω_{it}^R (Appendix Section C) on firm characteristics. Investor indicators equal one when the investor type holds equity in the firm that year; patent, layout and software stocks are cumulative counts. Columns (2) and (4) add directors' government, academic, finance and degree backgrounds, process node, registered capital, ties to each fund type, listing, cumulative subsidies and procurement; columns (3) and (4) add firm fixed effects. All columns include industry × year fixed effects; standard errors clustered by firm.

Table E.3: Correlates of Connections, by Fund Type

	Central				Local				Private			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
TFP (revenue)	-0.002	-0.003	0.000	-0.000	0.001	-0.001	0.003	0.003	-0.013***	-0.005	-0.002	-0.002
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
Firm age	-0.002**	-0.002	0.000	0.000	-0.001	-0.000	0.000	0.000	-0.003***	-0.002*	0.000	0.000
	(0.001)	(0.001)	(.)	(.)	(0.001)	(0.001)	(.)	(.)	(0.001)	(0.001)	(.)	(.)
asinh(invention patent stock)	0.059***	0.036***	0.032***	0.027***	0.050***	0.026***	0.030***	0.017***	0.070***	0.038***	0.032***	0.029***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
asinh(IC layout stock)	0.004	0.004	-0.006	-0.006	0.006	0.005	-0.001	-0.002	0.018**	0.011	0.002	0.002
	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Indicator: most advanced process in industry	0.243***	0.274***	0.036	0.034	-0.114	-0.063	0.014	0.014	-0.013	0.002	0.013	0.003
	(0.091)	(0.083)	(0.103)	(0.100)	(0.098)	(0.061)	(0.075)	(0.073)	(0.097)	(0.074)	(0.026)	(0.032)
asinh(capacity)	0.006	0.003	0.013	0.014	-0.002	-0.004	-0.007	-0.006	-0.001	-0.000	-0.003	-0.003
	(0.005)	(0.004)	(0.011)	(0.010)	(0.005)	(0.004)	(0.008)	(0.007)	(0.003)	(0.003)	(0.009)	(0.008)
log(capital)	0.009***	0.006*	-0.000	-0.001	0.002	0.000	0.007***	0.005***	0.012***	0.010***	0.001	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
log(employees)	0.008*	-0.000	0.013***	0.010***	0.009**	0.001	0.007**	0.002	-0.004	-0.004	0.002	-0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
High-Tech Enterprise	0.017	0.004	-0.003	-0.006	0.039***	0.010	0.009	-0.004	0.050***	0.017	0.009	0.006
	(0.013)	(0.014)	(0.009)	(0.009)	(0.012)	(0.013)	(0.008)	(0.008)	(0.014)	(0.014)	(0.009)	(0.009)
Number of directors (total)	0.038***	0.016***	0.031***	0.020***	0.035***	0.013***	0.030***	0.018***	0.034***	0.014***	0.027***	0.018***
	(0.003)	(0.003)	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
Number of directors with engineering or computer-science degree		0.041***		0.022		0.045***		0.017		0.043***		0.015
		(0.011)		(0.021)		(0.011)		(0.016)		(0.013)		(0.017)
Number of directors with finance or economics degree		-0.016		0.006		0.006		0.036*		-0.008		0.024
		(0.020)		(0.023)		(0.021)		(0.021)		(0.028)		(0.026)
asinh(total grants received)		0.003*		0.002**		0.003**		0.001		0.003**		0.001
		(0.002)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
Mean TFP (revenue)	4.70	4.70	4.70	4.70	4.70	4.70	4.70	4.70	4.69	4.69	4.69	4.69
Observations	26,989	26,989	26,640	26,640	26,989	26,989	26,640	26,640	30,395	30,395	30,028	30,028
R^2	0.25	0.31	0.79	0.80	0.24	0.32	0.79	0.79	0.22	0.29	0.80	0.80
Number of firm clusters	3,794	3,794	3,445	3,445	3,794	3,794	3,445	3,445	4,187	4,187	3,820	3,820
Firm fixed effects	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Industry × year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ownership, board, and subsidy controls	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y

Notes: The dependent variable is the firm's director and manager ties to the GP of a VC of the named type (same-province GPs for local government VCs), the tie measure of Table 1. Each four-column block reports selected regressors for the named fund type. All specifications include industry × year fixed effects. Columns (1) and (2) omit firm fixed effects; columns (3) and (4) include them. Columns (2) and (4) add the numbers of directors with engineering/computer-science or economics/finance degrees, total grants, registered capital, ownership indicators, the numbers of directors with government, SOE, finance, academic, or R&D experience or a master's degree, listing status, specialized-SME designations, cumulative local and central subsidies, and central and local procurement contracts. Firm age is omitted in columns (3) and (4) because it is collinear with the firm and industry-year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

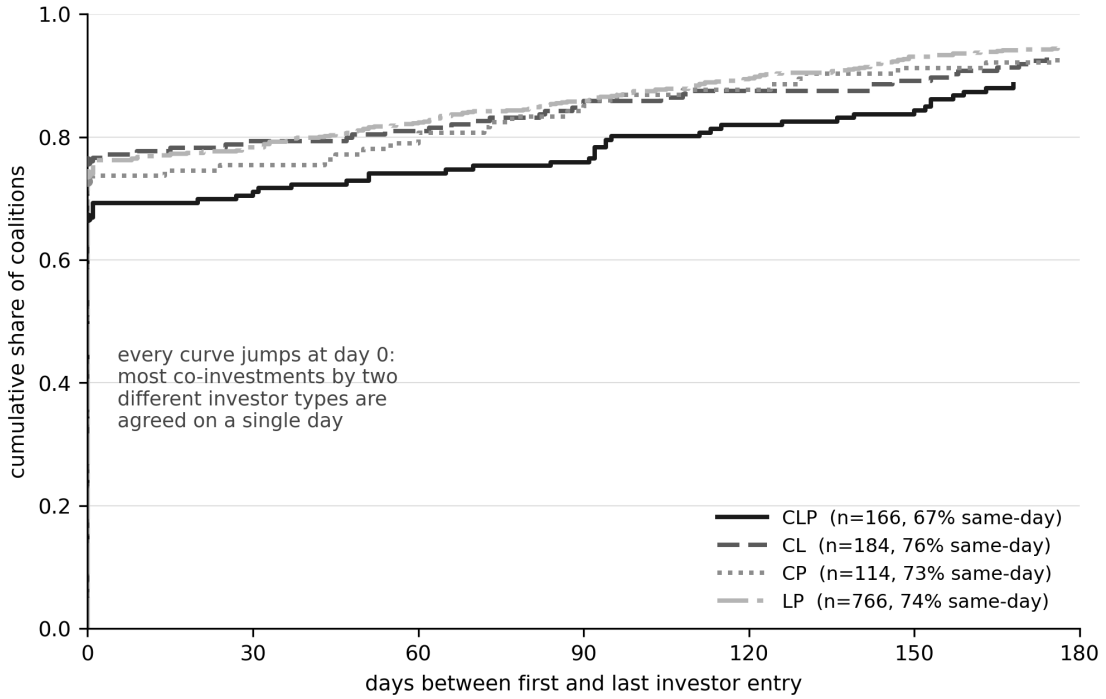


Figure E.4: CDF of the Number of Days Apart When Distinct VC Types Invest Together

Notes. Firms in which two or more VC types first invest in the same year, and whose shareholder register contains dates on the entries (n = 1,230). C, L and P denote central government, local government and private VCs: CL, CP and LP are firms where exactly those two types first invest in the same year, and CLP firms are the ones where all three types invest. Each curve is the cumulative share of firms by days between the first and the last type's registration. Across all four combinations, 73% of instances see all VC types become registered shareholders on the same day.

E.4 Which Firms Do Government and Private VCs Back?

Table E.4: Other Predictors of Central Government, Local Government, and Private Venture Capital Investment

	Central government VC (2)	Local government VC (2)	Private VC (2)
Ownership and previous investment			
1(local-government VC invested)	0.017***	–	0.021***
	(0.004)		(0.007)
1(central-government VC invested)	–	0.025***	0.002
		(0.009)	(0.010)
1(private VC invested)	0.004	0.016***	–
	(0.003)	(0.005)	
1(foreign invested)	0.010*	-0.009***	-0.011***
	(0.005)	(0.003)	(0.003)
1(SOE invested)	0.010***	0.011***	0.002
	(0.004)	(0.004)	(0.004)
Firm characteristics			
Firm age	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
asinh(invention patent stock)	0.001	0.000	-0.002
	(0.001)	(0.001)	(0.001)
asinh(IC layout stock)	-0.001	0.000	0.001
	(0.001)	(0.002)	(0.001)
asinh(software stock)	-0.000	0.001	0.003***
	(0.001)	(0.001)	(0.001)
asinh(registered capital)	-0.000	-0.000	-0.001
	(0.000)	(0.001)	(0.000)
asinh(capacity)	0.001	0.001**	0.001*
	(0.001)	(0.001)	(0.001)
1(most advanced process in industry)	-0.031***	-0.008	-0.003
	(0.012)	(0.021)	(0.022)
log(capital)	0.001**	0.002***	0.002***
	(0.000)	(0.001)	(0.000)
log(employees)	0.002**	0.001	0.001
	(0.001)	(0.001)	(0.001)

Continued on next page

Table E.4 continued

	Central government VC (2)	Local government VC (2)	Private VC (2)
Board characteristics			
Number of directors	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Number of directors with government experience	-0.002	-0.001	0.005
	(0.003)	(0.004)	(0.004)
Number of directors with SOE experience	0.001	-0.003**	-0.005***
	(0.001)	(0.002)	(0.001)
Number of directors with finance experience	-0.001	0.007***	0.005**
	(0.001)	(0.002)	(0.002)
Number of directors with technology/R&D experience	0.002	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
Number of directors with master's degree	-0.001	0.001	0.001
	(0.001)	(0.002)	(0.002)
Number of directors with foreign education	-0.002	-0.003	0.005
	(0.002)	(0.003)	(0.004)
Technology and policy exposure			
High-Tech Enterprise	0.002	0.004	0.004
	(0.003)	(0.003)	(0.003)
Specialized SME (national)	0.000	-0.012	-0.001
	(0.011)	(0.020)	(0.024)
asinh(total subsidies: grants + equity)	0.000	0.001**	0.001***
	(0.000)	(0.000)	(0.000)
Number of central-government procurements	0.000	-0.000	-0.001**
	(0.000)	(0.000)	(0.000)
Number of local-government procurements	-0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)
Mean dependent variable	0.01	0.02	0.01
Observations	22,472	23,902	20,874
R^2	0.04	0.05	0.04
Province × industry clusters	175	177	174
Industry × year fixed effects	Y	Y	Y

Notes. These are the other coefficients from the full specification, column (2) of Table 1, for each outcome; the productivity-rank and director-tie coefficients appear in that table. Dashes indicate a regressor not included for that outcome. Standard errors clustered by province × industry appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.5: Productivity Ranks and Director Ties as Predictors of Venture Capital Investment: Conditional Logit

	Central government VC		Local government VC		Private VC	
	(1)	(2)	(1)	(2)	(1)	(2)
National TFPR percentile (0–1)	1.438***	1.186**	-0.003	-0.126	1.060***	1.111***
	(0.549)	(0.583)	(0.364)	(0.369)	(0.318)	(0.348)
Provincial TFPR percentile (0–1)	-0.610	-0.552	0.847***	0.641**	0.446	0.230
	(0.514)	(0.514)	(0.318)	(0.318)	(0.318)	(0.325)
# directors tied to the GP of a:						
central government VC	0.061	0.004	-0.094***	-0.106***	-0.028	-0.059
	(0.038)	(0.043)	(0.033)	(0.035)	(0.049)	(0.050)
same-province local VC	0.011	0.026	0.128***	0.114***	-0.009	-0.054
	(0.029)	(0.029)	(0.031)	(0.029)	(0.032)	(0.034)
private VC	0.025	-0.081***	0.085***	-0.046**	0.108***	-0.012
	(0.029)	(0.031)	(0.018)	(0.023)	(0.036)	(0.042)
Mean outcome	0.01	0.01	0.02	0.02	0.01	0.01
N	14,818	14,778	19,924	19,870	17,514	17,514
Clusters (ind. × year)	77	77	109	109	110	110
Industry × year groups	Y	Y	Y	Y	Y	Y
Firm characteristics controls	N	Y	N	Y	N	Y

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Conditional logit of an indicator for the investor type first investing in year $t+1$, grouped on industry × year, standard errors clustered by industry × year. Coefficients are log-odds. As TFPR percentiles run from 0 to 1, a firm at the top of the national distribution relative to the bottom has $e^{1.438} \approx 4.2$ times the odds of being invested by a central government VC, within an industry-year. Industry-year cells with no investment contribute nothing to the conditional likelihood and are dropped, which is why N is below the linear-probability samples in Table 1. Percentiles rank revenue productivity (TFPR) among same-industry firms nationally and within the firm's province in year t. A tie is a link through education or an employment stint between a member of the firm's main personnel and a member of the main personnel of the VC type's GP. Both columns include industry × year fixed effects and indicators of whether the firm is already invested by the other VC types. Column (2) adds ownership indicators (foreign, SOE); firm age, log capital, log employment, and registered capital; patent, IC layout, and software stocks, production capacity, and an indicator for the industry's most advanced process; board size and the numbers of directors with government, SOE, finance, or R&D experience, a master's degree, or foreign education; High-Tech Enterprise and national specialized-SME status, total subsidies (grants and equity), and the number of central and local procurement contracts. Appendix Table E.6 shows the estimates for other covariates.

Table E.6: Other Predictors of Central Government, Local Government, and Private Venture Capital Investment: Conditional Logit

	Central government VC (2)	Local government VC (2)	Private VC (2)
Ownership and previous investment			
1(local-government VC invested)	0.848***	–	0.613***
	(0.202)		(0.192)
1(central-government VC invested)	–	0.340	-0.004
		(0.219)	(0.300)
1(private VC invested)	0.329*	0.620***	–
	(0.194)	(0.113)	
1(foreign invested)	0.432	-0.636***	-0.813***
	(0.298)	(0.218)	(0.285)
1(SOE invested)	0.538***	0.411***	0.025
	(0.193)	(0.124)	(0.178)
Firm characteristics			
Firm age	-0.085***	-0.076***	-0.067***
	(0.020)	(0.015)	(0.012)
asinh(invention patent stock)	0.052	-0.001	-0.066*
	(0.050)	(0.038)	(0.039)
asinh(IC layout stock)	-0.064	0.019	0.011
	(0.070)	(0.056)	(0.060)
asinh(software stock)	0.009	0.049	0.115***
	(0.052)	(0.042)	(0.041)
asinh(registered capital)	0.009	-0.018	-0.035
	(0.037)	(0.025)	(0.023)
asinh(capacity)	0.017	0.055**	0.060*
	(0.028)	(0.026)	(0.032)
1(most advanced process in industry)	†	0.133	0.221
		(1.164)	(1.127)
log(capital)	0.112	0.131***	0.129***
	(0.071)	(0.041)	(0.036)
log(employees)	0.254***	0.053	0.085
	(0.087)	(0.063)	(0.053)

Continued on next page

Table E.6 continued

	Central government VC (2)	Local government VC (2)	Private VC (2)
Board characteristics			
Number of directors	0.011	-0.002	0.004
	(0.024)	(0.010)	(0.015)
Number of directors with government experience	-0.052	-0.013	0.117
	(0.122)	(0.098)	(0.112)
Number of directors with SOE experience	0.070	-0.057	-0.106**
	(0.046)	(0.042)	(0.047)
Number of directors with finance experience	-0.003	0.186***	0.122*
	(0.065)	(0.052)	(0.067)
Number of directors with technology/R&D experience	0.105*	0.130***	0.128***
	(0.055)	(0.031)	(0.046)
Number of directors with master's degree	-0.065	0.022	0.041
	(0.055)	(0.050)	(0.069)
Number of directors with foreign education	-0.100	-0.133	0.147
	(0.132)	(0.088)	(0.117)
Technology and policy exposure			
High-Tech Enterprise	0.215	0.100	0.219
	(0.184)	(0.168)	(0.151)
Specialized SME (national)	-0.082	-0.302	0.030
	(0.517)	(0.455)	(0.616)
asinh(total subsidies: grants + equity)	0.027	0.047**	0.059***
	(0.025)	(0.021)	(0.018)
Number of central-government procurements	0.035	-0.005	-0.103**
	(0.025)	(0.008)	(0.051)
Number of local-government procurements	-0.064**	0.001	0.010
	(0.026)	(0.002)	(0.008)
Mean dependent variable	0.01	0.02	0.01
Observations	14,778	19,870	17,514
Industry × year clusters	77	109	110
Industry × year groups	Y	Y	Y

Notes. These are the other conditional logit coefficients from the full control specification, column (2) of Table E.5, for each outcome. Conditional logit of an indicator for the investor type first investing in year $t+1$, grouped on industry × year; coefficients are log-odds. Industry-year groups without any investment drop out, so observations are fewer than in the linear model. Dashes indicate a regressor not included for that outcome. † Not identified: the estimate diverges (quasi-complete separation), so it is not reported. Standard errors clustered by industry × year appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.7: Firm Characteristics in the Year Before Each Investor Type's First Entry: Levels and Industry-Year Percentiles

		Level		Industry-year percentile	
	Observations	**Median**	**IQR**	**Median**	**IQR**
Panel A: Age (years)					
Private	766	8	[5, 13]	33	[12, 65]
Local	720	8	[4, 13]	31	[11, 65]
Central	466	8	[5, 13]	31	[12, 62]
Population benchmark	47,958	11	[7, 16]	50	[25, 75]
Private, when first investor	550	9	[5, 14]	36	[12, 65]
Local, when first investor	358	8	[4, 13]	29	[9, 61]
Central, when first investor	128	8	[4, 14]	33	[10, 64]
Panel B: Employment (persons)					
Private	766	100	[36, 288]	60	[41, 77]
Local	720	96	[36, 298]	61	[43, 81]
Central	466	149	[54, 481]	68	[48, 84]
Population benchmark	47,958	60	[15, 231]	50	[25, 75]
Private, when first investor	550	101	[37, 288]	60	[42, 77]
Local, when first investor	358	74	[33, 203]	55	[40, 73]
Central, when first investor	128	138	[48, 379]	67	[47, 84]
Panel C: Revenue (million 2023 RMB)					
Private	766	73	[20, 231]	61	[38, 79]
Local	720	73	[20, 294]	63	[38, 82]
Central	466	118	[34, 396]	68	[45, 85]
Population benchmark	47,958	39	[8.0, 176]	50	[24, 75]
Private, when first investor	550	77	[20, 228]	62	[42, 79]
Local, when first investor	358	53	[16, 185]	56	[36, 75]
Central, when first investor	128	96	[34, 401]	69	[44, 89]
Panel D: Productivity (ω^R; level in logs)					
Private	766	4.85	[4.12, 5.50]	54	[25, 77]
Local	720	4.82	[4.13, 5.42]	49	[28, 75]
Central	466	4.89	[4.18, 5.52]	52	[26, 76]
Population benchmark	47,958	4.81	[4.09, 5.48]	50	[25, 75]
Private, when first investor	550	4.91	[4.21, 5.56]	57	[32, 78]
Local, when first investor	358	4.87	[4.08, 5.44]	52	[29, 76]
Central, when first investor	128	5.04	[4.26, 5.66]	61	[35, 82]

Notes. Characteristics in the year before each type's first entry into the firm. "When first investor" keeps entries in which the type is among the firm's first investors, joint entry included, so a firm can appear in more than one row. All panels use the same entries, at firms with productivity observed in that year. Percentiles rank firms within industry and year. The benchmark is all such firm-years, weighted to the timing of the entries.

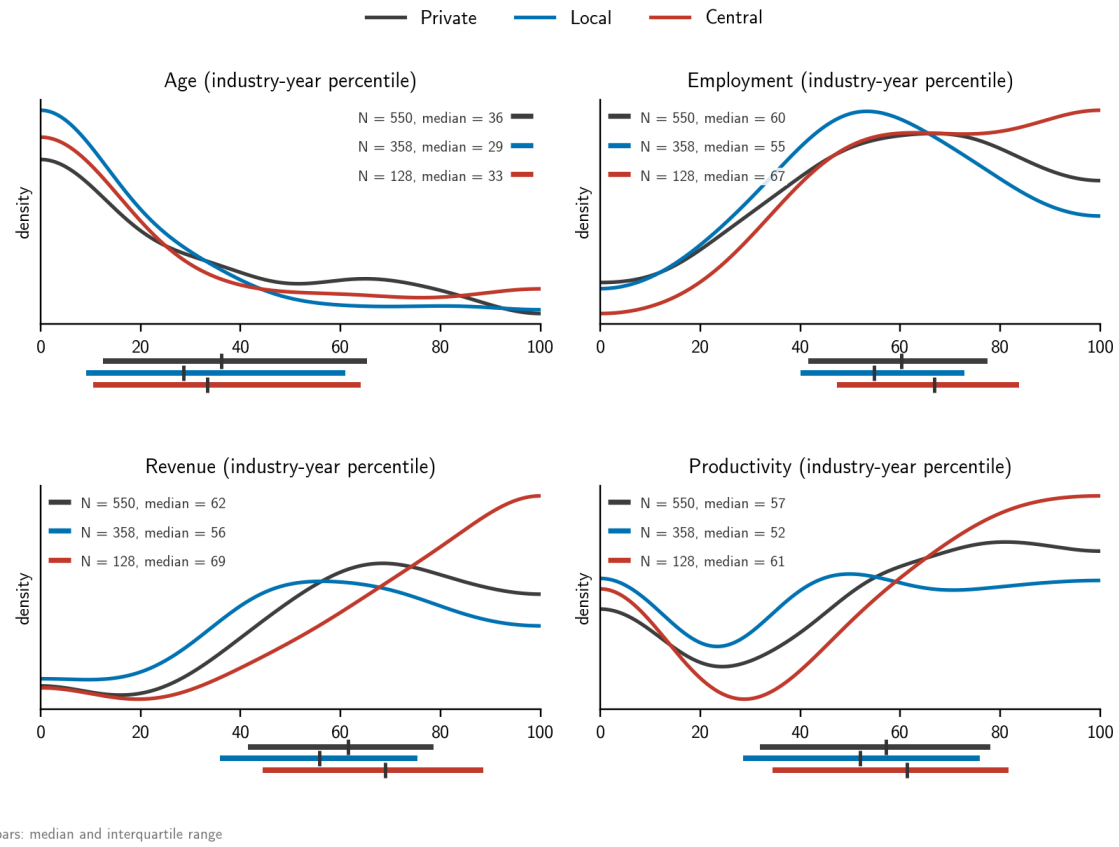


Figure E.5: Firm Characteristics in the Year Before Entry, by VC Type as First Investor

Notes. Kernel densities of the within industry-year percentile of key firm characteristics of firms that private/local government/central government VCs respectively will invest in next year as first investors. This figure does not calculate the percentile within age for employment, revenue, and productivity unlike in Figure 5, while showing the percentile of age at entry within industry-year rather than raw age.

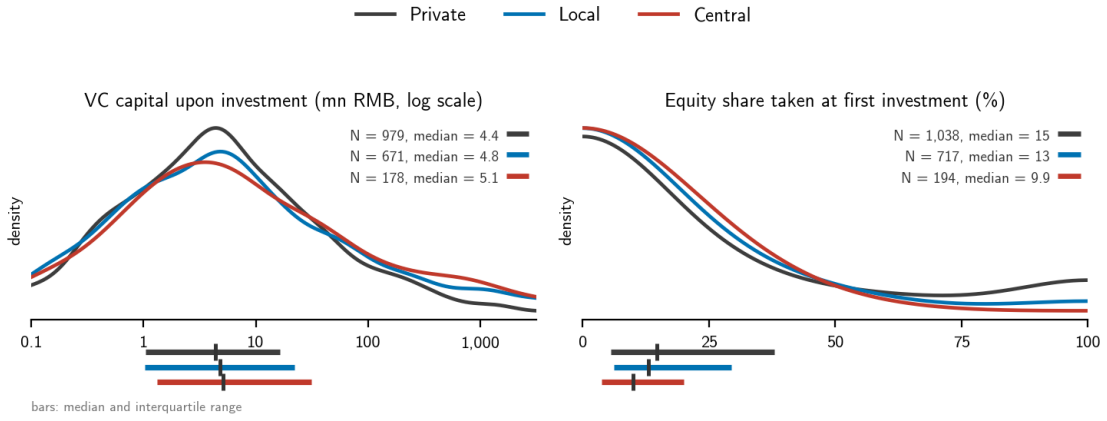


Figure E.6: Deal Terms at First Investment, by VC Type as First Investor

Notes. Raw money invested and shares obtained at each VC type's first investment in a firm, joint entry included. Panel (a): capital the type invests in the entry year (positive amounts, million RMB, log scale). Panel (b): equity share taken (%). Kernel densities; bars show the median and interquartile range.

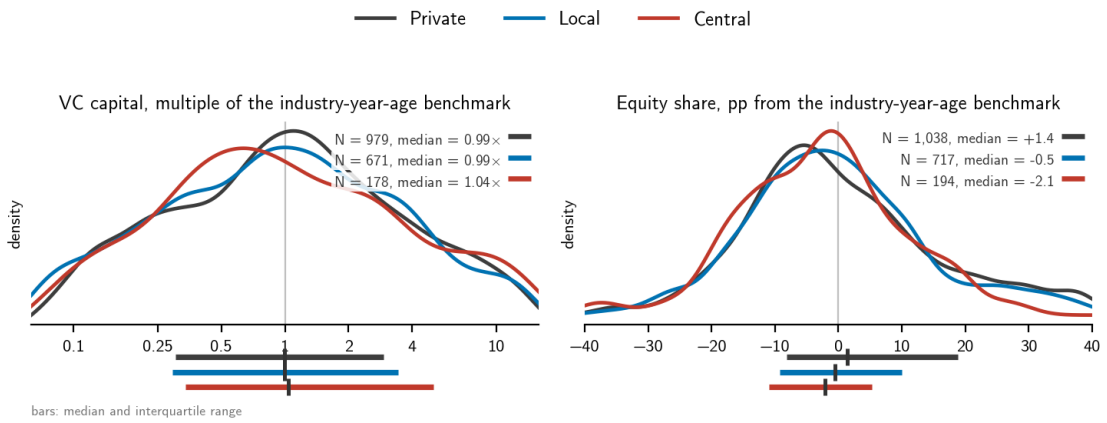


Figure E.7: Deal Terms at First Investment Relative to Comparable Deals, by VC Type as First Investor

Notes. Money invested and shares relative to the invested firm's industry-year and age, obtained at each VC type's first investment in a firm, joint entry included. Panel (a): capital the type invests in the entry year, as a multiple of the amount predicted by industry × year and firm-age-group effects; 1 is the typical deal. Panel (b): equity share taken, in percentage points from the same benchmark. Kernel densities; bars show the median and interquartile range.

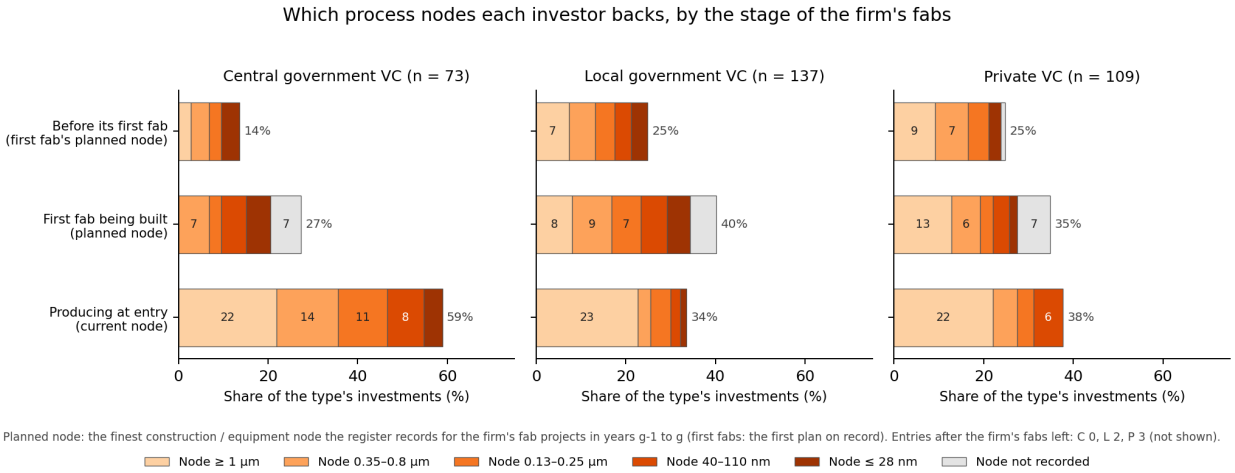


Figure E.8: Stage and Process Node of the Manufacturing Firms Each VC Type Invests In

Notes. Each panel shows the distribution of one VC type's investments in manufacturing firms in the SEMI plant-level data. Each bar corresponds to the status of the invested firm's fabs (semiconductor manufacturing plants) upon investment: *before its first fab* describes the situation in which the firm receives investment before the start of its first fab. *First fab being built* records the situation where the first fab is being built, and *producing at entry* represents the situation where the invested firm already has producing fabs. Bar length is the stage's share of the type's investments. Different color segments in each bar give the process node of either the planned process of the fab (if not yet built or being built) or the most advanced process of producing fabs the year before investment.

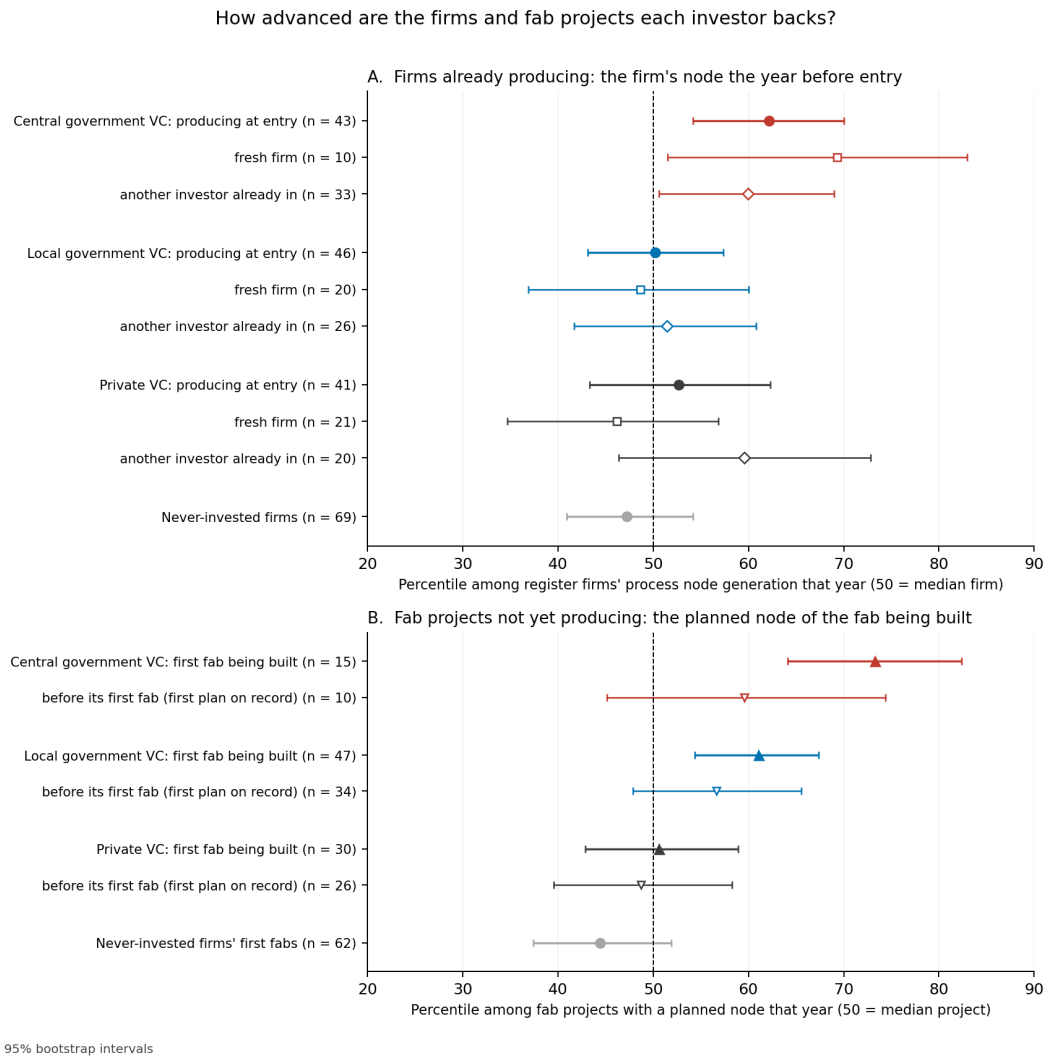


Figure E.9: Process Node Rank of the Firms and Fab Projects Each VC Type Invests In

Notes. The distribution of a VC type's firms' within-year process node generation percentile (the higher the more advanced) in the SEMI data. Bars are standard errors across years. Panel A covers investments in firms already producing. The outcome is the firm's percentile of process node generation (the integer ladder of Figure F.12) in year $g-1$ among all firms with a recorded node that year, 50 is the median process node in production among firms in that year. *Fresh firm*: no other VC type had invested before; *another investor already in*: at least one other VC type has invested upon investment. Panel B covers investments in firms not yet producing. The outcome is the planned node's percentile among all fab projects with a planned node in the same year, one observation per fab and year; 50 is the median project.

E.5 Determinants of Fund Managers Entering the Board

Table E.8: Fund directors at the firm: all fund types pooled, with a test of equal slopes

	Common slopes		Slopes by fund type
	(1)	(2)	(3)
Firm–fund distance (1,000 km)	−0.349***	−0.290***	−0.185**
	(0.062)	(0.060)	(0.090)
× central VC funds			−0.248
			(0.170)
× private VC funds			−0.116
			(0.125)
No. of firms in portfolio	−0.016***	−0.015***	−0.021***
	(0.004)	(0.004)	(0.005)
× central VC funds			+0.013*
			(0.007)
× private VC funds			+0.007
			(0.009)
Fund equity stake (%)	+0.031***	+0.030***	+0.027***
	(0.004)	(0.004)	(0.004)
× central VC funds			−0.005
			(0.009)
× private VC funds			+0.024**
			(0.011)
# pre-investment ties	+0.003**	+0.003**	+0.003***
	(0.001)	(0.001)	(0.001)
× central VC funds			+0.034***
			(0.009)
× private VC funds			+0.037***
			(0.010)
Central VC funds	−0.222**	−0.221*	−0.206
	(0.109)	(0.114)	(0.180)
Private VC funds	−0.087	−0.080	−0.259*
	(0.084)	(0.087)	(0.136)
Test that a slope is the same for all three fund types (p-value)			
distance			0.317
portfolio size			0.170
equity stake			0.075
pre-investment ties			0.000
all eight differences jointly			0.000
N (firm–fund GP years)	24,986	23,013	23,013
Pseudo R^2	0.26	0.28	0.28
Year and firm fixed effects	Y	Y	Y
Firm controls	N	Y	Y

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Poisson, year and firm fixed effects, standard errors clustered by firm. Unit: invested firm × fund GP × year; outcome: # persons concurrently on firm and VC fund GP's board. Local VC funds are the omitted type; in column (3) each block's first row is their slope and the rows below are differences. All columns control for capital invested and fund board size; firm controls cover TFPR, size, board composition, patents, ownership, subsidies and procurement.

Table E.9: Fund directors at the firm: comparing firms within the same fund GP

	Common slopes		Slopes by fund type
	(1)	(2)	(3)
Firm–fund distance (1,000 km)	−0.215**	−0.233**	−0.303**
	(0.095)	(0.102)	(0.132)
× central VC funds			+0.302
			(0.267)
× private VC funds			−0.027
			(0.191)
No. of firms in portfolio	−0.016***	−0.010**	−0.008
	(0.004)	(0.004)	(0.005)
× central VC funds			−0.004
			(0.007)
× private VC funds			−0.006
			(0.006)
Fund equity stake (%)	+0.023***	+0.020***	+0.018***
	(0.005)	(0.005)	(0.006)
× central VC funds			−0.005
			(0.014)
× private VC funds			+0.010
			(0.012)
# pre-investment ties	+0.013***	+0.022***	+0.017**
	(0.005)	(0.005)	(0.007)
× central VC funds			+0.115***
			(0.036)
× private VC funds			+0.002
			(0.009)
Firm TFPR percentile at entry	−0.119	−0.377	−0.343
	(0.187)	(0.247)	(0.248)
Firm size at entry (log employment)	+0.041	−0.017	−0.032
	(0.042)	(0.063)	(0.059)
Firm age at entry (years)	−0.029**	−0.021*	−0.024*
	(0.012)	(0.013)	(0.013)
Tests (p-value)			
entry characteristics jointly zero	0.035	0.028	0.018
slope the same for all three fund types:			
distance			0.430
portfolio size			0.603
equity stake			0.567
pre-investment ties			0.006
all eight differences jointly			0.103
N (firm–fund GP years)	9,267	8,545	8,545
Pseudo R^2	0.30	0.32	0.33
Year and fund GP fixed effects	Y	Y	Y
Firm controls	N	Y	Y

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Poisson, year and fund GP fixed effects, standard errors clustered by firm. Unit: invested firm × fund GP × year; outcome: # persons concurrently on firm and VC fund GP's board. With fund GP fixed effects each coefficient compares firms held by the same GP. Entry characteristics are measured the year before the GP's first investment in the firm. Local VC funds are the omitted type; in column (3) each block's first row is their slope and the rows below are differences. All columns control for fund-type indicators, capital invested and fund board size; firm controls as in Table E.8.

E.6 Determinants of Investor Exit

Table E.10: What Predicts an Investor Leaving the Share Register?

	Central government (1)	Local governments (2)	Private VC (3)	Government − private (4)	Equal across types (p) (5)
Firm performance at $t-1$ (rank within sector-year)					
Productivity growth	−2.38	+0.47	+0.08	−0.08	0.433
	(1.92)	(1.55)	(1.98)	(1.58)	
Employment growth	−4.34***	−1.52	−1.70	−0.28	0.272
	(1.68)	(1.06)	(1.37)	(1.26)	
Productivity level	+2.85	+0.85	−3.40	+4.58**	0.042
	(2.07)	(1.71)	(2.36)	(1.91)	
Employment level	+0.57	+1.15	−0.59	+1.65	0.637
	(2.38)	(1.35)	(2.00)	(1.82)	
Financing and listing					
Registered capital raised at $t-1$	−1.91**	−1.96***	−2.26***	+0.31	0.886
	(0.86)	(0.61)	(0.72)	(0.65)	
Received a subsidy at $t-1$	−0.43	−0.09	−0.17	+0.03	0.938
	(0.89)	(0.52)	(0.76)	(0.76)	
Before the IPO	−0.33	+2.14*	+2.42**	−0.69	0.179
	(0.99)	(1.16)	(1.20)	(0.90)	
IPO year	+9.08***	+21.55***	+22.83***	−3.33	0.013
	(3.43)	(4.36)	(4.02)	(3.02)	
After listing	+7.99***	+13.15***	+22.06***	−9.76***	0.000
	(1.82)	(1.73)	(1.73)	(1.79)	
The holding					
Stake (per 10 pp)	+0.19	+1.05***	+0.65**	+0.26	0.036
	(0.29)	(0.22)	(0.33)	(0.35)	
Largest shareholder	−3.27***	−5.20***	−4.76**	−0.12	0.382
	(1.14)	(0.94)	(2.10)	(2.22)	
Held through more than one fund	−1.98***	−2.99***	−3.01***	+0.18	0.404
	(0.71)	(0.38)	(0.75)	(0.78)	
Oldest fund aged 7+ years	+2.34**	+0.42	+1.56***	−0.82	0.092
	(0.96)	(0.45)	(0.57)	(0.69)	
A GP in the firm's city	−1.62**	−1.24***	+0.75	−2.05***	0.002
	(0.70)	(0.39)	(0.51)	(0.60)	
Other investors at $t-1$					
Another investor exited	+3.43**	+4.67***	+4.71***	−0.24	0.729
	(1.50)	(1.26)	(1.28)	(1.09)	
A new investor entered	+0.64	−0.72	+0.76	−1.25*	0.072
	(0.87)	(0.55)	(0.69)	(0.66)	
Exits per 100 holding-years	4.1	4.8	8.6		
Holding-years	3,623	18,422	26,445		
Exits	148	878	2,285		
Firms	895	2,351	2,244		

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. All columns come from one linear probability model of exit in year t (×100) pooling the three investor types, with every regressor, control and sector × year fixed effect interacted with type, so the coefficients in (1)–(3) equal separate regressions by type. Standard errors clustered by firm. Investor: the central government, a provincial or city government, or a private VC GP; insider vehicles excluded. Ranks run 0–1 within sector-year. Controls: years held, firm age, the investor's portfolio size, missing-data flags. Holding-years 2006–2023. (4): holding-year-weighted mean of (1) and (2) minus (3); (5): p-value that (1)–(3) are equal.

F Additional Event-Study Results

F.1 Productivity

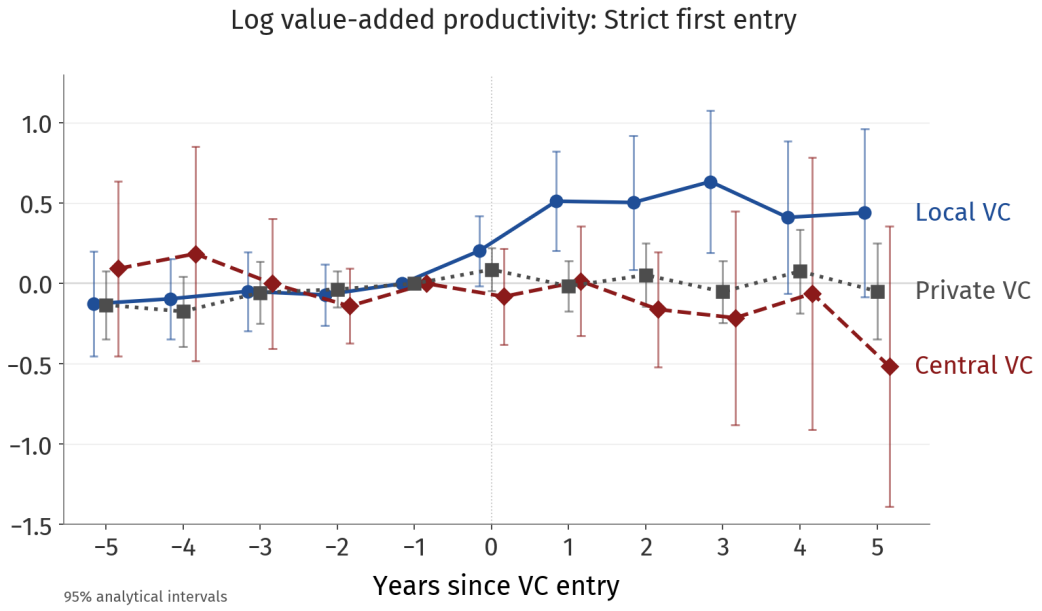
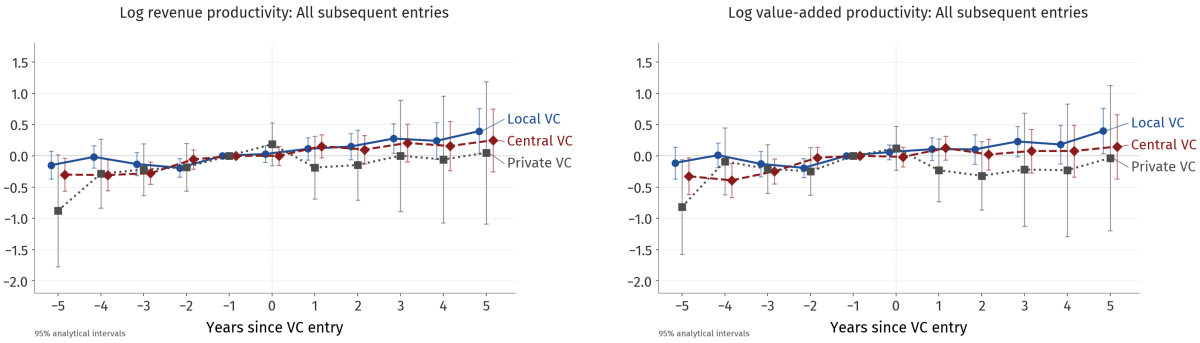


Figure F.1: Effects on Value-added Productivity by Initial VC Entrant

Notes. Central government, local government, and private VC ATT estimates $\theta_{\mathrm{C}}(\tau), \theta_{\mathrm{L}}(\tau), \theta_{\mathrm{P}}(\tau)$ for years relative to investment $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% confidence intervals from analytical standard errors. The treated group are firms which receive their first VC investment from the VC type in question, and the controls are same-sector firms not yet invested by any VC. The estimates are treated observation-weighted averages of primitive 2-period DiD estimates $ATT_{\mathrm{C},s}(g, \tau \mid \mathbf{g}^{-\mathrm{C}})$, $ATT_{\mathrm{L},s}(g, \tau \mid \mathbf{g}^{-\mathrm{L}})$ and $ATT_{\mathrm{P},s}(g, \tau \mid \mathbf{g}^{-\mathrm{P}})$ respectively, which are group-time treatment effects of central, local, and private VC investment conditional on sector s and VC investment history $\mathbf{g}^{-}$.



(a) Revenue Productivity **(b)** Value-added Productivity

Figure F.2: Productivity
de Chaisemartin and D'Haultfœuille (2023) Event Study Estimates, Subsequent Entry

Notes. Central government, local government, and private VC investment average treatment effects $\theta_{\mathrm{C}}(\tau), \theta_{\mathrm{L}}(\tau), \theta_{\mathrm{P}}(\tau)$ estimates for $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% analytical confidence intervals when the VC type strictly follows the entry of other VCs. The control group is firms that share the same investment history by other VC types as the treated, but have not yet received investment from the treatment VC at event time.

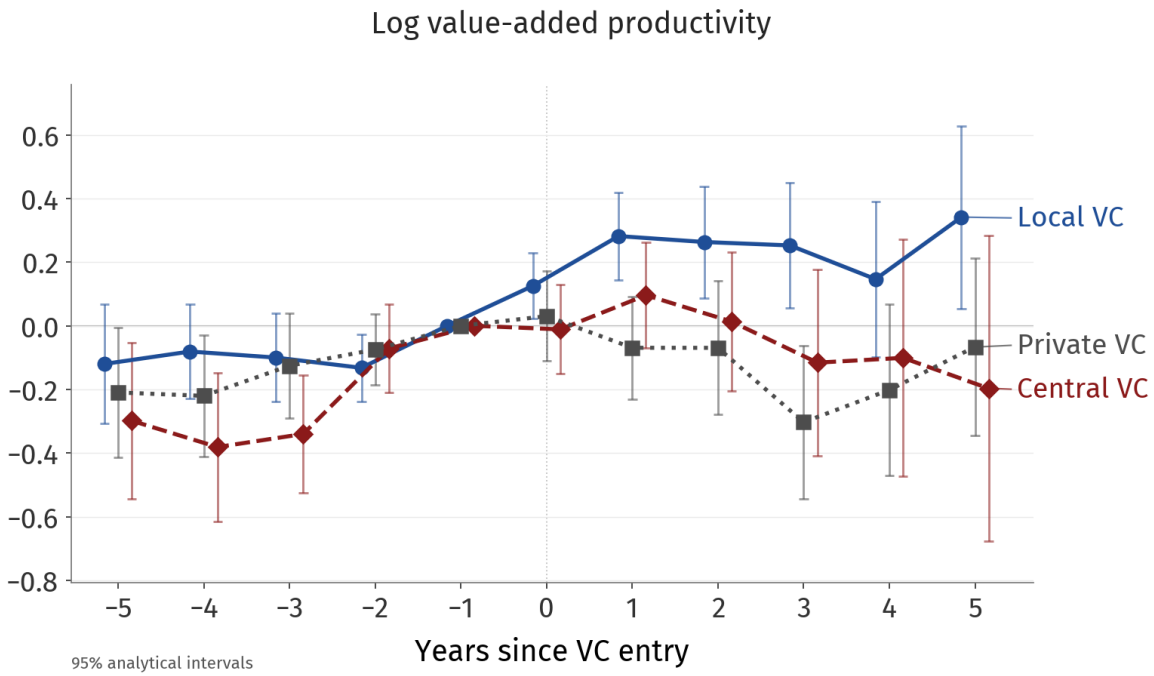
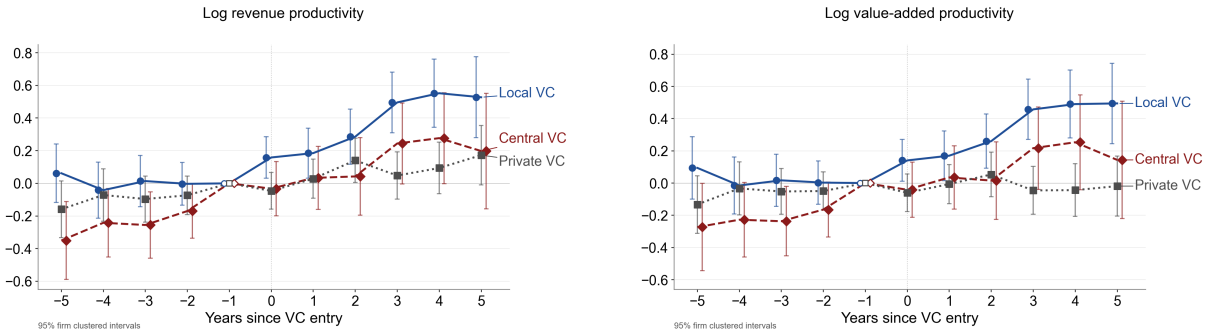


Figure F.3: Value-added productivity, de Chaisemartin and D'Haultfœuille (2023) Estimates

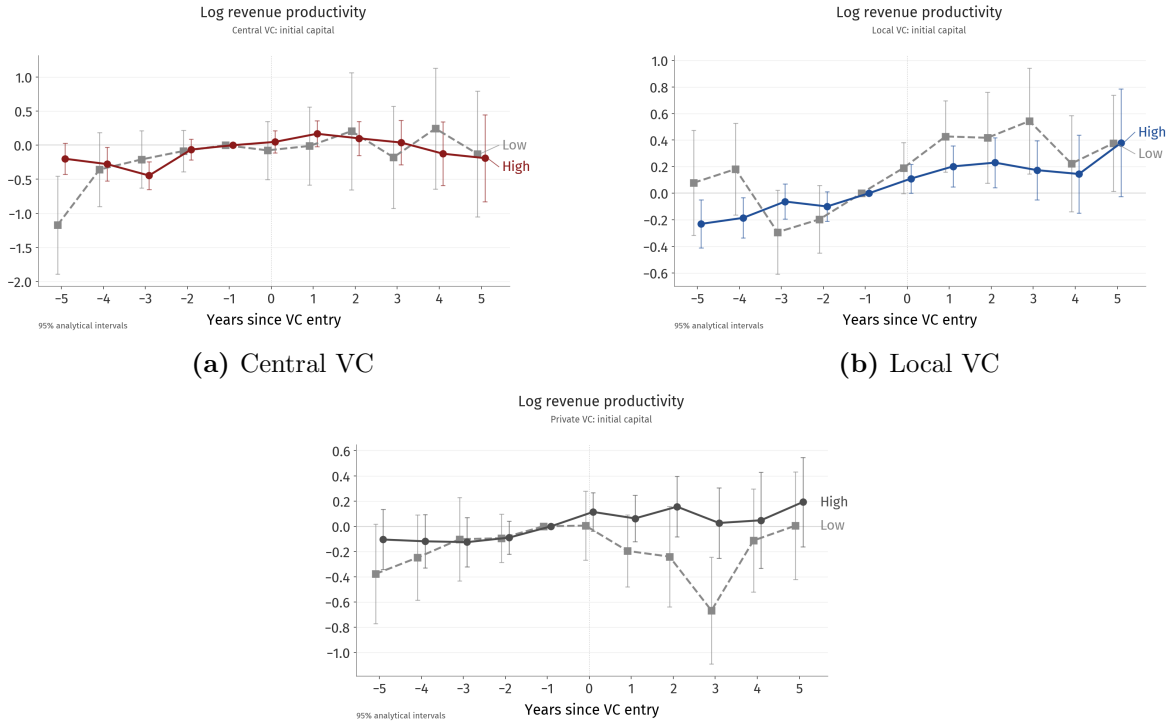
Notes. Central government, local government, and private VC investment average treatment effects $\theta_{\mathrm{C}}(\tau), \theta_{\mathrm{L}}(\tau), \theta_{\mathrm{P}}(\tau)$ estimates for $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% analytical confidence intervals. Following de Chaisemartin and D'Haultfœuille (2023), the estimates are observation-count-weighted averages of primitive 2-period DiD estimates $ATT_{\mathrm{C},s}(g, \tau \mid \mathbf{g}^{-\mathrm{C}})$, $ATT_{\mathrm{L},s}(g, \tau \mid \mathbf{g}^{-\mathrm{L}})$ and $ATT_{\mathrm{P},s}(g, \tau \mid \mathbf{g}^{-\mathrm{P}})$ respectively, which are group-time treatment effects of central, local, and private VC investment conditional on sector s and VC investment history $\mathbf{g}^{-}$ (including never invested by the other VCs).



(a) Revenue productivity **(b)** Value-added productivity

Figure F.4: Productivity, Two-way Fixed Effects (TWFE) Estimates

Notes. Central government, local government, and private VC investment coefficients $\beta_{\mathrm{C},\tau}, \beta_{\mathrm{L},\tau}, \beta_{\mathrm{P},\tau}$ for $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% confidence intervals based on firm-clustered standard errors, estimated by a two-way fixed effects regression of productivity on leads and lags from the first local government, central government, and private VC investment.



(a) Central VC

(b) Local VC

(c) Private VC

Figure F.5: Effects on productivity by initial capital

Notes. Low denotes aggregated event study estimates from sub-sample of firms below the industry–year median the year before the investment event; High denotes subsample with above-median capital. The comparison is thus between treated and control firms that are both below or above median industry size, as measured by capital, the year before treatment. Pointwise 95% analytical intervals.

Testing differences across investor types. Let $\widehat{\theta}_k(\tau)$ denote the estimated effect for investor type $k \in \{\mathrm{C}, \mathrm{L}, \mathrm{P}\}$ at event time τ described in Section D. The headline average estimate over $\tau = 0, \ldots, 5$ weights each event time coefficient by its observed treated units. Let $n_{k,\tau}$ be the number of treated firms of investor k τ years after investment. The headline estimate is $\widehat{\overline{\theta}}^{n}_{k} \equiv \frac{\sum_{\tau=0}^{5} n_{k,\tau} \widehat{\theta}_k(\tau)}{\sum_{\tau=0}^{5} n_{k,\tau}}$, and I test $\widehat{\overline{\theta}}^{n}_{k} - \widehat{\overline{\theta}}^{n}_{k'}$ for distinct VC types $k, k' \in \{\mathrm{C}, \mathrm{L}, \mathrm{P}\}$. Because the number of treated units declines with event time, later coefficients receive less weight.

For each primitive DiD comparison cell c containing n_{Tc} treated and n_{Cc} control firms, let $\widehat{\delta}_c = \overline{\Delta Y}_{Tc} - \overline{\Delta Y}_{Cc}$, and define the treated-count-weighted estimator

$$\widehat{\theta} = \sum_{c} \frac{n_{Tc}}{n_T} \widehat{\delta}_c, \qquad n_T \equiv \sum_{c} n_{Tc}. \tag{F.1}$$

Allowing the treated-cell weights themselves to be estimated, firm i's influence contribution is

$$\widehat{\mathrm{IF}}_i = \frac{1}{n_T} \sum_{c} \left[\mathbb{1}\{i \in \mathcal{T}_c\} \left\{ \Delta Y_i - \overline{\Delta Y}_{Tc} + \widehat{\delta}_c - \widehat{\theta} \right\} - \frac{n_{Tc}}{n_{Cc}} \mathbb{1}\{i \in \mathcal{C}_c\} \left(\Delta Y_i - \overline{\Delta Y}_{Cc} \right) \right]. \tag{F.2}$$

This score applies within an investor–horizon estimate. To account for the estimated weights across

horizons, let $m^s_{k,\tau i}$ indicate that firm i is a supported treated observation for investor k at horizon τ. The influence contribution for the treated-unit-weighted mean is

$$\widehat{\mathrm{IF}}^s_{ki} = \sum_{\tau=0}^{5} \frac{n^s_{k,\tau}}{n^s_k} \widehat{\mathrm{IF}}^s_{k,\tau i} + \frac{1}{n^s_k} \sum_{\tau=0}^{5} m^s_{k,\tau i} \left(\widehat{\theta}^s_{k,\tau} - \widehat{\bar{\theta}}^{s,n}_k \right). \tag{F.3}$$

The first term propagates uncertainty in the six event-time coefficients. The second term accounts for the estimation of the relative treated mass across horizons. For the investor contrast, the firm score is $\widehat{\mathrm{IF}}^s_{k-k',i} = \widehat{\mathrm{IF}}^s_{ki} - \widehat{\mathrm{IF}}^s_{k'i}$. With n firms, the analytical standard error is

$$\widehat{\mathrm{se}}_{\mathrm{IF}} \left(\widehat{\Delta}^{s,n}_{k-k'} \right) = \left[\frac{n}{n-1} \sum_{i=1}^{n} \left(\widehat{\mathrm{IF}}^s_{k-k',i} \right)^2 \right]^{1/2}, \tag{F.4}$$

and p_{IF} is the two-sided normal p-value of $\widehat{\Delta}^{s,n}_{k-k'}$ divided by this standard error. The term $\widehat{\delta}_c - \widehat{\theta}$ in the within-horizon score accounts for estimated cell weights, while the second term in $\widehat{\mathrm{IF}}^s_{ki}$ accounts for estimated horizon weights. Firm-level aggregation captures dependence caused by repeated use of the same firm across cells, horizons, or investor arms. The analytical formula remains conditional on the full-sample support rule. By contrast, the paired bootstrap also reproduces draws in which an otherwise supported cell loses its treated or control observations and is excluded in that draw. Because exact-history comparisons can be sparse, the bootstrap is the primary inference procedure and the analytical estimate is a fixed-support check.

I also test the equality of the complete paths within each window. Define $\widehat{\boldsymbol{\delta}}^s_{k-k',\mathcal{H}} = \{\widehat{\theta}^s_{k,\tau} - \widehat{\theta}^s_{k',\tau} : \tau \in \mathcal{H}\}$ and let $\widehat{\Sigma}^s_{k-k',\mathcal{H}}$ be its paired-bootstrap covariance matrix. The joint statistic is

$$\widehat{\boldsymbol{\delta}}^{s\prime}_{k-k',\mathcal{H}} \widehat{\Sigma}^{s,+}_{k-k',\mathcal{H}} \widehat{\boldsymbol{\delta}}^s_{k-k',\mathcal{H}}, \tag{F.5}$$

where $+$ denotes the Moore–Penrose inverse. I compare this statistic with a chi-squared distribution whose degrees of freedom equal the rank of $\widehat{\Sigma}$. Within each specification and horizon window, Holm-adjusted p-values account for the three pairwise investor comparisons.

These tests compare investor-specific ATT estimands. A difference can reflect both the investor type and heterogeneity in the firms receiving that investor type. Interpreting the contrasts as causal rankings therefore requires, in addition to the arm-specific parallel-trends assumptions, treatment-effect homogeneity or a transportability condition that maps the three estimates to a common treated-firm population.

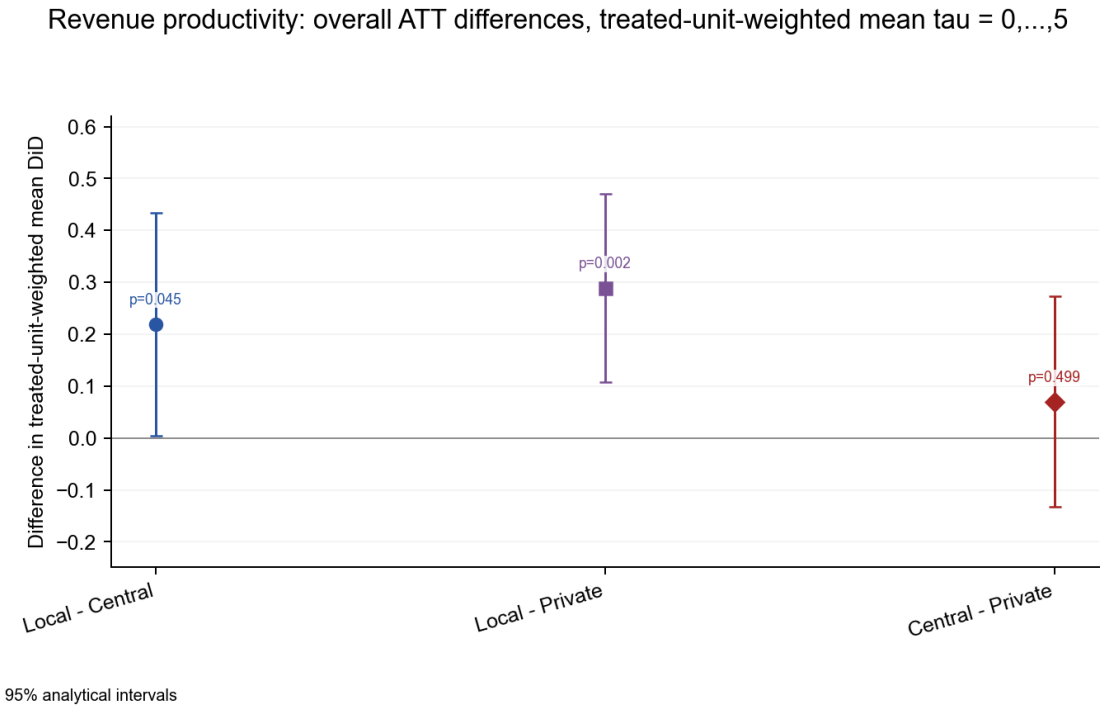


Figure F.6: Two-sided test of the difference in treated-units-weighted post-investment coefficients over $\tau = 0, 1, \ldots, 5$

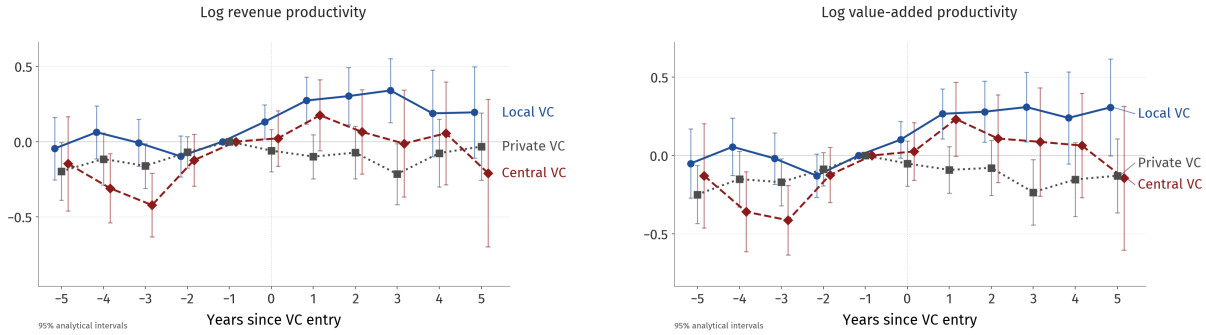
Notes. Differences between local government VC – private VC, local – central government VC, and central government VC – private VC average treatment effects, defined as $\widehat{\overline{\theta}}_k^n \equiv \frac{\sum_{\tau=0}^{5} n_{k,\tau} \widehat{\theta}_k(\tau)}{\sum_{\tau=0}^{5} n_{k,\tau}}$ where $n_{k,\tau}$ is the number of treated units by investor $k \in \{\mathrm{C}, \mathrm{L}, \mathrm{P}\}$ at event time τ and $\theta_{k,\tau}$ is the aggregate event study estimate.

F.2 Translog Production Function

To assess sensitivity to constant input elasticities, I also estimate sector-specific translog production functions separately for revenue and value added with respect to capital and labor. Let k_{it} and ℓ_{it} denote log capital and log employment. For outcome $y \in \{\ln R, \ln VA\}$ and industry j, the input component of the production function is

$$f_j^r(k, \ell) = \beta_{K,j}^r k + \beta_{L,j}^r \ell + \frac{1}{2}\beta_{KK,j}^r k^2 + \beta_{KL,j}^r k\ell + \frac{1}{2}\beta_{LL,j}^r \ell^2, \tag{F.6}$$

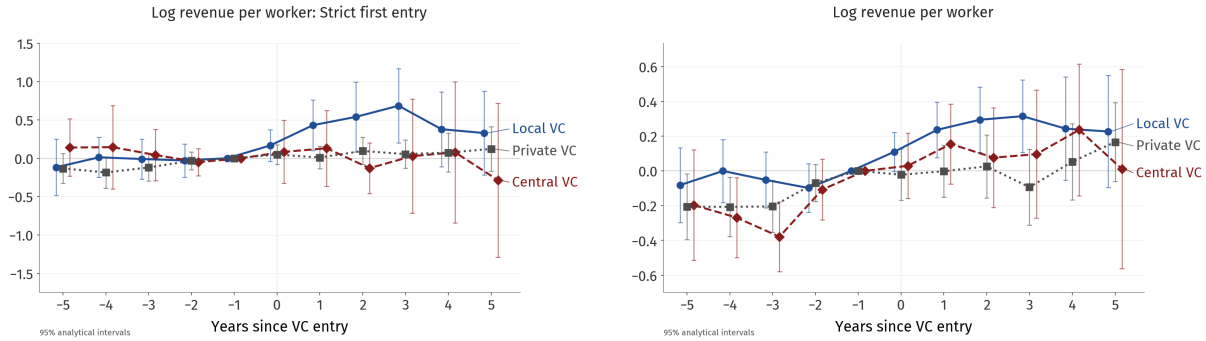
and the productivity measure is $\widehat{\omega}_{it}^r \equiv y_{it} - \widehat{f}_j^r(k_{it}, \ell_{it})$. Figure F.7 plots the event study coefficients, which show broadly similar trends to the Cobb-Douglas productivities.



(a) Revenue productivity **(b)** Value-added productivity

Figure F.7: Translog Productivity, Event Study Estimates

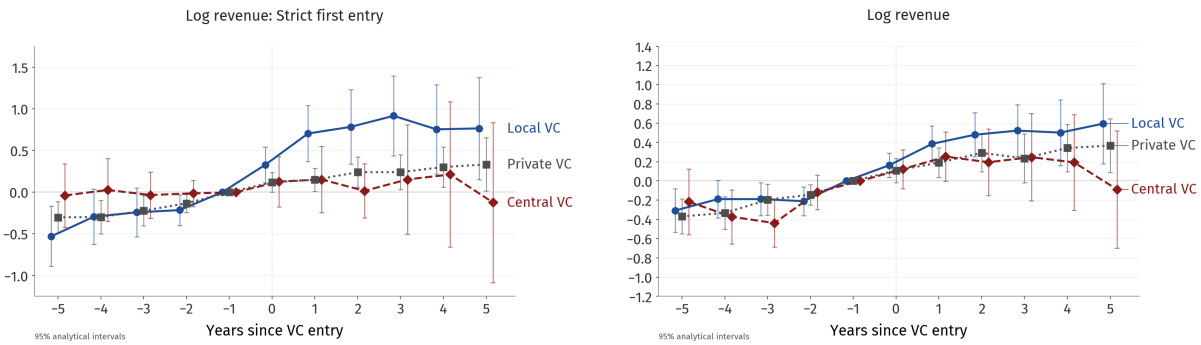
F.3 Revenue and Revenue Per Worker



(a) Strict First Entry **(b)** Aggregate Estimates

Figure F.8: Log (Revenue per Worker), Event Study Estimates

Notes. Central government, local government, and private VC investment average treatment effects $\theta_{\mathrm{C}}(\tau), \theta_{\mathrm{L}}(\tau), \theta_{\mathrm{P}}(\tau)$ estimates for $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% analytical confidence intervals. Following de Chaisemartin and D'Haultfœuille (2023), the estimates are observation-count-weighted averages of primitive 2-period DiD estimates $ATT_{\mathrm{C},s}(g, \tau \mid \mathbf{g}^{-\mathrm{C}})$, $ATT_{\mathrm{L},s}(g, \tau \mid \mathbf{g}^{-\mathrm{L}})$ and $ATT_{\mathrm{P},s}(g, \tau \mid \mathbf{g}^{-\mathrm{P}})$ respectively, which are group-time treatment effects of central, local, and private VC investment conditional on sector s and VC investment history $\mathbf{g}^{-}$. Panel (a) presents aggregated DiD estimates where treated and control firms had no other VC invested prior to the event, while Panel (b) presents estimates aggregated from both strict first entry and subsequent VC entries.



(a) Strict First Entry **(b)** Aggregate Estimates

Figure F.9: Log (Revenue), Event Study Estimates

Notes. Central government, local government, and private VC investment average treatment effects $\theta_{\mathrm{C}}(\tau), \theta_{\mathrm{L}}(\tau), \theta_{\mathrm{P}}(\tau)$ estimates for $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% analytical confidence intervals. Following de Chaisemartin and D'Haultfœuille (2023), the estimates are observation-count-weighted averages of primitive 2-period DiD estimates $ATT_{\mathrm{C},s}(g, \tau \mid \mathbf{g}^{-\mathrm{C}})$, $ATT_{\mathrm{L},s}(g, \tau \mid \mathbf{g}^{-\mathrm{L}})$ and $ATT_{\mathrm{P},s}(g, \tau \mid \mathbf{g}^{-\mathrm{P}})$ respectively, which are group-time treatment effects of central, local, and private VC investment conditional on sector s and VC investment history $\mathbf{g}^{-}$. Panel (a) presents aggregated DiD estimates where treated and control firms had no other VC invested prior to the event, while Panel (b) presents estimates aggregated from both strict first entry and subsequent VC entries.

F.4 Capital

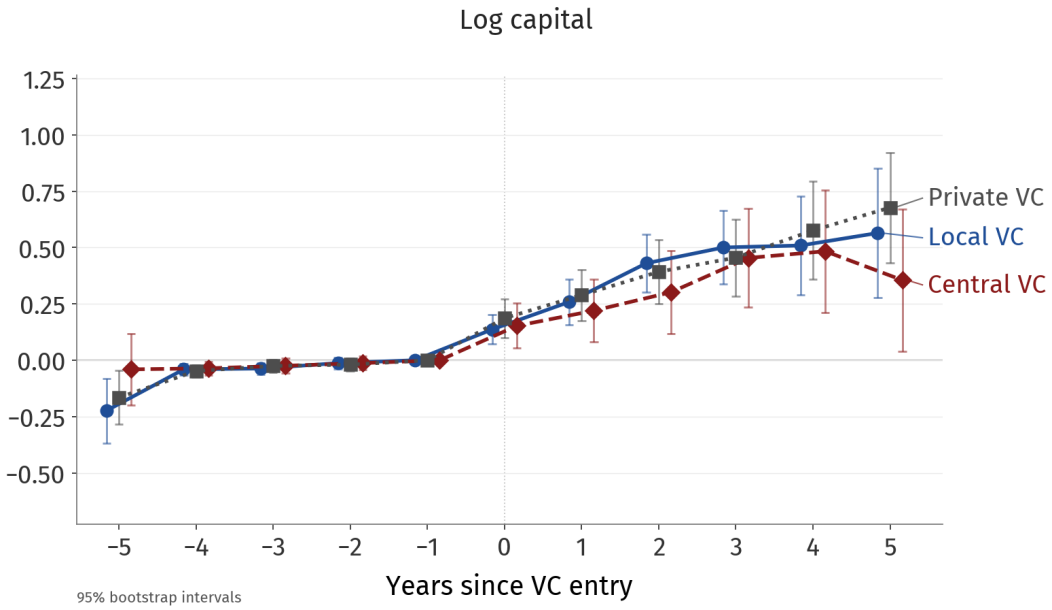
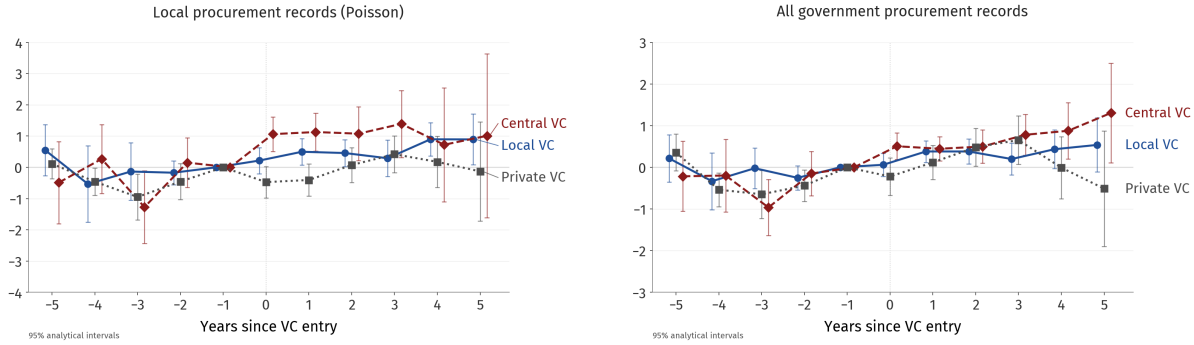


Figure F.10: Log (Capital), Synthetic Difference-in-Differences Estimates

Notes. Central government, local government, and private VC investment average treatment effects $\theta_{\mathrm{C}}(\tau), \theta_{\mathrm{L}}(\tau), \theta_{\mathrm{P}}(\tau)$ for $\tau = -5, -4, \ldots, -2, 0, \ldots, 4, 5$, estimated by synthetic difference-in-differences (Arkhangelsky et al., 2021). For each investor type and entry cohort g, firms not yet invested by that type receive nonnegative weights summing to one, chosen so that the weighted control units match the invested firms' average within-firm trends of log capital over the four years before entry. The share of firms already invested by each of the other two investor types in each of the pre-entry years is also matched. Each post-entry coefficient compares the change in the outcome from year $g-1$ to year $g+\tau$ for invested firms with the same change for the weighted control firms.

F.5 Procurement



(a) Local Government Contracts **(b)** All Contracts

Figure F.11: Government Procurement Contract Count, Event Study Estimates

Notes. Central government, local government, and private VC investment average treatment effects $\theta_{\mathrm{C}}(\tau), \theta_{\mathrm{L}}(\tau), \theta_{\mathrm{P}}(\tau)$ estimates for $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% analytical confidence intervals. Following de Chaisemartin and D'Haultfœuille (2023), the estimates are observation-count-weighted averages of primitive 2-period Poisson DiD estimates $ATT_{\mathrm{C},s}(g, \tau \mid \mathbf{g}^{-\mathrm{C}})$, $ATT_{\mathrm{L},s}(g, \tau \mid \mathbf{g}^{-\mathrm{L}})$ and $ATT_{\mathrm{P},s}(g, \tau \mid \mathbf{g}^{-\mathrm{P}})$ respectively, which are group-time treatment effects of central, local, and private VC investment conditional on sector s and VC investment history $\mathbf{g}^{-}$. Procurement contract value is not reported for 40% of the contracts collected (46,363 out of 77,151 total contracts reported value).

F.6 Innovation and Intellectual Property

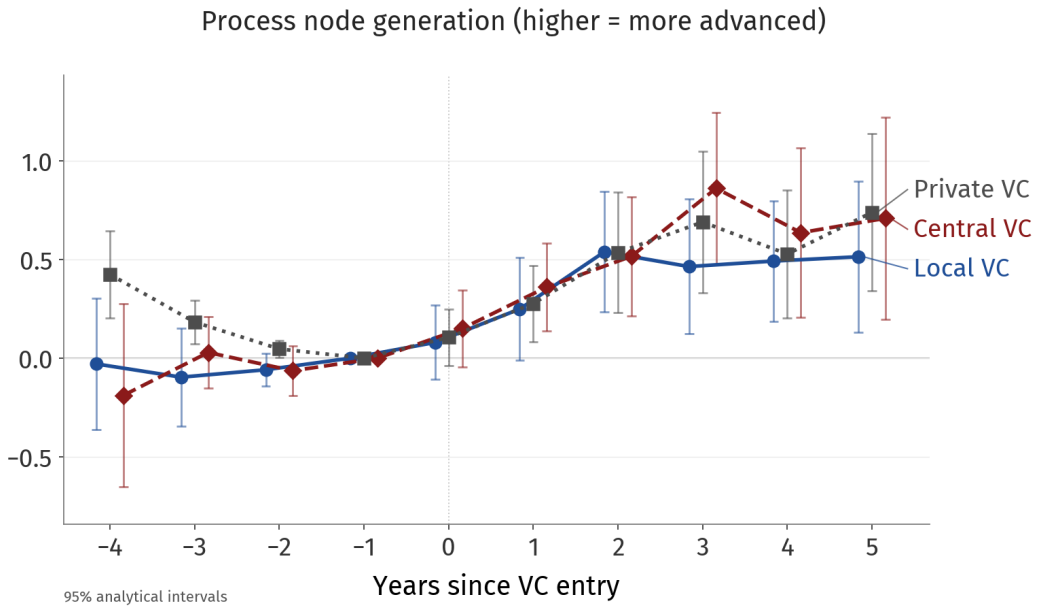
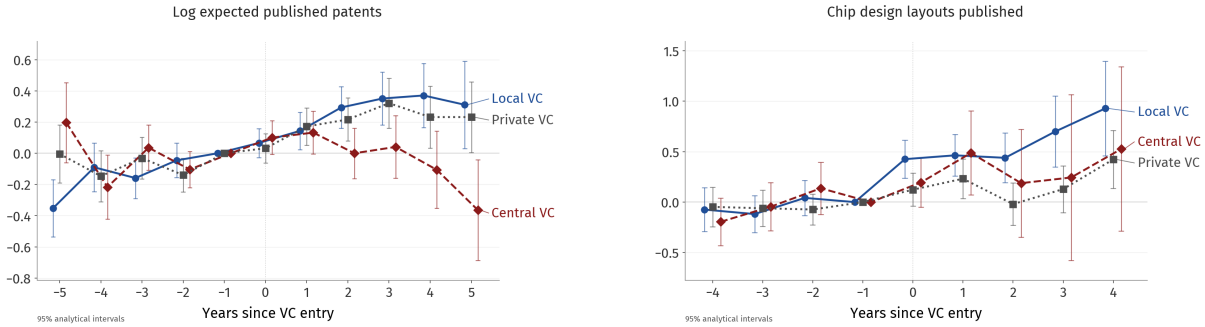


Figure F.12: Process Node Generations, Event Study Estimates

Notes. I convert semiconductor process nodes, measured in microns in the raw data, to integer-valued distinct node generations where higher indicates more advanced technologies. Central government, local government, and private VC investment average treatment effects $\theta_{\mathrm{C}}(\tau), \theta_{\mathrm{L}}(\tau), \theta_{\mathrm{P}}(\tau)$ estimates for $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% analytical confidence intervals. Following de Chaisemartin and D'Haultfœuille (2023), the estimates are observation-count-weighted averages of primitive 2-period DiD estimates $ATT_{\mathrm{C},s}(g, \tau \mid \mathbf{g}^{-\mathrm{C}})$, $ATT_{\mathrm{L},s}(g, \tau \mid \mathbf{g}^{-\mathrm{L}})$ and $ATT_{\mathrm{P},s}(g, \tau \mid \mathbf{g}^{-\mathrm{P}})$ respectively, which are group-time treatment effects of central, local, and private VC investment conditional on sector and VC investment history (including never invested by the other VCs).



(a) Newly Published Patents **(b)** Newly Published Chip-Design Layouts

Figure F.13: Intellectual Property, Event Study Estimates

Notes. Central government, local government, and private VC investment average treatment effects $\theta_{\mathrm{C}}(\tau), \theta_{\mathrm{L}}(\tau), \theta_{\mathrm{P}}(\tau)$ estimates for $\tau = -5, -4, \ldots, -2, 0, 1, \ldots, 5$ with 95% analytical confidence intervals. Following de Chaisemartin and D'Haultfœuille (2023), the estimates are observation-count-weighted averages of primitive 2-period DiD estimates $ATT_{\mathrm{C},s}(g,\tau \mid \mathbf{g}^{-\mathrm{C}})$, $ATT_{\mathrm{L},s}(g,\tau \mid \mathbf{g}^{-\mathrm{L}})$ and $ATT_{\mathrm{P},s}(g,\tau \mid \mathbf{g}^{-\mathrm{P}})$ respectively, which are group-time treatment effects of central, local, and private VC investment conditional on sector and VC investment history (including never invested by the other VCs).

G Mediation Analysis

G.1 Decomposition of the Productivity Effect

Joint relationship between post-entry changes. Let $c \in \mathcal{D} \equiv \{\{g, k, s, \mathbf{g}^{-k}, \tau\} : \mathcal{T}_{k,s}(g, \mathbf{g}^{-k}, \tau) \neq \emptyset, \mathcal{C}_{k,s}(g, \mathbf{g}^{-k}, \tau) \neq \emptyset\}$ index a primitive DiD comparison cell in the de Chaisemartin and D'Haultfœuille (2023) event study. Each c is composed of treated and control units in a DiD comparing the change in outcomes τ years after investor k's investment in year g, among firms in industry s with the same other VC investment history $\mathbf{g}^{-k}$ by year g. Define $\Delta_\tau V_{ic} \equiv V_{i,g+\tau} - V_{i,g-1}$ to be the change in i's outcome V between the year prior to treatment $g-1$ and year $g+\tau$. For each horizon $\tau \in \{3, 4, 5\}$, I jointly estimate

$$\begin{aligned}\Delta_\tau \omega_{ic} = \mu_c + \alpha_c \, \mathbb{1}\{\text{treated}_{ic}\} + \boldsymbol{\beta}_{k,\tau}^{\text{proc}'} \Delta_\tau \mathbf{M}_{ic}^{\text{procurement}} \\ + \boldsymbol{\beta}_{k,\tau}^{\text{lagged}'} \Delta_{\tau-1} \mathbf{M}_{ic}^{\text{personnel/subsidies/patents}} + u_{ic}\end{aligned} \tag{G.1}$$

$\Delta_\tau \mathbf{M}_{ic}^{\text{procurement}}$ contains the change in awarded central and local government procurement contracts and the contract amount awarded to firm i from year $g-1$ to $g+\tau$, while $\Delta_{\tau-1} \mathbf{M}_{ic}^{\text{personnel/subsidies/patents}}$ contains changes from year $g-1$ to $g+\tau-1$ in mediators of the following categories: board/management characteristics, shareholder paid-in capital, non-equity subsidies, and published patents and other intellectual property variables of firm i. Thus I allow changes in procurement to have an immediate effect on productivity, while changes in personnel, subsidies, and patents are lagged by one year. α_c is the coefficient measuring the remaining differences in productivity change between treated and control firms after accounting for the mediators. The headline estimate $\boldsymbol{\beta}_{k,\tau}$ summarizes the regression slope between the post-investment change in productivity and the mediators.

For each investor k, let $\widehat{\theta}_k(\tau)$ be the aggregated event study coefficient on productivity τ years after k's investment and $\widehat{\delta}_{k,m}(\tau)$ be the same event study coefficient on mediator $m \in \mathbf{M}$. As the

mediators could affect productivity with a lag, I focus on decomposing the average productivity effect over horizons $\tau \in \{3, 4, 5\}$. Define

$$\overline{\widehat{\theta}}_k \equiv \frac{1}{3} \sum_{\tau \in \{3,4,5\}} \widehat{\theta}_k(\tau) \tag{G.2}$$

to be the mean of the DiD coefficients over event time $\tau = 3, 4, 5$ and let $\mathcal{B}$ be a collection of mediators. Define the estimated contribution of mediators in $\mathcal{B}$ to the productivity change induced by VC k's investment as

$$\widehat{A}_{k,\mathcal{B}} \equiv \frac{1}{3} \sum_{\tau \in \{3,4,5\}} \sum_{m \in \mathcal{B}} \widehat{\beta}_{k,m,\tau} \widehat{\delta}_{k,m}(\tau - 1), \tag{G.3}$$

This sums up, across mediators m, the product of $\widehat{\delta}_{k,m}(\tau - 1)$, k's event study effect on mediator m_i in event time $\tau - 1$, and $\widehat{\beta}_{k,m,\tau}$, the regression slope of the change in productivity $\Delta_\tau \omega_{ic}$ on the lagged change in the mediator $\Delta_{\tau-1} m_{ic}$ (for procurement it's $\widehat{\delta}_{k,m}(\tau)$ and contemporaneous change $\Delta_\tau m_{ic}$). Thus $\widehat{\beta}_{k,m,\tau} \widehat{\delta}_{k,m}(\tau - 1)$ has the interpretation of how k's investment changes productivity via its effect on mediator m, $\widehat{\delta}_{k,m}(\tau - 1)$, whose changes correlate with productivity change via $\widehat{\beta}_{k,m,\tau}$.

The block $\mathcal{B}$'s measured contribution to VC k's productivity DiD $\overline{\widehat{\theta}}_k$ is then $\widehat{p}_{k,\mathcal{B}} \equiv 100 \frac{\widehat{A}_{k,\mathcal{B}}}{\overline{\widehat{\theta}}_k}$ which expresses it as the percentage of the DiD explained by the post-investment change in the mediators.

Accounting for the Local–Central difference. I further decompose the observed Local–Central productivity-effect gap $\widehat{\Delta}_{\mathrm{LC}} \equiv \overline{\widehat{\theta}}_{\mathrm{L}} - \overline{\widehat{\theta}}_{\mathrm{C}}$. For each group of mediators $\mathcal{B}$, define the local-central gap in the productivity effect via the mediators as

$$\widehat{\Delta}_{\mathrm{LC},\mathcal{B}} \equiv \widehat{A}_{\mathrm{L},\mathcal{B}} - \widehat{A}_{\mathrm{C},\mathcal{B}}. \tag{G.4}$$

These differences reflect both investors' DiD effects on the mediators and investor-specific slopes of change in mediators on change in productivity. The portion of the estimated local-central productivity gap attributable to the mediators is defined as $\widehat{p}_{\mathrm{LC},\mathcal{B}} \equiv 100 \frac{\widehat{\Delta}_{\mathrm{LC},\mathcal{B}}}{\widehat{\Delta}_{\mathrm{LC}}}$.

I consider the following classes of mediators: (1) personnel composition: the number of directors/managers with technical or R&D experience, engineering or computer-science education, foreign education or work experience, finance experience, and finance/economics or management/business education, and (2) board size and turnover: the number of board and management members and the numbers of persons joining and leaving. Other material factors include (3) the shareholders' paid-in capital, (4) government procurement contract counts and amounts awarded, (5) non-equity grants and subsidies, and (6) new invention patent applications, IC layout designs, and software copyrights following the VC investment. These outcomes also changed after government VC investment, and thus could be mechanisms that contribute to local government-invested firms' productivity growth.

Table G.1 reports $\widehat{p}_{\mathrm{LC},\mathcal{B}}$ for each class of mediators $\mathcal{B}$. Board management related variables jointly accounted for 44% of the observed local-central productivity gap. Differences in invested shareholder capital explain little, while non-equity subsidy variables account for about 10%. Thus the local government's differential propensity to participate actively in the management of firms it invested in accounts for a substantial difference in the post-investment performance of its firms.

Table G.1: Mediator slopes, responses, allocations, and the Local–Central productivity gap

Equal horizon averages: $\tau = 3, 4, 5$

Panel A. Individual mediator slopes and DiD responses

	Local government VC		Central government VC	
Mediator	$\bar{\beta}_L$	$\bar{\delta}_L$	$\bar{\beta}_C$	$\bar{\delta}_C$
	0.0960	0.4033	0.1641	0.2402
Technical and R&D personnel	[-0.042, 0.234]	[0.206, 0.600]	[-0.060, 0.388]	[-0.072, 0.552]
	-0.0003	0.0586	-0.0882	0.2371
Engineering / computer-science education	[-0.163, 0.162]	[-0.089, 0.206]	[-0.330, 0.153]	[-0.013, 0.487]
	0.0498	0.0431	0.0707	0.1085
Foreign education	[-0.107, 0.207]	[-0.039, 0.125]	[-0.248, 0.390]	[-0.049, 0.266]
	-0.2174	0.0010	-0.3052	0.2000
Foreign work experience	[-0.409, -0.026]	[-0.097, 0.099]	[-0.655, 0.045]	[0.034, 0.366]
	0.0830	0.2202	0.1045	0.1495
Finance personnel	[-0.097, 0.263]	[0.115, 0.326]	[-0.172, 0.381]	[-0.044, 0.343]
	-0.2468	0.0628	-0.4199	0.1203
Finance / economics education	[-0.436, -0.058]	[-0.025, 0.150]	[-0.758, -0.081]	[-0.038, 0.279]
	0.1527	0.0576	0.1313	0.1055
Management / business education	[-0.111, 0.416]	[0.006, 0.109]	[-0.309, 0.571]	[0.018, 0.193]
	0.0261	1.0454	0.0241	0.8306
Board and management count	[-0.011, 0.063]	[0.433, 1.658]	[-0.037, 0.086]	[0.058, 1.603]
	-0.0782	-0.0265	-0.1061	0.1966
Personnel joined	[-0.152, -0.004]	[-0.359, 0.307]	[-0.197, -0.016]	[-0.218, 0.611]
	0.0944	0.1016	0.1032	-0.0943
Personnel departed	[0.034, 0.155]	[-0.206, 0.409]	[0.025, 0.181]	[-0.566, 0.378]
	0.0719	0.3633	0.1323	0.2987
Shareholder Paid-in Capital	[-0.001, 0.145]	[0.113, 0.614]	[0.021, 0.243]	[-0.053, 0.651]
	-0.0836	0.0523	-0.1317	0.1394
Central procurement records	[-0.285, 0.118]	[-0.034, 0.138]	[-0.474, 0.210]	[0.027, 0.252]
	-0.0809	0.0857	0.2032	0.1499
Local procurement records	[-0.344, 0.182]	[-0.009, 0.180]	[-0.116, 0.523]	[0.033, 0.266]
	0.0742	0.0682	0.0888	0.0370
Central procurement amount	[-0.101, 0.250]	[-0.029, 0.165]	[-0.116, 0.293]	[-0.104, 0.178]
	0.0142	0.1126	-0.1433	0.2381
Local procurement amount	[-0.115, 0.143]	[-0.016, 0.241]	[-0.295, 0.008]	[0.048, 0.428]
	0.0754	0.0662	-0.0274	0.1383
Central subsidy records	[-0.042, 0.193]	[-0.035, 0.168]	[-0.194, 0.139]	[0.007, 0.269]
	0.2950	0.1473	0.1740	0.0605
Provincial subsidy records	[0.142, 0.448]	[0.067, 0.228]	[-0.076, 0.424]	[-0.060, 0.181]
	0.0673	0.0451	0.1306	0.0374
City / district subsidy records	[-0.053, 0.188]	[-0.034, 0.124]	[-0.061, 0.322]	[-0.067, 0.141]
	0.2118	-0.0020	0.3321	-0.0517
High-tech enterprise designations	[-0.015, 0.439]	[-0.052, 0.048]	[0.039, 0.626]	[-0.124, 0.020]
	0.0970	0.3626	0.1219	0.3194
Invention applications	[0.019, 0.175]	[0.182, 0.544]	[0.023, 0.221]	[0.065, 0.573]
	0.1970	-0.0069	0.1215	0.0979
IC layout records	[0.045, 0.349]	[-0.092, 0.078]	[-0.080, 0.323]	[-0.058, 0.254]
	0.1267	0.0329	0.1995	-0.0639
Software records	[0.016, 0.238]	[-0.113, 0.178]	[0.044, 0.355]	[-0.278, 0.150]

Panel B. Actor-specific and gap allocations

Class	A_L	A_C	$A_L - A_C$	Gap share (%)
	0.0447	-0.0542	0.0989	28.28†
Technical / foreign / finance personnel	[-0.023, 0.112]	[-0.149, 0.041]	[-0.019, 0.216]	[-15.9, 72.4]
	0.0410	-0.0131	0.0541	15.47†
Board size, joined and departed	[-0.019, 0.101]	[-0.077, 0.051]	[-0.031, 0.139]	[-13.8, 44.8]
	0.0272	0.0387	-0.0115	-3.29†
Shareholder Paid-in Capital	[-0.009, 0.064]	[-0.025, 0.102]	[-0.081, 0.058]	[-23.2, 16.7]
	-0.0001	-0.0289	0.0288	8.23†
Procurement	[-0.026, 0.026]	[-0.074, 0.016]	[-0.021, 0.078]	[-9.6, 26.1]
	0.0406	0.0060	0.0346	9.88†
Non-Equity Subsidy	[-0.003, 0.084]	[-0.053, 0.065]	[-0.037, 0.106]	[-12.0, 31.7]
	0.0417	0.0312	0.0106	3.02†
Patents / intellectual property	[-0.008, 0.092]	[-0.049, 0.111]	[-0.083, 0.104]	[-23.2, 29.2]
	0.1950	-0.0204	0.2154	61.59†
Total allocated	[0.068, 0.322]	[-0.207, 0.167]	[-0.015, 0.446]	[-26.2, 149.4]
	0.1293	-0.0050	0.1343	38.41†
Residual	[-0.075, 0.333]	[-0.387, 0.377]	[-0.306, 0.574]	[-49.4, 126.2]
	0.3243	-0.0255	0.3498	100.00
Observed treatment effect / gap	[0.110, 0.538]	[-0.375, 0.324]	[-0.088, 0.787]	[100.0, 100.0]

Notes: Panel A reports equal means of horizon-specific slopes and mediator DiDs. Slopes come from a joint firm-level regression with separate cell-by-treated/control-side intercepts; treated observations have weight one and controls n_T/n_C. Brackets report pointwise analytical 95% firm-cluster normal confidence intervals. Allocation intervals use the joint influence function of the within-horizon product $\beta_{m\tau}\delta_{m\tau}$; share intervals also include covariance with the observed treatment effect. † marks a share whose 95% Fieller set is unbounded because its denominator is weak. Allocations are descriptive conditional accounting, not identified causal mediation effects.

G.2 Differences in Effect on Mediators vs Differences in Mediators' Effect

Does the local-central effect attributed to board management come from the fact that local VCs change more personnel, or from the fact that local government-invested firms' productivity moves more from each unit of personnel? Following the logic of Oaxaca–Blinder accounting (Oaxaca, 1973; Blinder, 1973), I apply a symmetric decomposition (Reimers, 1983) to each mediator's local-central difference in the contributed treatment effect:

$$\widehat{\beta}_{\mathrm{L},m,\tau}\widehat{\delta}_{\mathrm{L},m,\tau} - \widehat{\beta}_{\mathrm{C},m,\tau}\widehat{\delta}_{\mathrm{C},m,\tau} = \bar{\beta}_{m,\tau} \underbrace{\left(\widehat{\delta}_{\mathrm{L},m,\tau} - \widehat{\delta}_{\mathrm{C},m,\tau}\right)}_{\text{local-central differences in DiD}} + \bar{\delta}_{m,\tau} \underbrace{\left(\widehat{\beta}_{\mathrm{L},m,\tau} - \widehat{\beta}_{\mathrm{C},m,\tau}\right)}_{\substack{\text{local-central differences} \\ \text{in productivity-mediator slope}}}$$

where $\bar{\beta}_{m,\tau} \equiv (\widehat{\beta}_{\mathrm{L},m,\tau} + \widehat{\beta}_{\mathrm{C},m,\tau})/2$ and $\bar{\delta}_{m,\tau} \equiv (\widehat{\delta}_{\mathrm{L},m,\tau} + \widehat{\delta}_{\mathrm{C},m,\tau})/2$. I sum these components within blocks of mediators and then average over event time τ.

Table G.2: Response and Slope Components of the Local–Central Allocation

Channel	Gap contribution	Response	Slope
Technical / foreign / finance personnel	0.099	0.097	0.001
Board size, joined, departed	0.054	0.046	0.008
Shareholder paid-in capital	−0.011	0.007	−0.018
Procurement	0.029	0.018	0.011
Non-equity subsidy	0.035	0.013	0.021
Patents / intellectual property	0.011	0.015	−0.004
All recorded channels	0.215	0.196	0.020
Share of the observed gap	61.6%	56.0%	5.6%

Notes. Response $= \bar{\beta}_{m,\tau}\left(\widehat{\delta}_{\mathrm{L},m,\tau} - \widehat{\delta}_{\mathrm{C},m,\tau}\right)$, which measures local-central differences in the treatment effects on the set of mediators $m \in \mathcal{B}$. Slope $= \bar{\delta}_{m,\tau}\left(\widehat{\beta}_{\mathrm{L},m,\tau} - \widehat{\beta}_{\mathrm{C},m,\tau}\right)$, the differences in the slope of the mediators to productivity. Components are summed within channels and averaged over $\tau = 3, 4, 5$.

Table G.2 shows that the overall differences in mediator DiD responses account for 0.196 log points, while overall differences in fitted slopes account for 0.020. Thus, approximately 91% of the recorded-channel allocation, or 56% of the full observed productivity difference, reflects local-central differences in the effects on the mediators. Local government-invested and central government-invested firms' productivity does not respond differently to the same change in the mediators. This pattern is particularly pronounced for personnel composition: its response component is 0.097, compared with a slope component of 0.001. The estimates therefore associate the local government's productivity advantage primarily with larger changes in recorded personnel and organizational measures, rather than with local government-invested firms' productivity being more responsive to board changes.

H Additional Models

TFPR/MRPK as sufficient dynamic statistic Let firm i's revenue production function be a Cobb-Douglas production function:

$$R_{it} = \exp(\omega_{it}) K_{it}^{\beta_K} L_{it}^{\beta_L}, \qquad \beta_K, \beta_L \in (0,1), \tag{H.1}$$

where ω_{it} denotes log TFPR. Capital is predetermined within the period, while labor adjusts flexibly after the firm observes its productivity state. Given the sector wage w_{st}, static optimization results in labor demand

$$L_{it}^* = \left(\frac{\beta_L \exp(\omega_{it}) K_{it}^{\beta_K}}{w_{st}} \right)^{\frac{1}{1-\beta_L}}. \tag{H.2}$$

Substituting equation (H.2) into revenue gives

$$\widetilde{R}_{it} = K_{it}^{\frac{\beta_K}{1-\beta_L}} R^K(\omega_{it}, w_{st}), \tag{H.3}$$

$$R^K(\omega, w) \equiv \left(\frac{\beta_L}{w} \right)^{\frac{\beta_L}{1-\beta_L}} \exp\left(\frac{\omega}{1-\beta_L} \right). \tag{H.4}$$

Thus, the firm's marginal revenue from capital, accounting for endogenous labor adjustment, is

$$\frac{\partial \widetilde{R}_{it}}{\partial K_{it}} = \frac{\beta_K}{1-\beta_L} K_{it}^{\frac{\beta_K+\beta_L-1}{1-\beta_L}} R^K(\omega_{it}, w_{st}) = \frac{\beta_K}{1-\beta_L} \frac{\widetilde{R}_{it}}{K_{it}}, \tag{H.5}$$

under constant returns to scale, $\frac{\partial \widetilde{R}_{it}}{\partial K_{it}} = R^K(\omega_{it}, w_{st})$ is strictly increasing in TFPR conditional on the wage. Else, under increasing or decreasing returns to scale, it is proportional to the marginal revenue product of capital ($MRPK_{it} \equiv \frac{\partial R_{it}}{\partial K_{it}} = \beta_K \frac{R_{it}}{K_{it}}$). Suppose also each yuan of government equity investment I_{it}^G at the beginning of year t buys $1/P_i^K$ units of physical capital, where P_i^K is the price of capital, i.e.

$$\frac{\partial K_{it}}{\partial I_{it}^G} = \frac{1}{P_i^K},$$

then the static marginal return of a firm's current sales per yuan of equity investment is simply

$$\frac{\partial \widetilde{R}_{it}}{\partial I_{it}^G} = \frac{\partial \widetilde{R}_{it}}{\partial K_{it}} \frac{\partial K_{it}}{\partial I_{it}^G} = \frac{MRPK_{it}}{P_i^K(1-\beta_L)} \tag{H.6}$$

To obtain a tractable characterization of the dynamic return of revenue to capital, suppose that the firm has a constant returns to scale technology and follows a Markov investment rate policy such that the *investment rate* $\frac{I}{K}$ is increasing in ω:

$$I_{it}^* = \iota(\omega_{it}) K_{it}, \qquad \iota'(\omega) \geq 0, \tag{H.7}$$

which obtains under the assumption that $C^I(I,K)$, the investment cost of adding capital I when current capital is K, is homogeneous in current capital $C^I(I,K) = Kc(\frac{I}{K}), \quad c''(\cdot) > 0$. The standard convex adjustment cost model $C^I(I,K) = c_0 K(\frac{I^2}{K^2}) = c_0 \frac{I^2}{K}$ satisfies this. To see this,

note that the firm solves the dynamic problem

$$V(K_{it},\omega_{it}) = \max_{\iota} \underbrace{\beta_K K_{it} R^K(\omega_{it}, w_{st})}_{\Pi_{it}(K_{it},\omega_{it})} - K_{it}c(\iota) + \delta_f \, \mathbb{E}[V((1-\delta+\iota)K_{it}, \omega_{it+1})|\omega_{it}] \tag{H.8}$$

in choosing the investment rate, as under constant returns Cobb-Douglas technology the firm's static profit $\Pi_{it}(K_{it},\omega_{it})$ is the capital share β_K times revenue $\widetilde{R}_{it} = K_{it}R^K(\omega_{it}, w_{st})$ and linear in capital. Note that V is homogeneous in K: $V(K_{it},\omega_{it}) = K_{it}v(\omega_{it})$ where

$$v(\omega_{it}) = \max_{\iota} \beta_K R^K(\omega_{it}, w_{st}) - c(\iota) + \delta_f(1-\delta+\iota) \, \mathbb{E}[v(\omega_{it+1})|\omega_{it}] \tag{H.9}$$

Thus the solutions for v and V are equivalent. The first-order condition of the problem is

$$c'(\iota(\omega_{it})) = \delta_f E[v(\omega_{it+1})|\omega_{it}] \tag{H.10}$$

which implicitly defines the optimal investment rate $\iota^*(\omega_{it})$. By the implicit function theorem,

$$\iota'(\omega_{it}) = \frac{\delta_f \frac{\partial}{\partial \omega} E[v(\omega_{it+1})|\omega_{it}]}{c''(\iota(\omega_{it}))} > 0$$

if TFPR ω is stochastically increasing ($\omega'_{it} > \omega_{it} \implies E(\omega'_{it+1}|\omega'_{it}) > E(\omega_{it+1}|\omega_{it})$) and investment cost is convex in ι as assumed.

Capital under an investment rate policy increasing in ω thus evolves according to

$$K_{i,t+1} = [1-\delta+\iota(\omega_{it})]\, K_{it} \equiv m(\omega_{it})K_{it}, \tag{H.11}$$

where

$$m'(\omega) = \iota'(\omega) \geq 0.$$

A more productive firm not only generates more current revenue from a given capital stock but also invests a weakly larger share of its capital and thus has more units of capital in the future. Continue to suppose that one yuan of government investment I^G_{it} creates $1/P^K_i$ units of productive capital in period t. Conditional on a future productivity realization path $\boldsymbol{\omega}$, the effect of this investment on the firm's capital stock in period $t+h$ is

$$\frac{\partial K_{i,t+h}}{\partial I^G_{it}}(\boldsymbol{\omega}) = \frac{1}{P^K_i} \prod_{\ell=0}^{h-1} m(\omega_{i,t+\ell}), \tag{H.12}$$

Equation (H.12) includes both the physical persistence of the government-financed capital and the subsequent private investment induced by the larger capital stock from the initial government investment.

Let government G discount future sales with discount factor β_G. The expected discounted marginal

increase in the firm's sales per government yuan invested is

$$\mathcal{M}_{it}^{G,\text{own}} = q_G^R(\omega_{it})/P_i^K, \tag{H.13}$$

$$q_G^R(\omega_{it}) \equiv E_t\left[\sum_{h=0}^{\infty}\beta_G^h\left\{\prod_{\ell=0}^{h-1}m(\omega_{i,t+\ell})\right\}R^K(\omega_{i,t+h},w_{s,t+h})\right]. \tag{H.14}$$

The statistic $q_G^R(\omega_{it})$ is the expected discounted sales generated by one additional unit of current productive capital. The dynamic marginal-sales statistic satisfies the recursive equation

$$q_G^R(\omega) = R^K(\omega,w) + \beta_G m(\omega)E\left[q_G^R(\omega') \mid \omega\right]. \tag{H.15}$$

Because $R^K(\omega,w)$ and $m(\omega)$ are increasing in ω, and because a higher current TFPR generates a stochastically higher distribution of future TFPR, the operator on the right-hand side of equation (H.15) maps increasing functions into increasing functions. Under the usual integrability and transversality conditions, $q_G^R(\omega)$ is therefore increasing in current TFPR. Consequently, assuming that wages, the price of capital P_i^K, depreciation, firms' private capital investment policies, and TFPR transition processes are shared across firms, a firm's current TFPR is a sufficient statistic for the expected discounted marginal increase in sales per yuan of government investment.

H.1 Downstream Electronics Demand and Induced Semiconductor Expenditure

The following model derives the Markovian semiconductor expenditures process with an additional layer of consumer demand and electronics production. Let a representative household consume a numeraire good C_t and final electronics E_t. Preferences are quasi-linear:

$$U_t(C_t,E_t) = C_t + \frac{\sigma_E}{\sigma_E-1}\Xi_t^{1/\sigma_E}E_t^{\frac{\sigma_E-1}{\sigma_E}}, \qquad \sigma_E > 1 \tag{H.16}$$

where Ξ_t is an aggregate electronics-demand shifter and σ_E is the price elasticity of final electronics demand. The household chooses (C_t,E_t) subject to the budget constraint $C_t + P_t^E E_t \le I_t$ where P_t^E is the price of electronics. The first-order condition implies

$$E_t = \Xi_t(P_t^E)^{-\sigma_E}. \tag{H.17}$$

Total expenditure on electronics is therefore

$$P_t^E E_t = \Xi_t(P_t^E)^{1-\sigma_E}. \tag{H.18}$$

Competitive electronics producers combine a semiconductor composite H_t with a composite of non-semiconductor inputs V_t to produce E_t with a CES production function

$$E_t = A_t^E\left[\beta_H^{1/\sigma_H}H_t^{\frac{\sigma_H-1}{\sigma_H}} + \beta_V^{1/\sigma_H}V_t^{\frac{\sigma_H-1}{\sigma_H}}\right]^{\frac{\sigma_H}{\sigma_H-1}}, \tag{H.19}$$

where A_t^E is the electronics sector's productivity and σ_H is the elasticity of substitution between

these two inputs. Let P_t^H and P_t^V be the prices of the semiconductor and non-semiconductor input composites, then the corresponding input-cost index for electronics is

$$\Gamma_t \equiv \left[\beta_H (P_t^H)^{1-\sigma_H} + \beta_V (P_t^V)^{1-\sigma_H}\right]^{\frac{1}{1-\sigma_H}}. \tag{H.20}$$

Cost minimization and constant returns to scale imply that marginal cost equals price, thus the competitive price of electronics is simply input cost divided by productivity

$$P_t^E = \frac{\Gamma_t}{A_t^E}. \tag{H.21}$$

Given output E_t, the cost-minimizing semiconductor composite is

$$H_t = \frac{E_t}{A_t^E} \beta_H \left(\frac{P_t^H}{\Gamma_t}\right)^{-\sigma_H}. \tag{H.22}$$

Thus

$$h_t \equiv \frac{P_t^H H_t}{P_t^E E_t} = \frac{\beta_H (P_t^H)^{1-\sigma_H}}{\beta_H (P_t^H)^{1-\sigma_H} + \beta_V (P_t^V)^{1-\sigma_H}} \tag{H.23}$$

is the semiconductor expenditure share in electronics production. Aggregate expenditure by the electronics sector on semiconductor inputs is then

$$P_t^H H_t = h_t P_t^E E_t = h_t \Xi_t (P_t^E)^{1-\sigma_E}, \tag{H.24}$$

from (H.18). The semiconductor composite H_t is assembled from sector-specific semiconductor composites $\mathcal{Q}_{st}$:

$$H_t = \left[\sum_{s \in \mathcal{S}} b_{st}^{1/\sigma_S} \mathcal{Q}_{st}^{\frac{\sigma_S - 1}{\sigma_S}}\right]^{\frac{\sigma_S}{\sigma_S - 1}}, \tag{H.25}$$

where b_{st} is a sector-specific demand or technology shifter and σ_S is the elasticity of substitution across semiconductor sectors. Let $\mathcal{P}_{st}^T$ denote the price of the sector-s semiconductor composite. The associated semiconductor price index is

$$P_t^H = \left[\sum_{s \in \mathcal{S}} b_{st} (\mathcal{P}_{st}^T)^{1-\sigma_S}\right]^{\frac{1}{1-\sigma_S}}. \tag{H.26}$$

Demand for the sector-s composite conditional on the demanded semiconductor composite H_t is

$$\mathcal{Q}_{st} = b_{st} H_t \left(\frac{\mathcal{P}_{st}^T}{P_t^H}\right)^{-\sigma_S}. \tag{H.27}$$

Define sector s's share of total semiconductor expenditure as

$$h_{st} \equiv \frac{\mathcal{P}_{st}^T \mathcal{Q}_{st}}{P_t^H H_t} = \frac{b_{st} (\mathcal{P}_{st}^T)^{1-\sigma_S}}{\sum_{r \in \mathcal{S}} b_{rt} (\mathcal{P}_{rt}^T)^{1-\sigma_S}}. \tag{H.28}$$

Sectoral semiconductor expenditure is therefore

$$\mathcal{X}_{st} \equiv \mathcal{P}_{st}^{T}\mathcal{Q}_{st} = h_{st}P_t^H H_t = h_{st}h_t P_t^E E_t = h_{st}h_t \Xi_t (P_t^E)^{1-\sigma_E}$$
$$= \frac{b_{st}(\mathcal{P}_{st}^T)^{1-\sigma_S}}{\sum_{r\in\mathcal{S}} b_{rt}(\mathcal{P}_{rt}^T)^{1-\sigma_S}} \frac{\beta_H (P_t^H)^{1-\sigma_H}}{\beta_H (P_t^H)^{1-\sigma_H} + \beta_V (P_t^V)^{1-\sigma_H}} \Xi_t \left(\frac{\left[\beta_H (P_t^H)^{1-\sigma_H} + \beta_V (P_t^V)^{1-\sigma_H}\right]^{\frac{1}{1-\sigma_H}}}{A_t^E}\right)^{1-\sigma_E} \tag{H.29}$$

Thus, total sectoral expenditure $\mathcal{X}_{st}$ is determined by aggregate electronics demand Ξ_t, the time-varying sectoral share b_{st}, the downstream electronics sector's productivity A_t^E, non-semiconductor input prices P_t^V, and the semiconductor composite price index P_t^H and sectoral prices $\mathcal{P}_{st}^T$. In my setting where Chinese firms individually have small shares, they take aggregate sectoral prices $\mathcal{P}_{st}^T$ and P_t^H as given. Then if Ξ_t, A_t^E follow a Markovian process, $\mathcal{X}_{st}$ is Markov.

H.2 Markov Downstream Demand and Induced Upstream Input Demand

From the Cobb-Douglas materials demand (C.2), the demand for materials M in semiconductor manufacturing sector s can be represented as $M_{it} = \left[\frac{\beta_M \exp(\omega_{it}) K_{it}^{\beta_K} L_{it}^{\beta_L} E(\epsilon_{it}^{\rho})}{P_{st}^M}\right]^{\frac{1}{1-\beta_M}}$ where $\exp(\omega_{it}) = P_{st}^D (Q_{st}^D)^{\frac{1}{\sigma}} A_{it}^{\rho}$. Aggregating across i and s, I obtain total materials demanded from semiconductor manufacturing sector s equaling

$$M_{st} = \sum_i M_{it} = \sum_i \left[\frac{\beta_M P_{st}^D (Q_{st}^D)^{\frac{1}{\sigma}} A_{it}^{\rho} K_{it}^{\beta_K} L_{it}^{\beta_L} E(\epsilon_{it}^{\rho})}{P_{st}^M}\right]^{\frac{1}{1-\beta_M}} \tag{H.30}$$

and aggregate expenditures on materials $\sum_s P_{st}^M M_{st}$. Thus it follows that aggregate expenditures on materials are determined by Q_{st}^D, P_{st}^D, firm productivity A_{it}, and random firm output shocks $E(\epsilon_{it}^{\rho})$. The output and price of sector s Q_{st}^D, P_{st}^D are determined by Markov $\mathcal{X}_{st}$ and A is assumed to be Markov. Hence aggregate expenditures on materials, allocated across domestic and foreign firms, are also Markov. For the upstream equipment sector, I assume that capital investment is strictly increasing in Markovian revenue productivity *conditional* on the existing capital stock and capital cost-reducing subsidies across firms. Thus demand for equipment, which comes from the investment decisions of manufacturing firms, is also Markovian.

I Quantitative Model

I.1 Construction of the Domestic Expenditure Shares

This appendix describes how I build each term of equation (5) by each semiconductor 4-digit subsector. All values are in current US dollars, with domestic firm sales converted at annual average exchange rates.

Trade lines. Trade flows come from UN Comtrade's China data, reported by the Chinese Customs, at the six-digit level of the Harmonized System (HS). Integrated circuit design, manufacturing, and assembly & testing share one HS code, HS 8542, even though they sit on different segments

of the integrated circuit supply chain. Discrete devices are matched to HS 854110–854130 (diodes, transistors and thyristors), and optoelectronics to light-emitting diodes, HS 854141. Before the 2022 revision of the HS created the line, LED trade is assumed to be a fixed share of the photosensitive device line HS 854140, which used to also contain photovoltaic cells.[12] LEDs' trade shares are assumed to be 0.75 of HS 854140 for imports and 0.82 for exports, which are LEDs' shares of the respective trade values in 2022–2024.

Double counting along the integrated-circuit chain. A fabless IC design firm's revenue already contains the wafers and packages it buys from mainland IC manufacturers (fabs) and assemblers. Simply summing up revenue across the three integrated circuit sectors results in double counting. To account for this, I remove from the foundry and assembly & testing sectors' domestic sales the estimated share billed to Chinese customers. I then sum up the three IC sectors' adjusted sales as follows

$$\tilde{R}_t^{\mathrm{IC}} = R_t^{\mathrm{design}} + \left(1 - b_t^{\mathrm{fab}}\right) R_t^{\mathrm{fab}} + \left(1 - b_t^{\mathrm{asm}}\right) R_t^{\mathrm{asm}},$$

where b_t^{fab} is Chinese pure-play foundries' share of wafer revenue times their China-billed share, from the filings of the two leading Chinese foundries SMIC and Hua Hong, which together took up 52% of the revenue of domestically owned foundries in 2023 (57–69% in 2015–2022). b_t^{asm} is the domestic-customer share of the top three listed assemblers (domestic sales share 47% in 2023 and 49–57% in 2016–2022).

Equipment and Materials. For equipment, the trade data's HS 8486 also covers flat-panel display tools. I therefore measure the share directly, as domestic makers' sales of semiconductor equipment in China over the size of that market. I use SEMI's China equipment billings from its annual World Semiconductor Equipment Market Statistics as the denominator. Materials has the same issue: HS 3818, 3707 and 280461 mix semiconductor inputs with general chemicals. Thus, I use SEMI's China semiconductor materials market values as the denominator.

Comparison with market research. IC Insights reports that chips made in China were 15.9% of China's integrated-circuit market in 2020[13] and 16.7% in 2021,[14] which match my estimates of 15.4% and 17.9%.

[12] The mirror problem encountered by Banares-Sanchez et al. (2026), discussed in their Appendix B.7.

[13] IC Insights, "China Forecast to Fall Far Short of its 'Made in China 2025' Goals for ICs," January 2021, https://design-reuse.com/news/49259/made-in-china-2025.html.

[14] IC Insights, "China-Based IC Production to Represent 21.2% of China IC Market in 2026," May 2022, https://design-reuse.com/news/51960/china-ic-marketshare-forecast.html.

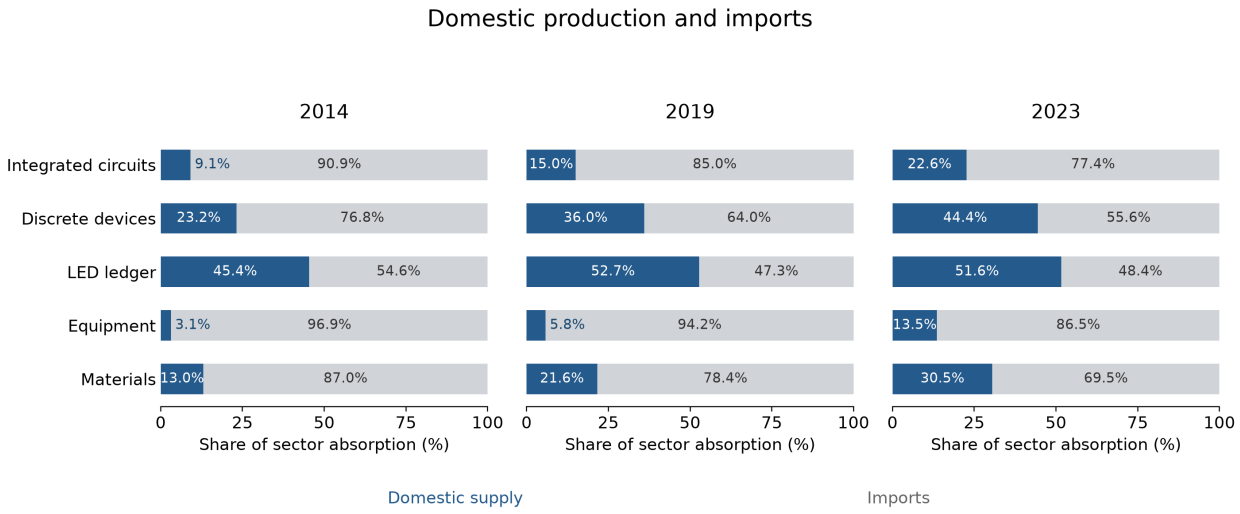


Figure I.1: Domestic Production and Imports, 2014, 2019, and 2023

Notes: Blue denotes domestic supply and gray denotes imports, expressed as percentages of their combined value. Domestic supply is production net of exports. Imports are customs flows for integrated circuits, discrete devices, and the LED market. Equipment and Materials instead use SEMI's total market size minus measured domestic supply as a residual foreign-supply measure.

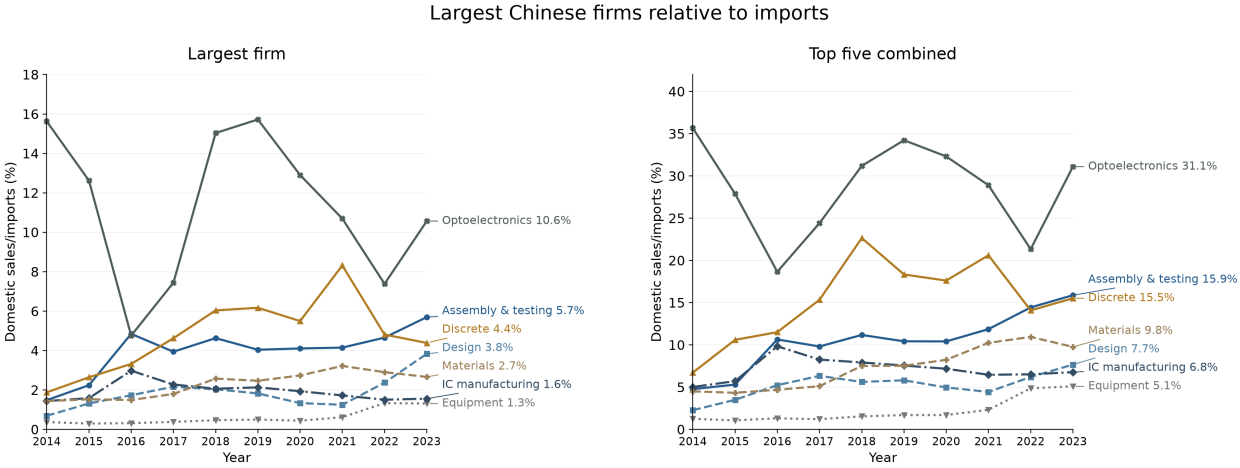


Figure I.2: Largest Chinese Firms' Domestic Sales Relative to Imports, 2014–2023

Notes: The panels report domestic sales of the largest firm and the five largest firms relative to imports, in percent. Domestic supply (domestic sales net of exports) is allocated across observed firms in proportion to their revenues, as firm-specific domestic sales and exports are not observed. Design, IC Manufacturing, and Assembly and Testing each use the pooled IC domestic-to-import ratio. Equipment and Materials use SEMI's total market size minus measured domestic sales.

I.2 VC Block Estimates

Table I.1: Predictors of Venture Capital Investment with Same-Year Coordination: Conditional Logit and Nested Pseudo-Likelihood, All Regressors

	Central government VC		Local government VC		Private VC	
	Clogit (1)	NPL (2)	Clogit (3)	NPL (4)	Clogit (5)	NPL (6)
Productivity ranks						
National TFPR percentile (0–1)	1.186**	1.124*	-0.126	-0.352	1.111***	1.171***
	(0.583)	(0.602)	(0.369)	(0.381)	(0.348)	(0.373)
Provincial TFPR percentile (0–1)	-0.552	-0.631	0.641**	0.648*	0.230	0.240
	(0.514)	(0.521)	(0.318)	(0.332)	(0.325)	(0.340)
# directors tied to the GP of a:						
central government VC	0.004	0.022	-0.106***	-0.094**	-0.059	-0.081
	(0.043)	(0.044)	(0.035)	(0.038)	(0.050)	(0.055)
same-province local VC	0.026	0.021	0.114***	0.129***	-0.054	-0.057
	(0.029)	(0.032)	(0.029)	(0.031)	(0.034)	(0.036)
private VC	-0.081***	-0.076**	-0.046**	-0.044*	-0.012	-0.005
	(0.031)	(0.032)	(0.023)	(0.025)	(0.042)	(0.048)
Ownership and previous investment						
1(local-government VC invested)	0.848***	1.083***	–	–	0.613***	0.387
	(0.202)	(0.289)			(0.192)	(0.255)
1(central-government VC invested)	–	–	0.340	0.340	-0.004	0.052
			(0.219)	(0.249)	(0.300)	(0.319)
1(private VC invested)	0.329*	0.544*	0.620***	1.174***	–	–
	(0.194)	(0.284)	(0.113)	(0.194)		
1(foreign invested)	0.432	0.529*	-0.636***	-0.564**	-0.813***	-0.875***
	(0.298)	(0.316)	(0.218)	(0.225)	(0.285)	(0.295)
1(SOE invested)	0.538***	0.505**	0.411***	0.440***	0.025	0.067
	(0.193)	(0.200)	(0.124)	(0.138)	(0.178)	(0.194)
Firm characteristics						
Firm age	-0.085***	-0.075***	-0.076***	-0.067***	-0.067***	-0.076***
	(0.020)	(0.020)	(0.015)	(0.015)	(0.012)	(0.015)
asinh(invention patent stock)	0.052	0.062	-0.001	0.009	-0.066*	-0.062
	(0.050)	(0.050)	(0.038)	(0.041)	(0.039)	(0.042)
asinh(IC layout stock)	-0.064	-0.065	0.019	0.015	0.011	0.011
	(0.070)	(0.074)	(0.056)	(0.058)	(0.060)	(0.067)
asinh(software stock)	0.009	-0.009	0.049	0.023	0.115***	0.128***
	(0.052)	(0.053)	(0.042)	(0.044)	(0.041)	(0.044)
asinh(registered capital)	0.009	0.020	-0.018	-0.009	-0.035	-0.039
	(0.037)	(0.038)	(0.025)	(0.027)	(0.023)	(0.026)
asinh(capacity)	0.017	0.012	0.055**	0.052**	0.060*	0.066*
	(0.028)	(0.030)	(0.026)	(0.027)	(0.032)	(0.035)
log(capital)	0.112	0.080	0.131***	0.105**	0.129***	0.143***
	(0.071)	(0.071)	(0.041)	(0.043)	(0.036)	(0.039)
log(employees)	0.254***	0.246***	0.053	0.042	0.085	0.094
	(0.087)	(0.087)	(0.063)	(0.060)	(0.053)	(0.057)

Continued on next page

Table I.1 continued

	Central government VC		Local government VC		Private VC	
	Clogit (1)	NPL (2)	Clogit (3)	NPL (4)	Clogit (5)	NPL (6)
Board characteristics						
Number of directors	0.011	0.009	-0.002	-0.006	0.004	0.005
	(0.024)	(0.024)	(0.010)	(0.010)	(0.015)	(0.016)
Number of directors with government experience	-0.052	-0.052	-0.013	-0.040	0.117	0.126
	(0.122)	(0.122)	(0.098)	(0.103)	(0.112)	(0.122)
Number of directors with SOE experience	0.070	0.083*	-0.057	-0.036	-0.106**	-0.134**
	(0.046)	(0.048)	(0.042)	(0.044)	(0.047)	(0.059)
Number of directors with finance experience	-0.003	-0.035	0.186***	0.163***	0.122*	0.162**
	(0.065)	(0.067)	(0.052)	(0.057)	(0.067)	(0.073)
Number of directors with technology/R&D experience	0.105*	0.075	0.130***	0.094**	0.128***	0.171***
	(0.055)	(0.062)	(0.031)	(0.037)	(0.046)	(0.058)
Number of directors with master's degree	-0.065	-0.068	0.022	0.029	0.041	0.036
	(0.055)	(0.059)	(0.050)	(0.053)	(0.069)	(0.077)
Number of directors with foreign education	-0.100	-0.095	-0.133	-0.140	0.147	0.142
	(0.132)	(0.132)	(0.088)	(0.090)	(0.117)	(0.135)
Technology and policy exposure						
High-Tech Enterprise	0.215	0.208	0.100	0.086	0.219	0.226
	(0.184)	(0.188)	(0.168)	(0.169)	(0.151)	(0.165)
Specialized SME (national)	-0.082	-0.071	-0.302	-0.306	0.030	0.017
	(0.517)	(0.553)	(0.455)	(0.454)	(0.616)	(0.731)
asinh(total subsidies: grants + equity)	0.027	0.015	0.047**	0.034	0.059***	0.064***
	(0.025)	(0.025)	(0.021)	(0.022)	(0.018)	(0.019)
Number of central-government procurements	0.035	0.040	-0.005	-0.000	-0.103**	-0.117**
	(0.025)	(0.027)	(0.008)	(0.008)	(0.051)	(0.057)
Number of local-government procurements	-0.064**	-0.063**	0.001	0.000	0.010	0.013
	(0.026)	(0.026)	(0.002)	(0.002)	(0.008)	(0.009)
Same-year coordination: rival's equilibrium probability of first investing in the firm						
central government VC	–	–	–	-1.298	–	0.399
				(1.891)		(2.273)
local government VC	–	3.067	–	–	–	-3.696*
		(2.164)				(2.027)
private VC	–	3.233	–	10.268***	–	–
		(2.194)		(3.372)		
Mean outcome (estimation sample)	0.015	0.015	0.022	0.022	0.022	0.022
Observations	14,778	14,760	19,870	19,870	17,514	17,514
Industry × year groups (clusters)	77	77	109	109	110	110
Same-year coordination terms	N	Y	N	Y	N	Y

Notes. The selection model for the quantification counterfactual uses a specification analogous to Tables E.5 and E.6 and adds the other two VC types' equilibrium probabilities of investing in the same firm in the same year. When another VC type has already invested in the firm, the term is zero. The coefficients are estimated by nested pseudo-likelihood. Each VC type's logit has an industry × year fixed effect, interpreted as the fixed cost of investment in the model, that matches its observed number of first investments in every industry × year. Other VCs' investment probabilities are the probabilities implied by the equilibrium estimates. Standard errors in parentheses are clustered by industry × year. NPL columns' standard errors are the variance of the NPL estimator that takes into account the fact that equilibrium probabilities respond to the parameters (Aguirregabiria and Mira, 2007). Dashes mark regressors that are not in an investor's equation (its own type's ownership; its own probability). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

I.3 Uniqueness of the Investment Equilibrium

Proposition 1 (Uniqueness)**.** *Let Φ collect the coordination coefficients, $\Phi_{kk'} = \phi_{k\leftarrow k'}$ and $\Phi_{kk} = 0$, and let $\mathrm{sym}(A) \equiv (A + A')/2$. If some positive diagonal matrix W satisfies $4W - \mathrm{sym}(W\Phi) \succ 0$, the investment equilibrium of every year is unique, for any state, budgets and choice sets.*

Intuition. The proposition is an application of the general principle of Rosen (1965): in a game in which each player's payoff is concave in its own strategy, the equilibrium is unique if, for some positive weights on each player, the decreasing returns of each player's own strategy dominate the effects the other players' strategies have on its marginal payoff. Intuitively, multiple equilibria arise only if coordination incentives from the estimated parameters $\phi_{k\leftarrow k'}$ are strong enough symmetrically in both directions: if instead they are small or asymmetric, the equilibrium implied by the estimated parameters is unique.

Proof. Let $n = |\mathcal{E}_k|$ be the size of k's choice set, and let $\Lambda_k(u; N) \in [0,1]^n$ be a vector representing k's choice probabilities under (3) at the vector of linear indexes u and budget N. Firm i's probability of investment is $p_i = \Lambda(u_i - \lambda)$, where the investment cost λ is set so that $\sum_i p_i = N$. For $0 < N < n$, this λ exists and is unique: as λ rises, $\sum_i \Lambda(u_i - \lambda)$ falls continuously from n to 0 with derivative $-\sum_i s_i < 0$, where $s_i \equiv p_i(1 - p_i)$.

A map $g : \mathbb{R}^n \to \mathbb{R}^n$ is co-coercive with constant $\beta > 0$ if

$$\big[g(u) - g(v)\big]'(u - v) \;\geq\; \beta \big\|g(u) - g(v)\big\|^2 \quad \text{for all } u, v \in \mathbb{R}^n.$$

By the Cauchy–Schwarz inequality, the left side is at most $\|g(u)-g(v)\|\,\|u-v\|$, so co-coercivity also implies $\|g(u) - g(v)\| \leq \|u - v\|/\beta$. For a linear map $g(u) = Mu$ with M symmetric, co-coercivity with constant β is equivalent to the eigenvalues of M lying in $[0, 1/\beta]$. If $g(u) = \Lambda_k(u\,; N)$ is co-coercive at $\beta = 4$, changing u by Δu changes the investor's investment probabilities by at most $\frac{\|\Delta u\|}{4}$.

Fix a year and drop the subscript t. Write investor k's propensity to invest in i (2) at beliefs of other's investment probabilities $\bar{\boldsymbol{\pi}}$ as

$$u_{ki}(\bar{\boldsymbol{\pi}}) = u_{ki}(\mathbf{0}) + \sum_{k' \neq k} \Phi_{kk'}\, \bar{\pi}_{k'i}, \qquad i \in \mathcal{E}_k,$$

where $u_{ki}(\mathbf{0})$ is the index at zero expected rival entry in the current year. $\bar{\pi}_{k'i} = 0$ for $i \notin \mathcal{E}_{k'}$.

Step 1: each investor's response is co-coercive. By the implicit function theorem, λ and $\Lambda_k(\cdot\,; N)$ are continuously differentiable in u. Differentiating $p_i = \Lambda(u_i - \lambda)$ and the budget gives $dp_i = s_i(du_i - d\lambda)$ and $\sum_i dp_i = 0$. Hence $d\lambda = \sum_i s_i\, du_i / \sum_i s_i$, and the Jacobian of the choice probabilities is

$$J_k(u) \;\equiv\; \frac{\partial \Lambda_k(u; N)}{\partial u'} \;=\; S - \frac{ss'}{\sum_i s_i}, \qquad S = \mathrm{diag}(s).$$

The Jacobian is symmetric. It is positive semidefinite, since $x'J_kx = \sum_i s_i x_i^2 - \big(\sum_i s_i x_i\big)^2 / \sum_i s_i$ is $\sum_i s_i$ times the variance of x under weights proportional to s. Its eigenvalues are at most $\max_i s_i$, since $J_k \preceq S$, and $\max_i s_i = \max_i p_i(1-p_i) \le \frac{1}{4}$ as $p_i \in [0,1]$.

Co-coercivity follows. For $u, v \in \mathbb{R}^n$, $\Lambda_k(u;N) - \Lambda_k(v;N) = M(u-v)$, where $M = \int_0^1 J_k\big(v + t(u-v)\big)\,dt$ is the average Jacobian on the segment from v to u. The matrix M is symmetric, and $0 \le x'Mx = \int_0^1 x'J_k\big(v+t(u-v)\big)x\,dt \le \frac{1}{4}\|x\|^2$ for every x, so its eigenvalues lie in $[0, \frac{1}{4}]$. Each eigenvalue m then satisfies $m \ge 4m^2$, so $M - 4M^2$ is positive semidefinite and $(u-v)'M(u-v) \ge 4(u-v)'M^2(u-v) = 4\|M(u-v)\|^2$. That is, for all $u, v \in \mathbb{R}^n$,

$$\big[\Lambda_k(u;N) - \Lambda_k(v;N)\big]'(u-v) \;\ge\; 4\,\big\|\Lambda_k(u;N) - \Lambda_k(v;N)\big\|^2. \tag{I.1}$$

For $N = 0$ and $N \ge n$, Λ_k is constant (no firm or every firm) and (I.1) holds trivially. The other investors expect $\bar\Lambda_k(u) \equiv \mathbb{E}_N\big[\Lambda_k(u;N)\big]$, the average over k's budget distribution. Taking expectations in (I.1) and using $\mathbb{E}\|X\|^2 \ge \|\mathbb{E}X\|^2$,

$$\big[\bar\Lambda_k(u) - \bar\Lambda_k(v)\big]'(u-v) \;\ge\; 4\,\big\|\bar\Lambda_k(u) - \bar\Lambda_k(v)\big\|^2. \tag{I.2}$$

Step 2: two equilibria coincide. Let $\bar{\boldsymbol\pi}$ and $\bar{\boldsymbol\pi}'$ be two equilibria under $\{u, N\}$, so that $\bar{\boldsymbol\pi}_k = \bar\Lambda_k\big(u_k(\bar{\boldsymbol\pi})\big)$ and $\bar{\boldsymbol\pi}'_k = \bar\Lambda_k\big(u_k(\bar{\boldsymbol\pi}')\big)$ for every investor. Let $D_{ki} = \bar\pi_{ki} - \bar\pi'_{ki}$, which is zero for $i \notin \mathcal{E}_k$, and let $D_i = (D_{ki})_{k\in\mathcal{K}}$ collect the differences at firm i. Beliefs enter the index linearly and only at the same firm, so $u_{ki}(\bar{\boldsymbol\pi}) - u_{ki}(\bar{\boldsymbol\pi}') = (\Phi D_i)_k$. Applying (I.2) to each investor, multiplying by $W_{kk} > 0$ and summing over investors,

$$\sum_i D_i' W\Phi\, D_i \;=\; \sum_k W_{kk} \sum_{i\in\mathcal{E}_k} D_{ki}\,(\Phi D_i)_k \;\ge\; 4\sum_k W_{kk} \sum_{i\in\mathcal{E}_k} D_{ki}^2 \;=\; 4\sum_i D_i' W D_i.$$

Since $x'Ax = x'\,\mathrm{sym}(A)x$ for every square matrix A,

$$\sum_i D_i'\big[4W - \mathrm{sym}(W\Phi)\big]D_i \;\le\; 0.$$

If $4W - \mathrm{sym}(W\Phi)$ is positive definite, every term of the sum is nonnegative and zero only when $D_i = 0$. Hence $D_i = 0$ at every firm and $\bar{\boldsymbol\pi} = \bar{\boldsymbol\pi}'$. □

Estimates satisfy the condition. The condition is equivalent to

$$\bar\phi \equiv \min_{W\succ 0 \text{ diagonal}} \lambda_{\max}\big(W^{-1/2}\,\mathrm{sym}(W\Phi)\,W^{-1/2}\big) < 4.$$

At the estimates of Table I.1, the coordination matrix, with rows for the entering investor and columns for the rival in the order (C, L, P), is

$$\hat\Phi = \begin{pmatrix} 0 & 3.07 & 3.23 \\ -1.30 & 0 & 10.27 \\ 0.40 & -3.70 & 0 \end{pmatrix}.$$

Under the weights $W = \mathrm{diag}(0.12, 0.40, 1)$, the eigenvalues of $4W - \mathrm{sym}(W\hat{\Phi})$ are 0.43, 1.58 and 4.06, all positive, and $\bar{\phi} = 1.14$. The condition therefore holds for any coordination matrix $c\,\hat{\Phi}$ with $0 \le c < 4/1.14 = 3.5$, and it holds in 97.5% of 400 draws from the sampling distribution of the six coefficients. Hence the equilibrium is unique in every sector-year.

I.4 Variable Markups Variant

Cournot markups. Let $h_{it} \equiv R_{it} / \sum_{i' \in \mathcal{J}_{st}} R_{i't}$ be firm i's share of domestic sales. Firms choose quantities q_{it} taking the quantities of other domestic firms as given, but they internalize that their output moves the domestic composite and the domestic price index. Applying Atkeson and Burstein (2008), firm i's perceived inverse demand elasticity is the domestic share-weighted average $(1-h_{it})/\sigma + h_{it}/\eta^D_{st}$ of $\frac{1}{\sigma}$, the inverse elasticity within the domestic nest, and $\frac{1}{\eta^D_{st}}$, the inverse elasticity between the domestic and foreign composite. Its markup over marginal cost is

$$\mu_{it} \equiv \frac{p_{it}}{MC_{it}} = \left[1 - \frac{1 - h_{it}}{\sigma} - \frac{h_{it}}{\eta^D_{st}}\right]^{-1}. \tag{I.3}$$

A small firm $h_{it} \to 0$ competes only with other domestic varieties and charges the constant markup $\sigma/(\sigma-1)$. A larger firm $h_{it} \to 1$ will affect the domestic price index and face less elastic demand, and hence will charge a higher markup. Because η^D_{st} falls as s^D_{st} rises, import substitution also raises the markups of large domestic firms, the mirror image of the pro-competitive effect of import competition.

Labor and optimized revenue. Given its capital, which is decided before year t begins, the firm hires labor at the common sector wage w_{st}. The first-order condition sets the wage bill to a share of revenue that is declining in the markup, $w_{st} L^*_{it} = (\alpha_L/\mu_{it}) R^*_{it}$. Substituting optimal labor into (9) gives

$$\log R^*_{it} = \frac{\omega_{it} + \beta_K \log K_{it} + \beta_L \log\left(\beta_L/(\rho\,\mu_{it} w_{st})\right)}{1 - \beta_L}. \tag{I.4}$$

Optimized revenue rises with revenue productivity and capital, amplified by the labor the firm hires as it grows, and falls with the markup: a firm with more market power hires less and sells less.

Counterfactual firm sales. Differencing (I.4) with the wage fixed, noting (9), gives

$$d\log R^*_{it} = \underbrace{\frac{\Delta^{\omega}_{it} + \beta_K \Delta^K_{it}}{1-\beta_L}}_{\text{direct treatment}} + \underbrace{\frac{\rho\, d\log P^D_{st} + \sigma^{-1} d\log R^D_{st}}{1-\beta_L}}_{\text{sector demand}} - \underbrace{\frac{\beta_L}{1-\beta_L}\, d\log \mu_{it}}_{\text{markup}} \tag{I.5}$$

The third term is what is new relative to (15). Given the same productivity change, the change in sales of firms is lower for firms with higher markups and initial domestic market share.

I.5 Product Market Equilibrium

I solve for the equilibrium as follows. Start with a candidate equilibrium change in industry sales $d\log R^D_{st}$. With expenditures $\mathcal{X}_{st}$ fixed, the domestic share grows proportionally to domestic revenue:

$$s^D_{st} = s^{D,0}_{st}\exp(d\log R^D_{st}) \tag{I.6}$$

With the foreign price P^F_{st} fixed, equation (7) links the change in domestic sales to the change in the domestic price index,

$$\frac{s^D_{st}/(1-s^D_{st})}{s^{D,0}_{st}/(1-s^{D,0}_{st})} = \left(\frac{P^D_{st}}{P^{D,0}_{st}}\right)^{1-\zeta} \tag{I.7}$$

Taking logs of (I.7) and substituting (I.6) gives the implied change in prices

$$d\log P^D_{st} = \frac{-d\log R^D_{st} + \log\left(1-s^{D,0}_{st}e^{d\log R^D_{st}}\right) - \log\left(1-s^{D,0}_{st}\right)}{\zeta-1}. \tag{I.8}$$

By (I.4), (14), and that $d\log R^D_{st} = d\log Q^D_{st} + d\log P^D_{st}$, the change in each firm's sales is given by (I.5). In the baseline constant markups case, the term $d\log\mu_{it}$ is zero. Otherwise, from updated firm shares $h_{it} = h^0_{it}\exp(d\log R^*_{it} - d\log R^D_{st})$ and the updated price elasticity of the domestic bundle, $\eta^D_{st} = 1+(\zeta-1)(1-s^D_{st})$, markups (eq. (I.3)) update as:

$$d\log\mu_{it} \equiv \log\frac{\mu_{it}}{\mu^0_{it}} = \log\left[\frac{1-\frac{1-h^0_{it}}{\sigma}-\frac{h^0_{it}}{\eta^{D,0}_{st}}}{1-\frac{1-h_{it}}{\sigma}-\frac{h_{it}}{\eta^D_{st}}}\right]. \tag{I.9}$$

An equilibrium simultaneously satisfies equations (I.5), (16), (I.8), and (I.9). The implementation tests candidate $d\log R^D_{st}$ until counterfactual market shares sum to 1: $\sum_{i\in\mathcal{J}_{st}} h_{it}(d\log R^D_{st}) = \sum_{i\in\mathcal{J}_{st}} h^0_{it}\exp(d\log R^*_{it} - d\log R^D_{st})(d\log R^D_{st}) = 1$.

How much of a firm's relative gain is a gain for the industry? A first-order version of these conditions shows how higher import shares limit within-domestic business stealing. Hold markups fixed, and let $\bar\Delta_{st} \equiv \sum_i h^0_{it}(\Delta^\omega_{it} + \beta_K\Delta^K_{it})/(1-\beta_L)$ be the sales-weighted sum of the firms' direct gains, the naive adding up of firm-level difference-in-differences effects. Linearizing Equations (16) and (I.8) gives

$$d\log R^D_{st} \approx \nu_{st}\,\bar\Delta_{st}, \qquad \nu_{st} \equiv \left[1+\frac{\rho/(\eta^D_{st}-1)-1/\sigma}{1-\beta_L}\right]^{-1}. \tag{I.10}$$

The multiplier ν_{st} is the share of a firm-level ATT in sales that represents gains in the domestic industry. It lies between zero and one because $\eta^D_{st} = 1+(\zeta-1)(1-s^D_{st}) \le \zeta = 3 < \sigma = 5$. It falls as domestic firms supply more of the market (s^D_{st} rises and $\eta^D_{st} = 1+(\zeta-1)(1-s^D_{st})$ falls), since a funded firm would then take more of its sales from domestic rivals.

Uniqueness. Given domestic sales, each firm's sales solve (I.5), in which a firm's own sales enter only through its markup: higher sales raise its share and markup, which lowers its labor and sales, so the condition has exactly one solution. The closure (16) then becomes a single equation in the

candidate industry sales change $d \log R_{st}^D$. The gap between summed firm sales and domestic sales falls strictly as domestic sales rise: higher domestic sales lower the domestic price index by enough to reduce every firm's sales, because $\sigma > \eta_{st}^D$ (the inequality that puts ν_{st} between zero and one). In the variable markups case, they also raise markups through larger shares and a less elastic domestic composite. The gap is positive as domestic sales fall toward zero and negative as the domestic share approaches one. Thus at one exact point domestic industry sales equal the sum of domestic firm sales. The equilibrium exists, is unique, and keeps $s_{st}^D < 1$ for any counterfactual history, with no restriction on the parameters beyond $\sigma > \zeta > 1$. Because simulated investment does not respond to product-market outcomes and the investment equilibrium is unique (Proposition 1), each simulated history implies a unique set of firm sales.

I.6 Calibrating Productivity and Capital Paths

Step 1: Outcomes, investment histories, and calibration targets. The calibration matches productivity and capital responses to VC investment with observed productivity and capital difference-in-differences ATTs. Investor types are $k \in \{\mathrm{C}, \mathrm{L}, \mathrm{P}\}$. Let G_{ki} be the year of type k's first investment in firm i and $\tau_{kit} \equiv t - G_{ki}$ its event age, with $\tau_{kit} = \emptyset$ for $t < G_{ki}$. I target synthetic difference-in-differences estimates (Arkhangelsky et al., 2021) of capital matching four pre-investment years. Productivity targets are the original event-study estimates. Each outcome contributes eighteen moments: three investor types at event years $\tau = 0, \ldots, 5$.

Step 2: Predict ordinary capital growth. I predict log-capital growth absent VC investment, $\log K_{it} - \log K_{i,t-1}$, with a flexible function $f_K^{\emptyset}$ of lagged capital and productivity. For a firm in sector s,

$$f_K^{\emptyset}(\log K_{i,t-1}, \omega_{i,t-1}; \mathbf{b}) = \delta_s + \delta_t + \mathbf{B}_s^K\left(z_{i,t-1}^K\right)' \mathbf{b}_s^K + \mathbf{B}_s^{\omega}\left(z_{i,t-1}^{\omega}\right)' \mathbf{b}_s^{\omega} + b_s^{K\omega} z_{i,t-1}^K z_{i,t-1}^{\omega},$$

where $z_{i,t-1}^K$ and $z_{i,t-1}^{\omega}$ are $\log K_{i,t-1}$ and $\omega_{i,t-1}$ standardized within sector, $\mathbf{B}_s^K$ and $\mathbf{B}_s^{\omega}$ are vectors of four quadratic spline basis functions, δ_s and δ_t are sector and year effects, and $\mathbf{b}$ collects all coefficients of $f_K^{\emptyset}$.

Step 3: Generate annual treatment innovations and state gaps. Let $\tilde{\theta}_k^{\omega}(\tau)$ and $\tilde{\theta}_k^K(\tau)$ denote the within-model effects of investor k on revenue productivity and on log-capital growth τ years after its first investment. They are assumed to be zero before entry and after $\tau = 5$, $\tilde{\theta}_k^{\omega}(\emptyset) = \tilde{\theta}_k^K(\emptyset) = 0$. Effects from overlapping investor types are assumed to be additive.

In the calibration, I compare the observed VC allocation $\mathbf{G}$ with the no-VC counterfactual $\mathbf{G}^{\emptyset}$, under which $\tau_{kit} = \emptyset$ for every k. Superscript $\emptyset$ marks outcomes under $\mathbf{G}^{\emptyset}$. Define the change in log productivity and capital as $\Delta_{it}^{\omega} \equiv \omega_{it} - \omega_{it}^{\emptyset}$ and $\Delta_{it}^K \equiv \log K_{it} - \log K_{it}^{\emptyset}$. The productivity gap obeys

$$\Delta_{it}^{\omega} = f_A' \, \Delta_{i,t-1}^{\omega} + \sum_k \tilde{\theta}_k^{\omega}(\tau_{kit}),$$

where f_A' is the slope of the no-VC AR(1) law of motion (12). This sector persistence is estimated

separately from productivity transitions among never-invested firms and held fixed during calibration. Due to AR(1) accumulation, the observed ATT from VC investments is the sum of the level effects in (11), discounted by the persistence parameter f'_A, with the ATT on ω τ years after k's investment being

$$\theta_k^{\omega}(\tau) = \sum_{\tau'=0}^{\min(\tau,5)} \left(f'_A\right)^{\tau-\tau'} \tilde{\theta}_k^{\omega}(\tau').$$

Capital innovation as a consequence of VC investments obeys

$$\begin{aligned}\Delta_{it}^K = \Delta_{i,t-1}^K &+ f_K^{\emptyset}(\log K_{i,t-1}, \omega_{i,t-1}; \mathbf{b}) \\ &- f_K^{\emptyset}\left(\log K_{i,t-1} - \Delta_{i,t-1}^K,\, \omega_{i,t-1} - \Delta_{i,t-1}^{\omega}; \mathbf{b}\right) + \sum_k \tilde{\theta}_k^K(\tau_{kit}).\end{aligned}$$

Productivity changes as a consequence of VC investments also affect capital through $f_K^{\emptyset}$. The capital innovations $\tilde{\theta}_k^K(\tau)$ flexibly model how VC investments may add capital on top of the productivity innovations. Steps 2 and 3 together give the capital policy (13), $f_K = \log K_{i,t-1} + f_K^{\emptyset}(\log K_{i,t-1}, \omega_{i,t-1}; \mathbf{b}) + \sum_k \tilde{\theta}_k^K(\tau_{kit})$. I assume no further productivity level shifts for $\tau > 5$. Past productivity effects continue to accumulate through f'_A, and past capital effects through $f_K^{\emptyset}$.

Step 4: Apply the empirical comparisons to model outcomes. Let $\chi_{k,\tau,it}^X$ denote the treated observation count weights for outcome $X \in \{\omega, K\}$, investor k, and event year τ, and collect the innovations in $\tilde{\boldsymbol{\theta}} \equiv \left(\tilde{\theta}_k^{\omega}(\tau), \tilde{\theta}_k^K(\tau)\right)_{k,\tau}$. For candidate parameters $(\tilde{\boldsymbol{\theta}}, \mathbf{b})$, the model-implied ATT event study moment, the counterpart of the empirical estimate $\widehat{\mathrm{DiD}}_k^X(\tau)$, is

$$\mathrm{DiD}_k^X(\tau; \tilde{\boldsymbol{\theta}}, \mathbf{b}) \equiv \sum_{i,t} \chi_{k,\tau,it}^X \, \Delta_{it}^X(\tilde{\boldsymbol{\theta}}, \mathbf{b}).$$

Define the raw moment loss averaged over the 18 moments from 3 investor types $\times$ 6 event times $\tau = 0, \ldots, 5$ from the event studies on $X \in \{\omega, K\}$:

$$\mathrm{MSE}_X(\tilde{\boldsymbol{\theta}}, \mathbf{b}) \equiv \frac{1}{18} \sum_{k \in \{\mathrm{C,L,P}\}} \sum_{\tau=0}^{5} \left[\mathrm{DiD}_k^X(\tau; \tilde{\boldsymbol{\theta}}, \mathbf{b}) - \widehat{\mathrm{DiD}}_k^X(\tau)\right]^2.$$

Step 5: Jointly fit ATT and capital prediction. Over the set $\mathcal{O}$ of observed firm-year transitions, the capital prediction loss with observed growth $\log K_{it} - \log K_{i,t-1}$ and lagged states is

$$\mathrm{MSE}_{f_K}(\tilde{\boldsymbol{\theta}}, \mathbf{b}) \equiv \frac{1}{|\mathcal{O}|} \sum_{(i,t) \in \mathcal{O}} \left[f_K^{\emptyset}(\log K_{i,t-1}, \omega_{i,t-1}; \mathbf{b}) + \sum_k \tilde{\theta}_k^K(\tau_{kit}) - \left(\log K_{it} - \log K_{i,t-1}\right)\right]^2.$$

The calibrated parameters $(\tilde{\boldsymbol{\theta}}, \mathbf{b})$ solve the equal-weight problem

$$\min_{\tilde{\boldsymbol{\theta}}, \mathbf{b} \,:\, \tilde{\theta}_k^K(\tau) \geq 0} \left\{\mathrm{MSE}_{\omega} + \mathrm{MSE}_K + \mathrm{MSE}_{f_K} + \frac{\|\mathbf{b}\|^2}{|\mathcal{O}|}\right\}.$$

All three MSE terms receive equal weights, while the regularization term $\frac{\|\mathbf{b}\|^2}{|\mathcal{O}|}$ penalizes large coefficients on the flexible capital predictor to avoid over-fitting. Table I.2 reports the targeted and fitted moments.

Table I.2: Empirical ATT Targets and Calibrated Firm Responses

Investor	Object	$\tau = 0$	1	2	3	4	5
A. Log capital, K							
Central	Empirical	0.191	0.252	0.280	0.323	0.317	0.699
	Model	0.189	0.238	0.275	0.331	0.339	0.698
Local	Empirical	0.096	0.233	0.313	0.436	0.496	0.389
	Model	0.082	0.196	0.273	0.386	0.403	0.426
Private	Empirical	0.170	0.324	0.453	0.659	0.247	0.539
	Model	0.167	0.332	0.451	0.546	0.464	0.496
B. Revenue productivity, ω							
Central	Empirical	0.009	0.124	0.068	0.018	0.006	-0.046
	Model	0.002	0.046	0.026	0.040	0.064	-0.028
Local	Empirical	0.137	0.302	0.329	0.345	0.256	0.457
	Model	0.072	0.155	0.173	0.188	0.177	0.259
Private	Empirical	0.041	-0.047	-0.020	-0.280	-0.123	0.063
	Model	0.015	-0.027	-0.013	-0.118	-0.024	0.009

Notes. Empirical entries are $\widehat{\mathrm{DiD}}_k^X(\tau)$: four-preyear SDID for capital and main event studies for revenue productivity, with focal investment cohorts 2014–2023. Model entries are $\mathrm{DiD}_k^X(\tau; \widehat{\boldsymbol{\theta}}, \widehat{\mathbf{b}})$, holding common demand, wages and markups fixed. Capital innovations are nonnegative; productivity innovations are unrestricted in sign. Both innovations are zero after event year 5, while inherited state gaps continue through the transition equations.

I.7 An Alternative Model: Local Government Foresight

Local foresight rather than local productivity treatment. This alternative allows local funds to identify firms whose revenue productivity would grow without their investment. I set the direct productivity innovations for all VCs to zero,

$$\tilde{\theta}_k^{\omega}(\tau) = 0 \qquad \text{for all } \tau, k \in \{\mathrm{C}, \mathrm{L}, \mathrm{P}\}.$$

VC investments can still affect capital.

With this assumption, the productivity growth associated with local VC investment is reinterpreted as anticipated growth rather than a causal local productivity effect: $\omega_{it}^0 = \omega_{it}^{\text{data}}$.

Information within the local VC's province. For each decision year t, I measure each firm's average productivity growth from $t-1$ to the years $t, \ldots, \min(t+5, 2023)$. Within each decision year, I regress this measure on the choice set's productivity, log capital, log employment and industry indicators. Let S_{it} denote the standardized residual.

A provincial investor receives a noisy signal only about firms in its own province. Its propensity to invest in firm i in province p becomes the logistic function of the linear index

$$u^F_{pit} = u_{pit} + \gamma\, \mathbf{1}\{p = \text{province}(i)\} \left(\frac{S_{it}}{2} + \frac{\varepsilon_{it}}{2} \right), \qquad \varepsilon_{it} \sim N(0,1),$$

where u_{pit} is the baseline investment index.

Calibration to the empirical comparisons. I choose the signal strength γ to minimize discrepancies between simulated Local productivity ATT at event years $0, \ldots, 5$ and the event-study targets. The simulation uses the calibrated selection model to predict the treatment cohorts and the event study comparison group, then compares the event coefficients under this simulation to the targeted ATT. I then recalibrate the capital innovations to the SDID targets.

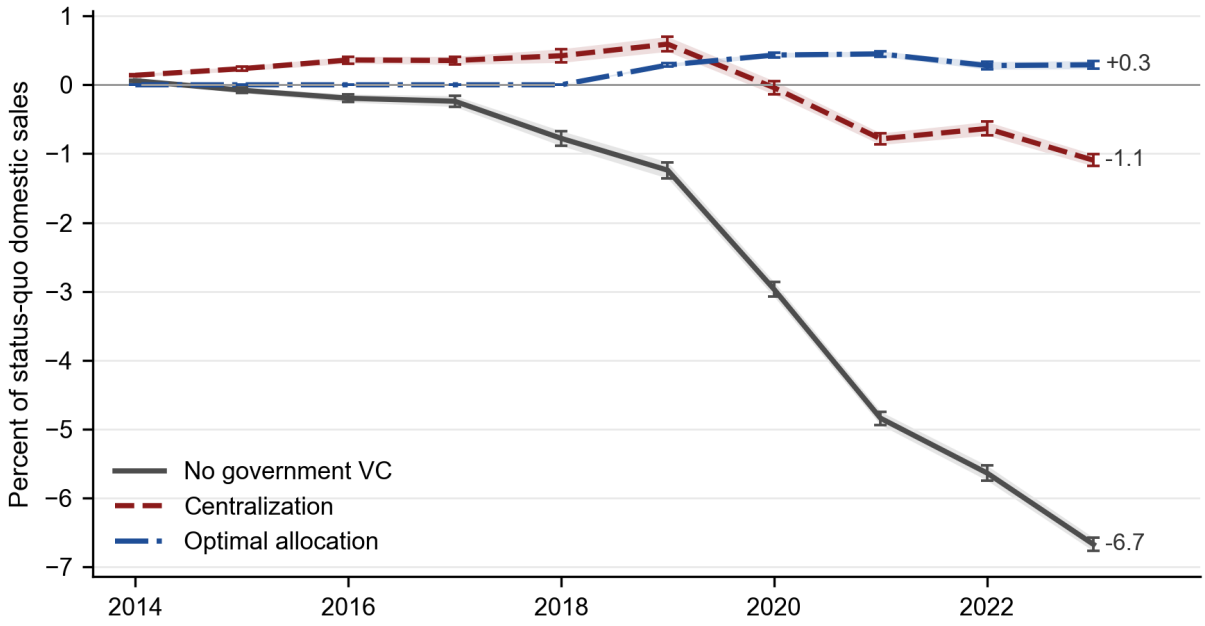


Figure I.3: Total Industry Sales Relative to Decentralized Status Quo, Local Government Foresight

Notes. Counterfactual industry sales minus status quo sales in the same year, expressed as a percentage of status quo sales. Results average over 100 simulated histories, holding firm entry and exit fixed. Counterfactuals under constant markups and elasticities $(\zeta, \sigma) = (3, 5)$.

I.8 Additional Results

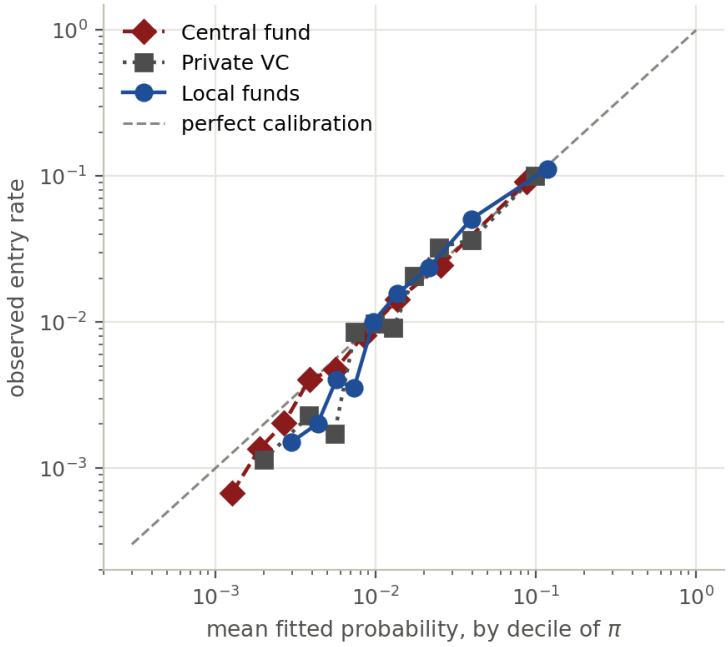


Figure I.4: Calibration of Fitted Entry Probabilities

Notes. For each investor type, the firm-years not yet invested in 2007–2024 are pooled across investor-years and split into ten equal-sized groups by the fitted entry probability. Each marker plots a decile's mean fitted probability against its observed rate of first entry, both on log scales, and the grey dashed line marks equality. Fitted probabilities are in-sample, from the nested pseudo-likelihood estimates, with each investor-year's hurdle set so that its fitted probabilities add up to its observed number of first entries. Each type's overall entry rate is therefore matched by construction, and the figure shows whether entry rates also rise across deciles as the model predicts.

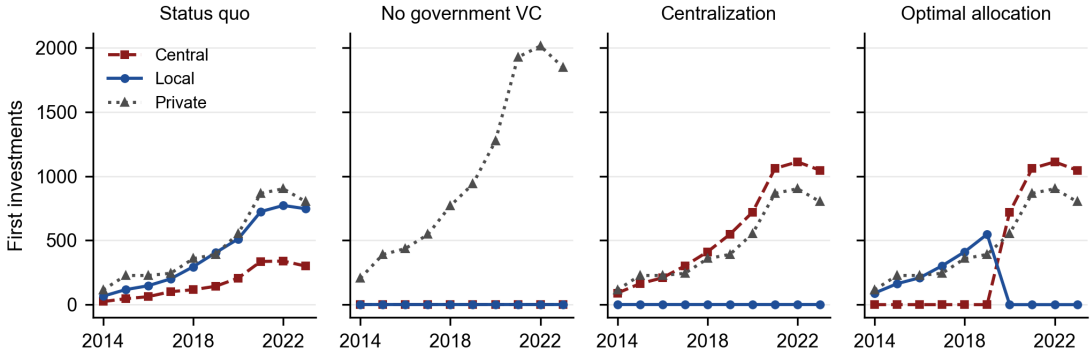


Figure I.5: Investments by Investor Under Each Allocation, 2014–2023

Notes. First investments (entry slots) by investor type and year, $N_{kt} = \sum_s N_{kst}$, 2014–2023, observed and under three counterfactual allocations. Every allocation keeps the total number of first investments in each sector and year fixed. The no-government-VC counterfactual gives all central and local slots to private VC; the centralization counterfactual gives the local slots to the central fund; the optimal allocation divides the government slots between the central fund and the local funds to maximize simulated 2023 domestic sales.

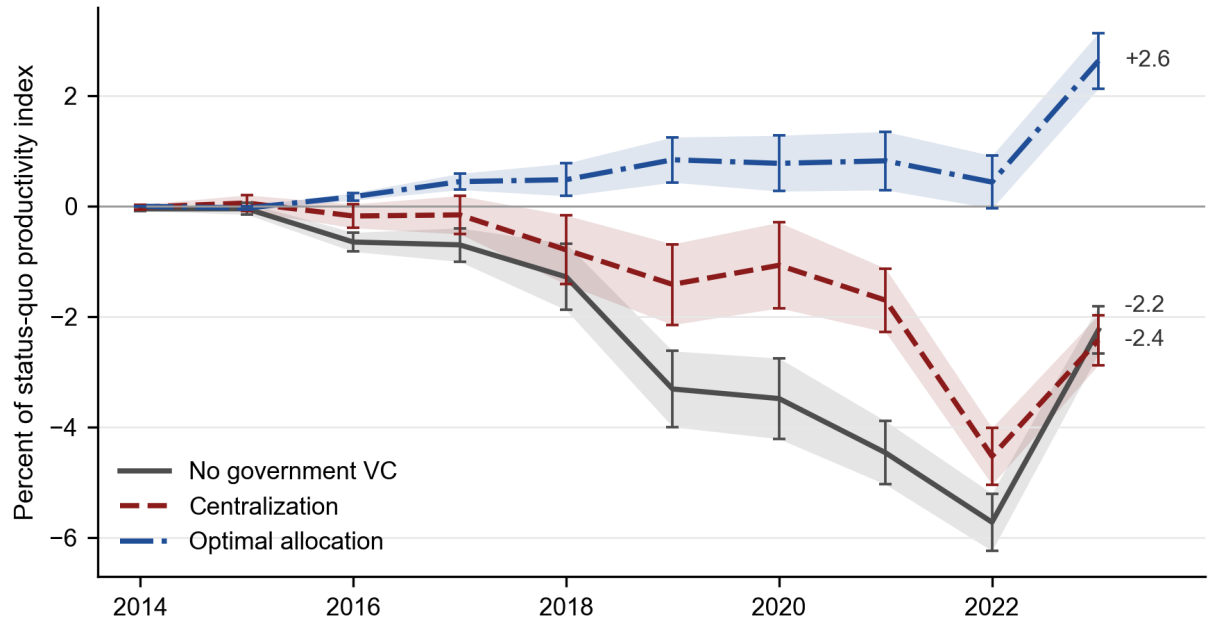


Figure I.6: Sales-Weighted Productivity Relative to the Decentralized Status Quo

Notes. Percentage differences in the sales-weighted productivity index relative to the modeled status quo in the same year. Percentage differences are averaged over 100 simulated histories. Firm entry and exit are held fixed. Counterfactuals use constant markups and elasticities $(\zeta, \sigma) = (3, 5)$.

Figure I.7 and Table I.3 repeat the counterfactuals of Figure 15 over the elasticity ranges of Table 5. The import elasticity ζ accounts for almost all of the variation, because it governs how far domestic sales can expand at the expense of imports: the 2023 loss without government VC ranges from 8.6% to 14.0%, the loss from centralization from 3.0% to 4.9%, and the gain from the optimal allocation from 1.5% to 2.5%. The sales-weighted productivity index barely moves, and the baseline optimal schedule remains the best of the five leading schedules in every configuration.

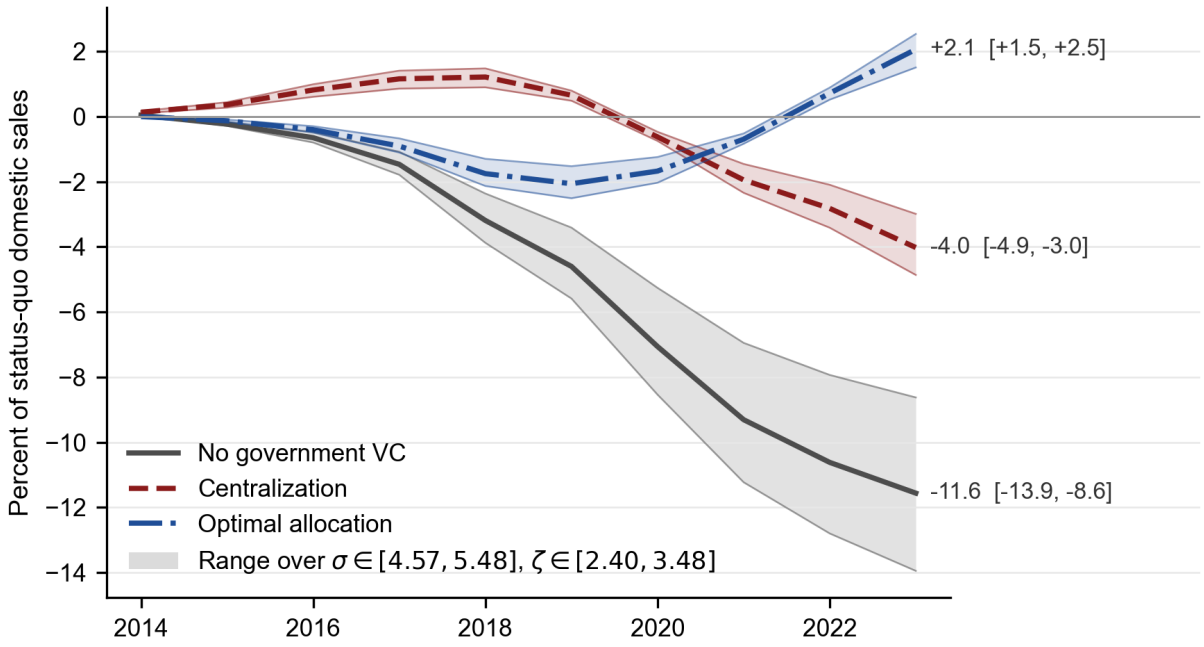


Figure I.7: Total Industry Sales Relative to Decentralized Status Quo, Alternative Demand Elasticities

Notes. Lines: the counterfactuals of Figure 15 at the baseline elasticities $(\zeta, \sigma) = (3, 5)$. Shaded areas: range over the 3×3 grid of $\sigma \in \{4.57, 5, 5.48\}$ and $\zeta \in \{2.40, 3, 3.48\}$; brackets give the 2023 range. Averages over 100 simulated histories; Monte Carlo standard errors are at most 0.12.

Table I.3: Sensitivity of the Counterfactuals to the Demand Elasticities

		2023 domestic sales (%)			2023 productivity index (%)		
σ	ζ	No gov. VC	Centralization	Optimal	No gov. VC	Centralization	Optimal
Baseline							
5	3	-11.56	-4.02	2.06	-2.24	-2.42	2.63
Import elasticity ζ							
5	2.40	-8.91	-3.09	1.56	-2.24	-2.41	2.64
5	3.48	-13.35	-4.65	2.42	-2.24	-2.43	2.62
Variety elasticity σ							
4.57	3	-12.05	-4.19	2.16	-2.29	-2.48	2.69
5.48	3	-11.14	-3.87	1.99	-2.19	-2.37	2.58
Joint bounds							
5.48	2.40	-8.62	-2.99	1.51	-2.19	-2.36	2.58
4.57	3.48	-13.95	-4.86	2.54	-2.29	-2.49	2.68

Notes. Percent differences from the status quo in 2023 under different elasticity values, both aggregate industry sales and productivity index: between domestic elasticity $\sigma \in [4.57, 5.48]$, domestic-foreign elasticity $\zeta \in [2.40, 3.48]$. The joint bounds give the smallest and largest effects over the 3×3 grid of $\sigma \in \{4.57, 5, 5.48\}$ and $\zeta \in \{2.40, 3, 3.48\}$ (2023 sales: no government VC -8.62 to -13.95, centralization -2.99 to -4.86, optimal allocation 1.51 to 2.54).