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Governmental Venture Capital and Startup AI Innovation: Evidence from China

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Abstract

This study examines whether governmental venture capital (GVC), relative to private venture capital (PVC), more effectively steers startup innovation toward strategic, high-uncertainty technologies, using the rise of artificial intelligence (AI) in China as our empirical setting. Our analysis is based on a comprehensive sample of Chinese startups (operating outside the core AI industry) that received venture capital between 2010 and 2019. We leverage the staggered rollout of GVC investments across Chinese startups as a quasi-natural experiment and employ a difference-in-differences (DID) design combined with propensity score matching (PSM). Our baseline results show that GVC-backed startups generate significantly more AI patents than PVC-backed counterparts. We also find that the innovation-promoting effect of GVC is amplified in regions with greater state-owned sector dominance but attenuated in regions with higher corruption. Our findings are robust to a series of tests, including parallel trends validation, placebo analyses, an instrumental variable (IV) strategy using regional GVC fund density and alternative specifications. Further heterogeneity analyses indicate that this effect is stronger for startups backed by VCs with less specialization or lower IPO experience, and that it becomes significantly more pronounced in the latter half of the 2010s as China's AI policy ecosystem matured. Overall, this study demonstrates how GVC shapes corporate innovation strategy in emerging technological waves, with direct implications for the design of public venture programs and innovation policy in technology-driven economies.

Keywords Governmental venture capital; Startup innovation; Artificial intelligence; Technology hype; Institutional environment

1. Introduction

Extant research has established that governmental venture capital (GVC) can promote firm innovation by providing patient capital, mitigating financing constraints, and conferring certification benefits that alleviate information asymmetry (Bertoni et al., 2015; Bertoni & Tykvová, 2015; Colombo et al., 2016). However, this literature has a crucial limitation: it has largely examined innovation as a technologically neutral outcome, paying insufficient attention to how the social construction of innovation as a "fashionable" trajectory reshapes investor behavior.

This limitation is particularly salient in the context of artificial intelligence. AI represents more than a distinct technological domain; it constitutes a paradigmatic technology fashion wave, one characterized by heightened collective attention, powerful future-oriented narratives, and pronounced bandwagon dynamics (Abrahamson & Fairchild, 1999; Wang, 2010). In such contexts, investment decisions are driven not only by assessments of technological feasibility or expected cash flows but also by legitimacy concerns, strategic positioning, and alignment with dominant innovation narratives. Consequently, participation in AI innovation often reflects firms' and investors' willingness to engage with fashionable yet highly uncertain technological trajectories.

Despite the growing prominence of AI as a fashion-driven innovation domain, existing studies have not systematically examined whether different types of venture capital respond differently to such fashion dynamics (Bertoni et al., 2019; Colonnelli et al., 2024; Douglas, 2006). In particular, the literature remains silent on a critical comparative question: *are GVCs more or less inclined than private venture capital (PVC) investors to promote firms' engagement with fashionable innovation waves?* Whereas PVC is disciplined by profit maximization and market-based risk-return considerations, GVC operates under a hybrid logic in which financial objectives coexist with strategic and political mandates (Brander et al., 2015; Zhang & Mayes, 2018). This dual mandate may render GVC especially receptive to technology fashions that align with national development priorities—yet it may also expose GVC to symbolic investment pressures and herding behavior.

Moreover, prior research frequently treats GVC as a homogeneous policy instrument (Douglas, 2006), overlooking how its effectiveness in fashion-driven innovation contexts is

conditioned by the institutional environment in which it is embedded. As a form of state-market hybrid, GVC's capacity to translate support for fashionable technologies into substantive innovation outcomes depends critically on regional governance quality (Beraja et al., 2024). Weak institutions may amplify the risks of symbolic compliance and misallocation, whereas stronger institutions may enable GVC to discipline technological fashion and channel resources toward genuine capability building. Taken together, these gaps point to an unresolved puzzle in the literature: *does GVC merely follow technology fashion, or can it shape firms' engagement with fashionable innovation in a more disciplined and developmentally effective manner—and under what institutional conditions?*

This study seeks to address these dual gaps by rigorously examining the impact of GVC on startup AI innovation, with particular emphasis on the contingent role of the institutional environment. Focusing on China, we theorize that GVC's effectiveness is systematically moderated by two institutional dimensions: the degree of state ownership permeating the regional economy and the quality of institutional governance, proxied by regional corruption. We posit that these factors jointly govern the efficiency with which GVC translates financial injections into tangible AI innovation outputs, offering a nuanced, contingent framework for understanding state-led financing in emerging technological waves.

Empirically, we identify the causal effect of GVC by employing a quasi-experimental design that combines propensity score matching (PSM) with a time-varying difference-in-differences (DID) estimator. Our analysis is based on a unique firm-level panel dataset, constructed by merging comprehensive venture capital investment records from CVSource with detailed AI patent data from the Incopat database, covering the period 2010–2019. The final matched sample comprises 1,345 startups, yielding 6,206 firm-year observations. The results provide robust evidence that GVC backing exerts a significant positive effect on startups' AI innovation output. We demonstrate that this relationship is not uniform but is critically moderated by key features of the regional institutional environment. Further empirical analysis reveals that the innovation-promoting effect of GVC is amplified in regions with a higher dominance of the state-owned sector, yet attenuated in regions with higher levels of corruption, underscoring the contextual contingency of public venture capital efficacy. These baseline findings withstand an extensive series of robustness and endogeneity checks, including parallel

trends tests, placebo analyses, an instrumental variable (IV) strategy using regional GVC fund density, and alternative model specifications.

Our study contributes to the literature in the following ways: First, this study shifts the focus of the GVC literature from its effects on firms' technological capability and innovation outcomes to its role in shaping firms' *propensity to engage in technology fashion waves*. Rather than examining whether GVC enhances the level of technological development (Colonnelli et al., 2024; Devarakonda & Liu, 2024), we investigate how GVC influences firms' strategic inclination to pursue fashionable, high-uncertainty technologies such as artificial intelligence. By conceptualizing AI as an archetypal technology fashion, our analysis provides large-sample causal evidence that GVC does not merely support innovation ex post, but actively steers firms toward participation in salient technological trajectories. This perspective moves beyond the dominant capability- and resource-based view of GVC (Brander et al., 2015; Zhang & Mayes, 2018) and highlights its influence on firms' innovation orientation and strategic positioning.

Second, we advance a legitimacy-centered explanation of GVC's effects in fashion-driven innovation contexts. Distinct from the conventional view of GVC as a source of certification or endorsement (Beraja et al. 2024; Guerini and Quas 2016; Zhang et al. 2024), we argue that GVC operates as a *behavioral catalyst* that motivates firms to *actively seek legitimacy* by aligning with state-prioritized and socially salient technological fashions. In this sense, GVC does not simply confer legitimacy upon firms; rather, it reshapes firms' incentives and strategic calculus, encouraging them to pursue innovation paths that are perceived as legitimate, future-oriented, and policy-aligned. This reframing redirects attention from how GVC supplies resources to how it induces legitimacy-seeking behavior under conditions of heightened uncertainty.

Third, by embedding this legitimacy-seeking mechanism within a broader institutional framework, we illuminate how the effectiveness of GVC in promoting firms' engagement with technology fashions is contingent on regional institutional conditions. Specifically, we demonstrate that state ownership and regional corruption moderate the relationship between GVC and firms' propensity to pursue fashionable technologies. These findings deepen our understanding of GVC as an institutionally embedded governance mechanism (Bertoni et al., 2019; Douglas, 2006) and show how institutional environments shape whether GVC-driven

legitimacy seeking translates into substantive technological engagement or devolves into symbolic compliance. Collectively, our study offers a more nuanced institutional account of state-led financing in technology fashion waves.

The remainder of the paper proceeds as follows. Section 2 presents the literature review and the development of the research hypotheses. Section 3 details the sample construction, model specification, and variable measurement. Section 4 reports the empirical results of the baseline regressions and discusses the endogeneity and robustness tests. Finally, Section 5 concludes the study.

2. Literature review and hypothesis development

2.1 Technology fashion theory

Fashion is a pervasive phenomenon influencing social and cultural domains such as art, theatre, and apparel. In business, fashion theory initially gained prominence in product marketing. Seymour (2008) argues that fashion dynamics substantially influence the adoption of major consumer products, including electronics, furniture, and automobiles. This logic extends to managerial practices. The rapid proliferation of management theories has led to frequent shifts in organizational focus, with firms often adopting new management techniques in a bandwagon fashion (Abrahamson, 1996). Management fashions—defined as management techniques or ideologies widely perceived as progressive and enthusiastically adopted within a short period (Abrahamson, 1996)—are driven by the interplay between demand for managerial solutions and their supply by consultants, business schools, and media (Abrahamson, 1999). Importantly, fashion dynamics do not merely shape consumption choices; they also influence how organizations interpret uncertainty and make strategic investment decisions.

Building on this foundation, Information Technology (IT) Fashion Theory emerged as a distinct strand (Abrahamson, 1991). An IT fashion is a transitory collective belief that a specific information technology is novel, efficient, and at the forefront of practice. Unlike mature IT innovations, IT fashions are characterized by early-stage diffusion, intense promotion before broad institutionalization, and high uncertainty regarding their long-term viability (Baskerville & Myers, 2009). Scholars argue for treating technology fashions separately from management fashions due to higher switching costs, unique implementation paths, and faster hype cycles associated with technological investments (Fichman, 2004; Wang, 2010; Lee & Collar, 2003). These characteristics make IT fashions particularly consequential for investors, as capital

commitments are often made well before technological viability and commercial value can be credibly assessed.

The investment trajectory of an IT fashion often follows a 'hype cycle' (Fenn & Raskino, 2008; Gartner, 2010), beginning with a technology trigger, rising to a 'peak of inflated expectations' fueled by herd behavior, potentially falling into a 'trough of disillusionment', and, for a select few, eventually reaching a plateau of productivity. This cycle presents firms with a critical strategic dilemma: whether, when, and to what extent to invest in a high-uncertainty innovation that may become a dominant paradigm or a transient fad. Early investment can confer first-mover advantages and legitimacy (Dos Santos & Peffers, 1995; Wang, 2010), but also carries the risk of sunk costs in technologies that fail to mature. Conversely, late adoption risks technological obsolescence and competitive disadvantage (Hoppe, 2000; Stratopoulos & Lim, 2010). Thus, navigating the fashion phase of a technology involves balancing the risks of premature commitment against the costs of being left behind. Yet these strategic trade-offs are rarely made in isolation. External investors, particularly venture capital, play a central role in shaping when and how firms engage with such fashion-driven technologies.

Recent research continues to explore the implications of IT fashions. Studies have examined how association with trendy IT innovations can legitimize firms (Wang, 2010), how to model the risk-return profile of IT fashion investments within innovation portfolios (Fridgen, 2013), and the role of search data and opinion leaders in fueling specific tech trends like big data (Madsen, 2016; Choi & Varian, 2012). Ultimately, while IT innovation is crucial for competitive advantage (Clark & Guy, 1998; Melville et al., 2004), its early 'fashion' stage demands mindful investment strategies that carefully assess the innovation's specific attributes and maturation path (Ramiller, 2004). Unlike mature technologies, IT fashions are often heavily promoted prior to broad institutional acceptance, presenting firms with asymmetric risks. Early adoption may confer legitimacy and competitive advantages, while delayed adoption risks technological obsolescence and strategic disadvantage (Wang, 2010; Stratopoulos and Lim, 2010). Empirical studies further confirm that investment in technology fashions is driven not only by fundamental economic considerations but also by attention dynamics, social contagion, and legitimacy-seeking behavior (Choi & Varian, 2012; Madsen, 2016). However, despite rich insights into attention dynamics and legitimacy-seeking behavior, existing studies have paid limited attention to how different types of institutional investors shape firms' engagement with technology fashions—particularly in state-influenced contexts.

2.2 Venture capital logics in strategic innovation waves

2.2.1 AI as a strategic technology fashion

Research in management and strategy conceptualizes emerging technologies through the lens of technology fashion theory, which emphasizes cycles of heightened attention, speculative investment, and collective sense-making surrounding novel technological paradigms (Abrahamson, 1991; Fenn & Raskino, 2008; Furr, 2021). Within this framework, AI is characterized by elevated expectations, uncertain commercial viability, and long development horizons—features that substantially increase strategic risk and complicate investment decision-making.

AI innovation exhibits several attributes that distinguish it from those of traditional manufacturing and even earlier waves of internet-based innovation (Birkinshaw, 2023). Its development is highly data-intensive, computationally costly, and reliant on sustained iterative experimentation, often with limited short-term commercial feedback. These characteristics raise capital requirements, prolong payback periods, and heighten technological uncertainty, thereby discouraging early-stage investment by purely profit-oriented private venture capital (Kapoor & Lahiri, 2021). At the same time, AI has been elevated to a national strategic priority in many economies, including China, generating strong policy signals and institutional legitimacy that shape investor attention and resource allocation (Hao et al., 2025).

Despite the growing salience of AI, existing research has not systematically examined how different types of venture capital respond to AI as a strategic technology fashion, nor how the broader institutional environment conditions this response. This omission is consequential, as AI embodies precisely the type of high-uncertainty, high-externality innovation for which GVC is theoretically designed to intervene.

2.2.2 Venture capital and startup innovation

An extensive literature establishes VC as a critical institution for alleviating financing constraints and fostering innovation in startups. Beyond capital provision, VCs contribute governance, monitoring, certification, and strategic guidance, reducing information asymmetry and agency costs under uncertainty (Hellmann & Puri, 2000; Puri & Zarutskie, 2012). Research focuses on two stages: selection and post-investment influence. During selection, startups signal quality to attract investment. Patents serve as a salient, verifiable signal of technological capability, significantly increasing funding likelihood (Hsu & Ziedonis, 2013). The application process itself provides updated information for VC assessment (Haeussler et al., 2014), though this signaling value may diminish in later rounds as information asymmetry declines (Hoenen et al., 2014). Post-investment, VCs enhance innovation through several channels. As active

'insiders', they are motivated to increase portfolio value for profitable exits (Barry et al., 1990). Since innovation drives valuation—patent-intensive firms command IPO premiums (Hsu & Ziedonis, 2013)—VCs actively support R&D. Mechanisms include rigorous monitoring and governance (Kaplan & Strömberg, 2001), value-added services like managerial expertise and network access (Sorenson & Stuart, 2001; Hsu, 2006), and screening/coaching to optimize R&D trajectories (Fitza et al., 2009; Lahr & Mina, 2016). Consistent evidence shows VC-backed firms produce more patents and innovation output (Lerner, 2000; Cumming et al., 2016).

However, this established logic largely reflects the incentives of PVC, which prioritizes financial returns and thus favors projects with shorter commercialization horizons, clearer appropriability, and predictable payoff structures (Lerner, 2002). This return-oriented calculus becomes strained in technological domains characterized by extreme uncertainty, long development cycles, and highly skewed returns—precisely the defining attributes of strategic 'technology fashion' waves like AI.[1] Investment at this stage carries significant risks, including potential commercial failure resulting in substantial sunk costs, and the danger of technology lock-in with inferior, transient solutions. Consequently, the profound uncertainty and strategic risk inherent in AI innovation render it a comparatively unattractive domain for conventional, financially-disciplined PVC.

In contrast, GVC operates under a distinct institutional logic, designed to correct such market failures. GVC pursues a dual mandate that balances financial sustainability with public policy objectives, including technological upgrading, industrial transformation, and regional development (Bertoni et al., 2015). This dual mandate aligns with the challenges of AI innovation in three key ways. First, GVC is institutionally incentivized to respond to national strategic priorities. AI's status as a policy cornerstone confers legitimacy and creates a powerful 'strategic pull' for GVC investment, serving as a pragmatic decision heuristic in a complex technical domain. Second, GVC provides patient capital and a higher tolerance for failure, which is essential for AI's long gestation periods and exploratory research (Bertoni & Tykvová, 2015). Third, through its governmental affiliations, GVC can facilitate access to complementary public resources, such as data, application scenarios, and R&D infrastructure, which are critical for AI development. Collectively, these mechanisms lower the barriers for startups to engage in

[1] A contrasting perspective cautions that the observed VC-innovation link may not reflect enhanced technological novelty. Hirukawa & Ueda (2008) find VC backing correlates with patent counts but not with total factor productivity as an alternative innovation metric, suggesting VC may facilitate patent formalization rather than spur fundamentally new technologies. Thus, while the baseline logic is established, VC's net effect in high-uncertainty domains warrants scrutiny.

AI innovation, suggesting that GVC's institutional logic may be particularly suited to financing strategic technology fashions.

To summarize, these literature streams converge to reveal a critical gap in our understanding of state-led investment under technology fashion waves. While prior research has examined how venture capital—and governmental venture capital in particular—affects firms' innovation outcomes, it has paid limited attention to how different types of investors shape firms' propensity to engage with fashionable, high-uncertainty technological trajectories. As a result, we lack a systematic understanding of whether GVC's distinct institutional logic makes it especially influential in steering startups toward participation in technology fashion waves such as AI, rather than merely enhancing innovation performance ex post. Moreover, existing studies rarely consider how the effectiveness of GVC in fashion-driven innovation contexts is contingent on the institutional environments in which it is embedded. Because GVC operates at the intersection of state objectives and market mechanisms, its capacity to motivate firms' legitimacy-seeking behavior—by encouraging alignment with state-prioritized and socially salient technologies—is likely to vary systematically across regions. Yet how regional institutional conditions condition GVC's influence on firms' engagement with technology fashions remains largely unexplored.

To address this gap, we integrate technology fashion theory into our exploration of the relationship between GVC and startup AI innovation. We examine whether and under what institutional conditions GVC most effectively steers startups toward fashionable technological trajectories.

2.3 Hypothesis development

2.3.1 Governmental venture capital and startup AI innovation

We theorize that GVC's distinct institutional logic makes it especially effective at motivating startup firms to engage with strategic technology fashion domains such as artificial intelligence (AI). Unlike PVC, which is primarily driven by short- to medium-term profit expectations and disciplined by market risk-return trade-offs, GVC operates with a dual mandate that explicitly incorporates strategic policy objectives and social value considerations (Cumming et al., 2017). In technology fashion contexts where uncertainty, early hype, and ambiguous profitability elevate the importance of social legitimacy and policy alignment, GVC's institutional embeddedness equips it to catalyze legitimacy-seeking behavior among startups.

First, GVC's heightened responsiveness to national strategic priorities signals policy recognition and institutional endorsement of trendy technologies like AI. By directing capital toward AI in line with publicly articulated strategic agendas, GVC helps startups externalize alignment with socially and politically valued innovation trajectories (Colombo et al., 2016), reinforcing perceived legitimacy in the eyes of stakeholders. This legitimacy effect serves as an influential heuristic that lowers the perceived social and cognitive barriers to pursuing AI innovation.

Second, GVC's provision of patient capital and higher tolerance for exploration and failure aligns with the long development cycles and deep uncertainty characteristic of frontier technologies. AI innovation often involves extended experimentation, data accumulation, and iterative model refinement before commercial viability is demonstrated. GVC's willingness to absorb longer payback horizons (Brander et al., 2015) reduces the downside visibility of engaging in such high-uncertainty innovation and enables startups to persist in early-stage AI experimentation that private investors might avoid.

Third, through its organizational proximity to government and broader public sector networks, GVC can facilitate startup access to complementary public resources (e.g., public infrastructure, regulatory support, data platforms). These affiliations can reduce transaction costs and open doors to institutional actors whose inputs are central to AI development ecosystems, further enhancing the social legitimacy and resource foundation for startup innovation.

In sum, these mechanisms operate through legitimacy-enhancing incentives that make startups more inclined to enter, remain engaged with, and deepen their involvement in AI as a strategic innovation domain. Accordingly, we propose the following hypothesis:

Hypothesis 1 GVC promotes AI innovation in startup firms.

2.3.2 Moderating role of regional institutional environment

Institutional environments exert persistent and systematic influences on firm behavior. Startups, which typically lack internal resources, organizational slack, and political capital, are particularly sensitive to institutional incentives and constraints. Consequently, regional institutional conditions are likely to play a critical moderating role in shaping the extent to which GVC facilitates AI innovation.

State-owned sector dominance. As a state-funded or state-led investment vehicle, GVC is designed to guide market activity and provide risk-bearing support for nationally prioritized emerging industries. In doing so, GVC can leverage political connections and access intangible public resources, reducing institutional and policy-related barriers that typically constrain

young firms (Cumming et al., 2017). The regional share of the state-owned economy captures the mobilizability and coordination capacity of these government-controlled resources, with higher state ownership reflecting an institutional environment characterized by strategic coordination (Hao et al., 2025), where GVC operates as a core component of the national innovation system.

AI, as a technology fashion wave, is characterized by high uncertainty, early-stage hype, and elevated collective expectations (Abrahamson, 1991; Fenn & Raskino, 2008). Its development often requires large-scale deployment scenarios, access to high-quality data, and iterative experimentation before commercial viability is demonstrated. In regions with a dominant state-owned sector, GVC is uniquely positioned to address these challenges. Through embedded state-owned enterprise (SOE) networks, GVC can efficiently connect AI startups with real-world deployment environments and proprietary datasets, while also coordinating upstream and downstream actors across government-affiliated entities. This embeddedness reduces transaction costs, provides institutional legitimacy, and mitigates the social and cognitive barriers associated with investing in a trendy but uncertain technology.

Furthermore, the multi-objective nature of the state-owned system—emphasizing technological self-reliance, industrial security, and societal value alongside financial performance—enhances GVC's capacity to provide patient capital and tolerate the exploratory failures inherent to early-stage AI projects (Bertoni et al., 2019). By absorbing downside risk at the system level while amplifying strategic returns from successful innovation, GVC can sustain engagement with AI despite its high-risk, fashion-driven characteristics.

In sum, these mechanisms collectively reinforce GVC's capacity to promote AI innovation in startup firms. We thus propose the following hypothesis:

Hypothesis 2 The positive effect of GVC on startup AI innovation is strengthened in regions with a higher share of the state-owned economy.

Regional corruption. While GVC's distinct institutional logic equips it to promote AI innovation through legitimacy signaling, patient capital provision, and access to public resources, the effectiveness of these mechanisms depends critically on the regional institutional environment, especially the level of corruption in local governance. AI, as a quintessential technology fashion wave, is characterized by elevated collective expectations, diffuse early signals of promise, and deep uncertainty about eventual viability and commercial payoffs (Abrahamson, 1991; Fenn & Raskino, 2008). In such contexts, legitimacy-seeking behavior becomes a central driver of firms' strategic engagement decisions: startups interpret external endorsements and institutional attention as cues that reduce ambiguity and justify risk-taking.

In regions with low corruption, institutional signals are more credible, transparency is higher, and interactions between public and private actors are more predictable. Under these conditions, GVC investment conveys a strong, unambiguous legitimacy signal about AI's salience as a strategic innovation trajectory, thereby lowering social and cognitive barriers for startups to enter and persist in AI experimentation (Wang, 2010; Colombo et al., 2016). Furthermore, low corruption environments reduce transaction costs and the need for rent-seeking, allowing startups to redirect scarce attention and resources toward productive activities such as AI R&D. In such settings, GVC's patient capital and government network leverage reinforce one another: legitimized by clean institutions, startups gain not only financial slack but also broader institutional support for navigating a fashion-driven technological frontier.

By contrast, in regions with high corruption, the ability of GVC to shape legitimacy perceptions and resource flows is systematically weakened. Opaque regulatory practices and entrenched rent-seeking incentives dilute the informational and social value of GVC backing (Bertoni et al., 2015), as stakeholders may attribute investment decisions to political maneuvering rather than technological promise. High corruption increases uncertainty and compliance costs, leading startups to allocate attention toward navigating informal networks rather than engaging deeply with AI's uncertain yet strategically fashionable opportunities. Under such conditions, even though GVC resources may be deployed, the underlying mechanisms—legitimacy enhancement, patient support, and access to public resources—are compromised, attenuating the net effect of GVC on startup involvement in AI innovation.

Accordingly, regional corruption is expected to systematically moderate the relationship between GVC and AI innovation. We thus propose:

Hypothesis 3 The positive effect of GVC on startup AI innovation is weakened in regions with higher regional corruption.

3. Data and methodology

3.1 Sample construction

We construct our sample by integrating data from CVSource (provided by the Zero2IPO Group), the IncoPat patent database, and the China Stock Market and Accounting Research (CSMAR) database. CVSource is a widely used venture capital database in academic research (Gu and Lu, 2014; Hu et al., 2021; Hao et al., 2025) and provides detailed information on VC institutions—including founding year and ownership structure—as well as investment events (e.g., investment date, financing round, investment amount, and exit status) and startup

characteristics (e.g., founding year, geographic location, and industry classification). Patent data are obtained from IncoPat, which offers comprehensive coverage of patent applications and transfers in China, including detailed patent titles and abstracts. We use these data to identify and measure firm-level AI innovation. Additional firm-level financial variables and macro-level market indicators, such as annual IPO counts, are sourced from CSMAR. We begin with a comprehensive sample of Chinese startups outside the core AI industry that received venture capital funding between 2010 and 2019, a period that coincides with the emergence and rapid expansion of AI-related innovation and venture capital activity in China.[2]

To address potential selection bias arising from non-random GVC investment, we implement PSM prior to DID estimation. As our investment data records only realized GVC deals, the counterfactual—startups evaluated but not funded by GVCs—is unobservable. Ignoring this issue could lead to biased estimates of treatment effects. Following Hao et al. (2025), we approximate the VC investment opportunity set by constructing potential GVC–startup pairings. We implement the matching procedure in three steps. First, we construct a comprehensive potential matching pool. For each GVC institution and each year from 2010 to 2019, we identify all startups founded before that year that had not yet received GVC funding. This generates a GVC-year-startup dataset that reflects the feasible investment opportunities GVCs confronted annually. Second, we perform covariate selection and matching. We include five key VC-level characteristics in the propensity score model: VC age, number of funds under management, VC reputation, an indicator for joint-venture VC status, and VC investment concentration. We implement propensity score matching using a logit model with three nearest neighbors with replacement, imposing a caliper of 0.05. Third, we construct the panel dataset. After matching, we form a firm-year panel, excluding observations prior to a firm's founding to ensure temporal consistency.[3] Following the construction of this matched sample, we implement a staggered DID model to identify the causal effect of GVC investment on AI innovation. Our final matched sample consists of 1,345 unique startups, yielding 6,206 firm-year observations over the period 2010–2019.

[2] The sample period is chosen for two reasons. First, the COVID-19 pandemic in 2020 led to substantial disruptions in venture capital markets, which could confound causal inference. Second, innovation outcomes—particularly patenting activity—exhibit lagged responses to investment. Ending the observation window in 2019 allows for at least four subsequent years to observe patent outputs, thereby capturing longer-term innovation performance.

[3] To validate the matching quality, we assess the balance of covariates between the treated and matched control groups, and find the matched samples exhibit nearly identical distributions of key firm and VC characteristics, confirming that selection bias is substantially mitigated.

3.2 Model specification and variable measurement

In this study, startups receive GVC investments in different years. To identify the causal effect of GVC investment on firm-level AI innovation, we employ a multi-period DID research design. This model leverages the variation in the timing of GVC entry across firms, comparing changes in AI innovation outcomes for treated firms (those receiving GVC) to the contemporaneous changes in non-treated control firms before and after each treatment event. The key identifying assumption is that, absent the GVC investment, the trends in AI innovation for treated and control firms would have evolved in parallel. Accordingly, to test Hypothesis 1, we estimate the following baseline specification:

$$AI_Innovation_{i,t} = \alpha_0 + \beta_1 GVC_Treated_{i,t} + \gamma X_{i,t} + \vartheta_i + \mu_t + \varepsilon_{i,t} \quad (1)$$

where $AI_Innovation_{i,t}$ denotes the forward-looking AI innovation output of firm *i*. It is measured as the natural logarithm of one plus the cumulative number of AI patents filed by startup *i* over the five-year window over the five-year window [*t*, *t*+4]. $GVC_Treated_{i,t}$ is our key treatment variable. It is a binary indicator that switches from 0 to 1 in the year firm *i* receives its first GVC investment and remains 1 for all subsequent years. This variable is set to 0 for all firm-years for firms that never receive GVC; $X_{i,t}$ is a vector of time-varying control variables that may influence both the propensity to receive GVC and innovation outcomes; ϑ_i and μ_t represent firm and year fixed effects, respectively. The firm fixed effects control for all time-invariant unobserved heterogeneity across firms, while the year fixed effects absorb common macroeconomic shocks affecting all firms; and $\varepsilon_{i,t}$ is the error term.

To test the contingent effects hypothesized in H2 and H3, we extend our baseline DID model. We propose that the impact of GVC investment on startup AI innovation is not uniform but is systematically moderated by the institutional context of the firm's location. Specifically, we examine whether the treatment effect is amplified in regions characterized by greater state-owned sector dominance (H2) or lower regional corruption (H3). To test these contingent relationships, we augment our DID framework by introducing regional-level moderators and their interaction with the treatment indicator. For each hypothesis, we estimate the following moderated specification:

$$AI_Innovation_{i,t} = \alpha_0 + \beta_1 GVC_Treated_{i,t} + \delta_1 \phi_{i,t} + \delta_2 (GVC_Treated_{i,t} \times \phi_{i,t}) + \gamma X_{i,t} + \vartheta_i + \mu_t + \varepsilon_{i,t}$$

where $\phi_{i,t}$ denotes the moderating variable measured at the regional level. The interaction term captures how institutional conditions condition the effect of GVC on AI innovation. All continuous moderators are mean-centered prior to interaction to facilitate interpretation.

Our dependent variable, *AI_Innovation*, captures a startup's forward-looking AI innovation output. For firm *i* in year *t*, it is measured as the natural logarithm of one plus the cumulative number of AI-related patent applications filed over the five-year window from year t to $t+4$. Identifying AI-related inventions in startups presents distinct challenges, as these firms typically produce fewer and more focused patents. Following Miric et al. (2023) and the conceptual definition of AI innovation in Cockburn et al. (2018), we implement a supervised machine learning framework—specifically, a random forest algorithm—to classify AI-related patents at the firm level. This approach enhances classification accuracy and scalability, making it particularly suitable for analyzing AI innovation in startups within large panel datasets. It overcomes limitations inherent in composite indices designed for regional studies, as well as the scalability constraints of keyword-based or survey-based firm-level measures.[4] To account for the development lag characteristic of early-stage R&D, we construct a forward-looking measure: for each startup in year *t*, *AI_Innovation* is defined as the natural logarithm of one plus the cumulative number of AI patents filed over the subsequent five-year window [*t*, *t*+4], consistent with Hall and Harhoff (2012).

Our primary explanatory variable, $GVC_Treated_{i,t}$, is a binary indicator for whether firm *i* has received an investment from a GVC fund by year *t*. The identification of GVC funds follows the classification in Chen et al. (2021). For a treated firm, the indicator switches from 0 to 1 in the fiscal year of the first GVC investment and remains 1 for all subsequent years; it is set to 0 for all firm-years for firms that never receive GVC.

We investigate two key regional institutional factors posited to condition the relationship between GVC infusion and startup AI innovation. Both are measured at the provincial level and lagged by one year ($t-1$) in our regressions. *State_Owned_Asset* captures the share of the state-owned sector in the regional economy. Following prior studies, we measure it as the proportion of total fixed asset investment in a province contributed by state-owned and state-holding enterprises. *Regional_Corruption* is a proxy for regional governance quality. We construct an inverse measure as the number of duty-related crime cases per 10,000 public officials in the province. Consequently, a higher value of this index indicates higher regional corruption.

[4] Existing studies at the national or regional level construct composite AI development indices using methods such as entropy weighting, DEA, PCA, or G1 CRITIC models (e.g., Qiao, 2023; Chen et al., 2023; Li et al., 2022; Zhou et al., 2023; Li et al., 2023; Luo et al., 2023). These approaches typically focus on infrastructure, policy, human capital, or industrial development and are ill suited for firm level analysis. Firm level studies often rely on single dimension proxies, such as keyword frequencies related to automation or AI adoption (Dauth and Findeisen, 2017) or survey based measures of AI equipment usage (Fujii, 2018). However, keyword based approaches are sensitive to dictionary construction and difficult to scale accurately, while survey data are rarely available for large samples.

To address potential confounding factors and strengthen causal identification, our empirical specification incorporates a comprehensive set of control variables that could jointly influence both the probability of receiving GVC funding and subsequent innovation performance. These controls span venture capital characteristics, investment strategy metrics, and startup market conditions. At the VC level, we control for key characteristics including: the VC firm's experience (*VC_Age*), its status as a Sino-foreign joint venture (*Joint_VC*), its market reputation based on a top 50 industry ranking (*VC_Reputation*), and its track record of successful exits in the relevant industry (*IPO_Experience*). We further account for strategic and network dimensions, including: the VC's prominence within syndication networks (*VC_Network_Centrality*), its experiential depth in the focal startup's industry (*Industry_Focus*), its financial commitment to the focal startup's industry (*Industry_Capital_Intensity*), the diversification of its overall investment portfolio (*Investment_Diversification*), and its propensity for early-stage investment (*Early_Stage*). At the startup's market level, we control for local competitive intensity using a Herfindahl–Hirschman Index (HHI) measured at the industry-province level (*Market_Competition*), where higher values indicate greater market concentration and reduced competition in the startup's primary operating environment. These controls help isolate the effect of GVC from other observable factors that could otherwise drive observed differences in startup AI innovation outcomes.

4. Empirical results

4.1 Descriptive statistics

Table 1 reports the descriptive statistics, including the mean, standard deviation, minimum value, and maximum value of the main variables. The table provides an overview of the distributional characteristics of the data and offers a preliminary understanding of the variation across firms and over time.

Our key dependent variable, *AI_Innovation*, has a mean of 0.262, indicating moderate but varied AI-related patenting activity across firms. The treatment variable, *GVC_Treated*, shows that approximately 14.5% of the firm-year observations correspond to startups that received funding from governmental venture capital. All moderating and control variables exhibit reasonable variation, supporting the feasibility of subsequent multivariate and quasi-experimental analysis.

------ Please insert Table 1 here------

Table 2 reports the correlation matrix for the variables used in the regression analysis. The majority of correlation coefficients are well below 0.6 in absolute magnitude. The strongest observed correlation is -0.876 between *State_Owned_Asset* and *Industry_Capital_Intensity*. To formally assess potential multicollinearity, we compute variance inflation factors (VIFs) for the baseline specifications reported in Table 3. In all models, the maximum VIF value remains below the conventional threshold of five, indicating that multicollinearity does not pose a material threat to the precision or interpretation of our coefficient estimates (Snee & Marquardt, 1984).

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4.2 Baseline results

To test Hypothesis 1, which posits that GVC fosters startup innovation in artificial intelligence, we estimate a series of baseline regression models. The dependent variable is our primary measure of startup AI innovation (*AI_Innovation*).

Table 3 presents the results.[5] Column (1) reports estimates from a model with firm and year fixed effects but no other controls. The coefficient on the GVC treatment indicator (*GVC_Treated*) is positive and statistically significant (0.067, $p<0.01$), indicating a strong unconditional relationship. Column (2) introduces a full set of VC- and startup-level controls, but omits fixed effects. In this specification, the *GVC_Treated* coefficient becomes substantially larger (0.567, $p<0.01$). The low R^2 in the pooled OLS specification suggests that time-invariant firm heterogeneity explains most of the variation in AI innovation, justifying our fixed-effects approach. Column (3) includes both the full set of controls and firm and year fixed effects. This approach isolates within-firm variation over time while accounting for observable firm characteristics. Here, the coefficient on *GVC_Treated* remains positive and significant (0.059, $p<0.05$), with a magnitude smaller than that in Column (1). The adjusted R^2 rises sharply to 0.891, indicating that the model explains nearly all systematic variation in the dependent variable.

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The stability and significance of the *GVC_Treated* coefficient across specifications, particularly in the rigorous fixed-effects model in Column (3), provide robust support for Hypothesis 1. The results suggest that, after controlling for firm-specific time-invariant factors,

[5] To mitigate the influence of outliers, we re-estimate our baseline regressions with all continuous variables winsorized at the 1st and 99th percentiles. The results are quantitatively and statistically consistent with our main findings. This confirms that our core results are not sensitive to extreme observations.

year effects, and relevant observables, startups receiving GVC funding achieve significantly higher AI innovation output compared to the control group. This finding underscores the role of GVC as a catalyst for innovation in the strategic field of artificial intelligence.

4.3 Regional institutional environment interaction

Next, we analyze how the regional institutional environment moderates the relationship between GVC and startup AI innovation by estimating the models specified in Hypotheses 2 and 3.

Table 4 presents the results of these moderation analyses. We first examine the moderating effect of the regional state-owned economy share (Hypothesis H2). As shown in Column (1) of Table 4, the coefficient on the interaction term between *GVC_Treated* and *State_Owned_Asset* is positive and statistically significant at the 1% level (0.053, $p < 0.05$). This suggests that the positive impact of GVC on AI innovation is amplified in regions with a larger state-owned sector. Consistent with Hypothesis H2, we conclude that the presence of a state-coordinated economic structure enhances the AI innovation-promoting effect of GVC. In such regions, the institutional environment features greater state-led economic coordination and resource mobilization capacity. GVC-backed startups can more effectively leverage embedded networks with SOEs to access complementary assets critical for AI development—such as proprietary data, large-scale deployment scenarios, and public R&D infrastructure. Furthermore, the multi-objective logic of the state-owned system, which tolerates longer payback horizons and exploratory failure, aligns with and reinforces GVC's provision of patient capital.

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We then investigate the moderating effect of regional corruption (Hypothesis H3). The results are presented in Column (2) of Table 4. The coefficient on the interaction term between *GVC_Treated* and *Regional_Corruption* is negative and statistically significant (-0.049, $p < 0.01$). Since a higher index value denotes higher corruption, this negative interaction implies that the positive effect of GVC is weaker in more corrupt environments. Consistent with Hypothesis H3, this finding suggests that the positive effect of GVC on AI innovation is attenuated in more corrupt institutional environments. High corruption engenders opacity, increases transactional uncertainty, and distorts resource allocation away from productive innovation activities toward rent-seeking (Shleifer & Vishny, 1993). In such contexts, the legitimacy signal conveyed by GVC backing is diluted, as stakeholders may attribute the investment to political maneuvering rather than technological merit. Moreover, the transaction costs associated with navigating a corrupt bureaucracy divert managerial attention and scarce

resources from substantive R&D efforts. Consequently, while GVC may still provide capital, its core mechanisms for promoting AI innovation—legitimacy enhancement, patient capital, and facilitated access to public resources—are systematically undermined by poor governance quality.

Finally, Column (3) of Table 4 reports the full model incorporating both moderators simultaneously. The coefficient on the *GVC_Treated* indicator remains positive and significant (0.054, $p < 0.05$). Both interaction terms retain their expected signs and statistical significance (*GVC*×*State_Owned_Asset*: 0.043, $p < 0.1$; *GVC*×*Regional_Corruption*: -0.039, $p < 0.05$). The stability of these results confirms that the two institutional dimensions—state sector dominance and corruption—exert distinct and robust conditioning effects on GVC's efficacy. They demonstrate that the innovation-enhancing effect of GVC is not uniform but is systematically shaped by the regional institutional environment, being stronger in contexts characterized by greater state-led economic coordination and higher institutional transparency.

4.4 Robustness tests

4.4.1 Parallel trends test

A valid DID design requires that the parallel trends assumption holds: absent the GVC infusion, the evolution of AI innovation in treated and control firms would have followed similar paths. To test this assumption and trace the dynamic treatment effects, we estimate a dynamic event-study model. We modify our baseline specification by replacing the post-investment indicator with a series of event-time dummies centered on the year of the initial GVC investment ($t = 0$). The year immediately prior to investment ($t = -1$) serves as the omitted benchmark. The specification is as follows:

$$AI_Innovation_{i,t} = \alpha + \sum_{\substack{k=-4 \\ k\neq -1}}^{4} \beta_k \cdot GVC\,{}^{k}_{i,t+k} + \gamma X_{i,t} + \vartheta_i + \mu_t + \varepsilon_{i,t} \qquad (3)$$

where $AI_Innovation_{i,t}$ is, as defined in Section 3.2, the natural logarithm of one plus the cumulative number of AI patents filed by firm *i* over the five-year window [*t*,*t*+4]. $GVC\,{}^{k}_{i,t+k}$ is an indicator equal to one if firm *i* is observed *k* years before ($k < 0$) or after ($k \geq 0$) its initial GVC investment in year *t*, and zero otherwise. The parallel trends assumption would be supported if the pre-treatment coefficients β_{-4} through β_{-2} are statistically indistinguishable from zero. We then estimate the model and plot the coefficients with confidence intervals, as shown in Fig.1, where the x-axis denotes event time and the y-axis reports the estimated coefficients. The event-study plot reveals a pattern consistent with a valid DID design. All pre-

treatment coefficients are statistically insignificant, confirming no systematic divergence in AI innovation trends prior to the GVC investment. Following the treatment, the coefficients turn positive, statistically significant, and exhibit an increasing trajectory over time. This clear temporal pattern—null effects before the event and a positive response after—provides strong evidence in favor of the parallel trends assumption and bolsters a causal interpretation of the GVC treatment effect on AI innovation.

------Please insert Figure 1 here------

4.4.2 Placebo test

A key threat to our causal interpretation is that the observed positive relationship between GVC investment and startup AI innovation could be driven by pre-existing, unobserved trends rather than the treatment itself. To rule out this alternative explanation, we conduct a placebo test by artificially advancing the treatment timing. Specifically, we create two false treatment indicators: *GVC_Treated (1-Year Lead)* and *GVC_Treated (2-Year Lead)*. These indicators are set to one in the year before (or two years before) the actual GVC investment occurs, and remain one thereafter for the treated firms. They are always zero for control firms. If the observed increase in startup AI innovation is genuinely attributable to GVC, then there should be no significant divergence in startup innovation outcomes between treatment and control firms in these falsified pre-event periods. Conversely, significant coefficients would indicate that the post-GVC surge in startup AI innovation cannot be causally linked to the treatment. Statistically, we therefore anticipate an insignificant coefficient on the placebo treatment indicator.

The results, presented in Table 5, align with the causal interpretation: the coefficients on both the one-year lead (0.009) in Column (1) and the two-year lead (-0.032) in Column (2) are statistically insignificant. from zero. Consequently, the placebo test affirms that our baseline estimates are unlikely to be confounded by pre-trends, strengthening the causal interpretation that GVC infusion fosters startup AI innovation.

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4.4.3 Two-stage least squares (2SLS) instrumental variable analysis

To address potential endogeneity—specifically, omitted firm-level variables and reverse causality—we estimate an instrumental variable (IV) model via two-stage least squares (2SLS). We instrument the GVC treatment indicator, $GVC_Treated_{i,t}$ with the contemporaneous number of GVC funds operating in startup *i*'s home province. This instrument leverages plausibly exogenous regional variation in GVC supply, which influences a startup's likelihood of receiving funding (satisfying the relevance condition) but is unlikely to be directly correlated

with its idiosyncratic startup AI innovation trajectory after conditioning on firm-level controls and fixed effects (thereby satisfying the exclusion restriction).

Table 6 presents the results of the two-stage least squares (2SLS) regressions. Column (1) shows the estimates for the first-stage regression in which the dependent variable is *GVC_Treated* indicator and the instrument is the raw count of GVC funds in startups' home province (*GVC_Fund_Count*). Columns (2) presents the corresponding second-stage results, where the dependent variable is our measure of startup *AI_Innovation*. Two concerns with 2SLS are (1) the potential for weak instrument and (2) correlation between the instrument and regression error term (i.e., overidentification). The first-stage *Cragg-Donald F-statistics* (21.61) exceed the Stock and Yogo (2005) threshold of 16.38, indicating that our instrument is not weak. The second-stage coefficient on $GVC_Treated_{i,t}$ is 3.255 and statistically significant at the 1% level. This estimate is directionally consistent with and quantitatively similar to our baseline DID coefficient, confirming a positive causal effect of GVC investment on startup AI innovation. Collectively, the IV analysis corroborates our main findings and mitigates concerns that they are driven by severe endogeneity.

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4.4.4 Alternative models with negative binomial and logistic regressions

Our baseline analysis employs the natural logarithm of AI patent counts as the primary innovation measure. To ensure our results are not driven by functional form assumptions or the treatment of zero-valued outcomes, we conduct robustness checks using two alternative model specifications.

Table 7 presents the results. In column (1), we re-estimate our model using a negative binomial regression with the raw count of AI patents as the dependent variable. The descriptive statistics indicate substantial overdispersion in the patent count distribution, with the variance (0.821) markedly exceeding the mean (0.262). This pattern violates the equidispersion assumption of the standard Poisson model. We therefore estimate a negative binomial regression model using *AI_Innovation_Count*, the cumulative number of AI patents filed to a startup within the five-year window following potential GVC investment—as the dependent variable. This model explicitly accounts for overdispersion in the count data by incorporating a gamma-distributed error term with variance α. As reported in Column (1), the dispersion parameter (*lnAlpha*) is positive and significant ($p < 0.01$), validating our choice of this model. The coefficient on the GVC treatment indicator remains positive and significant, with an economic magnitude similar to our baseline estimate. In column (2), to examine the impact of GVC funding on the extensive margin of innovation—the probability of a startup achieving any

AI innovation—we transform our dependent variable. We construct a binary indicator, *AI_Innovator*, which equals one if a startup is filed one or more AI patents within the five-year window following potential GVC funding, and zero otherwise. We then estimate a logistic regression model. As shown in Column (2), the coefficient on the GVC treatment indicator remains positive and statistically significant (0.556, $p<0.01$). The associated average marginal effect indicates that receiving GVC funding increases a startup's probability of becoming an AI innovator.

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These specifications include the same set of controls and fixed effects as our baseline regression. We do not include firm fixed effects in these maximum likelihood models to avoid the incidental parameters problem (Greene, 2004) and to ensure model convergence, following recent practice in the literature (Dutordoir et al., 2024). Collectively, the consistent, positive, and significant coefficients across linear, negative binomial, and logistic specifications—using both continuous and binary innovation measures—provide robust evidence that GVC investment substantively promotes startup AI innovation. These results confirm that our core findings are not sensitive to distributional assumptions or the specific operationalization of the innovation outcome.

4.5 Heterogeneity analysis

While our baseline results establish an average treatment effect of GVC on startup AI innovation, the magnitude and significance of this relationship may vary systematically across different venture capital characteristics and market environments. To explore such heterogeneity, we conduct cross-sectional analyses in terms of multiple dimensions derived from our variable set: VC investment specialization, syndicate structure, exit track record, and temporal market evolution. We present the estimation results in Table 8.

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4.5.1 Venture capital industry focus

We first examine whether the degree of a VC's industry specialization moderates the innovation impact of GVC collaboration. Specialized VCs, with concentrated portfolios, possess deep technical expertise and sector-specific networks (Gompers et al., 2005). This existing capability may either substitute for or synergize with the unique institutional resources provided by GVCs. The results, presented in Columns (1) and (2) of Table 8, reveal a pronounced asymmetry. The positive effect of GVC is economically substantial and statistically significant only for startups backed by low-focus (more diversified) VCs ($\beta = 0.153$, $p < 0.01$).

In contrast, the coefficient for startups backed by high-focus (specialized) VCs is negligible and statistically indistinguishable from zero (β = 0.031). This pattern suggests a complementarity between GVC's institutional resources and the generalist nature of low-focus VCs. For diversified VCs, GVC partnerships provide critical, non-redundant assets—policy navigation and public-sector connectivity—that compensate for their lack of deep industry-specific knowledge, thereby significantly enhancing their portfolio companies' innovation capacity. Conversely, for specialized VCs, whose value proposition is already built on technical expertise and sectoral networks, the marginal value added by GVC's institutional resources appears limited. This finding indicates potential diminishing returns or even substitution between private and public forms of specialized support.

4.5.2 Venture capital exit experience

We next investigate whether a VC's track record of successful exits conditions the GVC effect. VCs with established IPO experience possess superior exit networks, investor credibility, and market-timing capabilities. These private-sector advantages may interact with GVC's institutional resources in distinct ways: experienced VCs may leverage GVC partnerships for strategic regulatory navigation and public-market access, while less-experienced VCs may rely more fundamentally on GVC for legitimacy, certification, and procedural oversight. The results, presented in Columns (3) and (4) of Table 8, show that the innovation-promoting effect of GVC is concentrated among startups backed by VCs with low IPO experience (β= 0.094, $p < 0.05$). In contrast, the effect is negligible and statistically insignificant for startups backed by VCs with high IPO experience (β = 0.008). This pattern is consistent with an institutional mentorship hypothesis. For novice VCs, a GVC partnership provides critical certification and facilitates access to regulatory and bureaucratic knowledge, thereby accelerating their learning curve and enhancing their ability to support portfolio companies in navigating the uncertain AI landscape. For experienced VCs, who already possess established reputations and sophisticated support infrastructures, the marginal value of GVC's additional certification and guidance appears limited, suggesting either diminishing returns to institutional endorsement or a strategic focus on different value-adding activities.

4.5.3 Temporal evolution: 2010-2014 versus 2015-2019

Finally, we examine whether the effect of GVC evolved as China's innovation ecosystem and AI policy framework matured over the sample period. Columns (5) and (6) of Table 8 compare estimates from the early (2010–2014) and late (2015–2019) sub-periods. The results reveal a marked temporal shift: the GVC effect is statistically indistinguishable from zero in the earlier years (β = 0.030) but becomes economically meaningful and highly significant in the

later period (β = 0.100, p < 0.01). This pattern suggests substantive institutional and programmatic learning. Initial GVC initiatives may have been less targeted, with less refined selection criteria and weaker post-investment governance. By the latter half of the 2010s, GVC programs likely benefited from accumulated operational experience, clearer performance metrics, and stronger alignment with a maturing national AI strategy (Lerner, 2002). Concurrently, the AI innovation landscape itself grew more technically complex and capital-intensive, raising the marginal value of the patient, strategically-aligned capital that GVC provides. The increasing efficacy of GVC over time thus reflects a co-evolution of state financing instruments and the technological frontier they are designed to advance.

5. Conclusions and discussion

AI, as a quintessential 'technology fashion', presents a profound strategic dilemma for investors. It resides at the 'peak of inflated expectations' in its hype cycle, where investment is characterized by extreme uncertainty regarding its ultimate commercial viability and the risk of costly technological lock-in. This high-risk profile, combined with the technology's capital intensity and long development horizon, misaligns with the financial-return calculus of PVC, which favors projects with clearer appropriability and shorter payoff timelines. This misalignment creates a financing gap for early-stage AI innovation. We theorize that GVC is uniquely positioned to address this gap, not as a homogeneous actor, but through mechanisms activated by the specific context of a strategic technology wave.

This study analyzes the effects of GVC on startup AI innovation using a sample of Chinese startups. A key feature of our design is the integration of a quasi-natural experiment (the staggered rollout of GVC programs) with institutional moderators, allowing us to isolate causal effects and examine their boundary conditions.

This study makes a unified contribution to the literature on governmental venture capital, innovation strategy, and technology fashion (Brander et al., 2015; Colonnelli et al., 2024; Devarakonda & Liu, 2024; Zhang & Mayes, 2018). Rather than examining how GVC affects the level of technological capability or innovation output, we show that GVC fundamentally shapes firms' propensity to engage in fashionable, high-uncertainty technological trajectories. Using AI as an archetypal technology fashion wave, our findings demonstrate that GVC operates not merely as a provider of financial resources or technological support, but as an

institutionally embedded force that redirects firms' strategic attention toward state-prioritized and socially salient innovation domains. This influence works through a legitimacy-seeking channel: GVC motivates firms to actively pursue legitimacy by aligning with dominant technological narratives, rather than passively benefiting from state endorsement. Moreover, we reveal that this GVC-induced legitimacy-seeking behavior is highly contingent on regional institutional conditions. Stronger state ownership and lower regional corruption condition whether GVC-driven engagement with technology fashions translates into substantive technological participation rather than symbolic compliance. By integrating technology fashion theory with an institutional perspective on state-led finance, this study advances a more nuanced understanding of how governments shape firms' innovation orientation in periods of heightened technological uncertainty.

Our findings offer clear, policy-relevant implications for the design and implementation of GVC programs. Crucially, the innovation-enhancing effect of GVC is contingent on institutional context. Policymakers should, therefore, prioritize improving regional governance quality—through transparent, market-based investment mechanisms and strong anti-corruption safeguards—to mitigate resource misallocation. In parallel, programs can be tailored to leverage local economic structures; in regions with a significant state-owned sector, GVC should be strategically deployed to facilitate resource synergies, such as by granting portfolio firms access to public data, application scenarios, and R&D infrastructure. This shift from a purely financial intermediary to an orchestrator of innovation ecosystems can substantially increase the efficacy of public capital in fostering strategic, long-horizon technologies like AI.

Overall, our study underscores that GVC's role in fostering innovation is not uniform but critically dependent on both the technological domain and the institutional context. For policymakers, this implies that designing effective GVC programs requires alignment with local institutional conditions and strategic integration into broader innovation ecosystems. For scholars, we highlight the importance of moving beyond average treatment effects to examine how institutional and technological contingencies moderate state investment outcomes. Future research could extend this line of inquiry through cross-country comparisons, dynamic analysis of institutional evolution, and richer measurement of AI innovation outputs.

References

Abrahamson E (1991) Managerial fads and fashions: the diffusion and rejection of innovations. Acad Manag Rev 16(10):586–612.

Abrahamson E, Fairchild G (1999) Management fashion: lifecycles, triggers, and collective learning processes. Adm Sci Q 44:708–740.

Barry CB, Muscarella CJ, Peavy JW III, Vetsuypens MR (1990) The role of venture capital in the creation of public companies: evidence from the going-public process. J Financ Econ 27(2):447–471.

Baskerville RL, Myers MD (2009) Fashion waves in information systems research and practice. MIS Q 33:647–662.

Baum JAC, Calabrese T, Silverman BS (2000) Don't go it alone: alliance network composition and startups' performance in Canadian biotechnology. Strateg Manag J 21(3):267–294.

Baumol WJ, Strom RJ (2007) Entrepreneurship and economic growth. Strateg Entrep J 1(3/4):233–237.

Benders J, Nijholt J, Heusinkveld S (2006) Using print media indicators in management fashion research. Qual Quant 41(6):815–829.

Beraja M, Peng W, Yang DY, Yuchtman N (2024) Government as venture capitalists in AI. NBER Working Paper No. w32701.

Bertoni F, Colombo MG, Quas A (2015) The patterns of venture capital investment in Europe. Small Bus Econ 45:543–560.

Bertoni F, Colombo MG, Quas A (2019) The role of governmental venture capital in the venture capital ecosystem: an organizational ecology perspective. Entrep Theory Pract 43(3):611–628.

Bertoni F, Tykvová T (2015) Does governmental venture capital spur invention and innovation? Evidence from young European biotech companies. Res Policy 44(4):925–935.

Birkinshaw J (2023) How incumbent firms respond to emerging technologies: comparing supply-side and demand-side effects. Calif Manag Rev 66(1):48–71.

Boasson V, Boasson E (2015) Firm value, spatial knowledge flow, and innovation: evidence from patent citations. China Finance Rev Int 5:132–160.

Bowen HP, Clercq DD (2008) Institutional context and the allocation of entrepreneurial effort. J Int Bus Stud 39(4):747–767.

Brander JA, Amit R, Antweiler W (2010) Venture-capital syndication: improved venture selection vs. the value-added hypothesis. J Econ Manag Strateg 11(3):423–452.

Brander JA, Du Q, Hellmann T (2015) The effects of government-sponsored venture capital: international evidence. Rev Finance 19(2):571–618.

Dos Santos BL, Peffers K (1995) Rewards to investors in innovative information technology applications: first movers and early followers in ATMs. Organ Sci 6(3):241–259.

Brickley JA, Smith CW, Zimmerman JL (2010) Management fads and organizational architecture. Soc Sci Electron Publ 10(2):24–39.

Brown SL, Eisenhardt KM (1997) The art of continuous change: linking complexity theory and time-paced evolution in relentlessly shifting organizations. Adm Sci Q 42:1–34.

Chen J, Chen T, Song Y, Xu L (2021) A dataset on affiliation of venture capitalists in China between 2000 and 2016. Sci Data 8(1):201.

Chen Y, Xu S, Lyulyov O, Pimonenko T (2023) China's digital economy development: incentives and challenges. Technol Econ Dev Econ 29(2):518–538.

Cho TS, Hambrick DC (2006) Attention as the mediator between top management team characteristics and strategic change: the case of airline deregulation. Organ Sci 17(4):453–469.

Choi H, Varian H (2016) Predicting the present with Google Trends. Econ Rec 88:2–9.

Claessens S, Feijen E, Laeven L (2008) Political connections and preferential access to finance: the role of campaign contributions. J Financ Econ 88(3):554–580.

Clark J, Guy K (1998) Innovation and competitiveness: a review. Technol Anal Strateg Manag 10(3):363–395.
Cockburn IM, Henderson R, Stern S (2018) The impact of artificial intelligence on innovation. NBER Working Paper No. w24449.
Colombo MG, Cumming DJ, Vismara S (2016) Governmental venture capital for innovative young firms. J Technol Transf 41:10–24.
Colonnelli E, Li B, Liu E (2024) Investing with the government: a field experiment in China. J Polit Econ 132(1):248–294.
Correia S (2015) Singletons, cluster-robust standard errors and fixed effects: a bad mix. Working Paper, http://scorreia.com/research/singletons.pdf.
Cumming D, Henriques I, Sadorsky P (2016) 'Cleantech' venture capital around the world. Int Rev Financ Anal 44:86–97.
Cumming D, Meoli M, Vismara S (2019) Investors' choices between cash and voting rights: evidence from dual-class equity crowdfunding. Res Policy 48(8):103740.
Dauth W, Findeisen S, Südekum J, Woessner N (2017) German robots-the impact of industrial robots on workers. IZA Discussion Paper No. 10776.
David A, Nadler D, et al (1999) The organization of the future: strategic imperatives and core competencies for the 21st century. Organ Dyn 28(1):45–60.
DiMaggio PJ, Powell WW (1983) The iron cage revisited: institutional isomorphism and collective rationality in organizational fields. Am Sociol Rev 48(2):147–160.
Douglas C (2006) Government policy towards entrepreneurial finance: innovation investment funds. J Bus Venturing 22(2):193–235.
Duriau VJ, Reger RK, Pfarrer MD (2007) A content analysis of the content analysis literature in organization studies: research themes, data sources, and methodological refinements. Organ Res Methods 10(1):5–34.
Dutordoir M, Li S, Neto JQF (2024) Issuer motivations for corporate green bond offerings. Br J Manag 35(2):952–973.
Dutta N, Sobel R (2016) Does corruption ever help entrepreneurship? Small Bus Econ 47(1):179–199.
Ettorre B (1997) What's the next business buzzword? Manag Rev 86(2):33–36.
Fenn J, Raskino M (2008) Mastering the hype cycle: how to choose the right innovation at the right time. Harv Bus Rev 34(2):63–85.
Fichman RG (2004) Real options and IT platform adoption: implications for theory and practice. Inf Syst Res 15(2):132–154.
Fichman RG, Carroll WE (2017) Going beyond the dominant paradigm for information technology innovation research: emerging concepts and methods. J Assoc Inf Syst 15(2):132–154.
Fitza M, Matusik SF, Mosakowski E (2009) Do VCs matter? The importance of owners on performance variance in start-up firms. Strateg Manag J 30(4):387–404.
Fridgen G, Moser F (2013) Using IT fashion investments to optimize an IT innovation portfolio's risk and return. J Decis Syst 22:298–318.
Fujii H, Managi S (2018) Trends and priority shifts in artificial intelligence technology invention: a global patent analysis. Econ Anal Policy 58:60–69.
Furr NR (2021) Technology entrepreneurship, technology uncertainty. In: Furr NR, Gawer A, George G, et al (eds) Strategic management: state of the field and its future. Oxford University Press, Oxford, pp 205–224.
Gompers P, Kovner A, Lerner J, Scharfstein D (2008) Venture capital investment cycles: the role of experience and specialization. *J Financ Econ* 81(1), 649-679.
Greene W (2004) Fixed effects and bias due to the incidental parameters problem in the Tobit model. Econom Rev 23(2):125–147.
Grilli L, Murtinu S (2014) Government, venture capital and the growth of European high-tech

entrepreneurial firms. Res Policy 43(9):1523–1543.
Gu Q, Lu X (2014) Unraveling the mechanisms of reputation and alliance formation: a study of venture capital syndication in China. Strateg Manag J 35(5):739–750.
Guerini M, Quas A (2016) Governmental venture capital in Europe: screening and certification. J Bus Venturing 31(2):175–195.
Guler I (2007) Throwing good money after bad? Political and institutional influences on sequential decision making in the venture capital industry. Adm Sci Q 52(2):248–285.
Haeussler C, Harhoff D, Mueller E (2014) How patenting informs VC investors—the case of biotechnology. Res Policy 43(8):1286–1298.
Hall BH, Harhoff D (2012) Recent research on the economics of patents. Annu Rev Econ 4(1):541–565.
Hall PA, Taylor RCR (1996) Political science and the three new institutionalisms. Polit Stud 44(5):936–957.
Hao B, Feng Y, Tan H, Li X (2025) Taking a second look at the bait: attention to upside potential versus downside risk in venture capitalists' staged investment. Entrep Theory Pract 49(1):283–311.
Hellmann T, Puri M (2002) Venture capital and the professionalization of start-up firms: empirical evidence. J Finance 57(1):169–197.
Hirukawa M, Ueda M (2008) Venture capital and innovation: which is first? Pac Econ Rev 13(4):421–465.
Hochberg YV, Ljungqvist A, Lu Y (2007) Whom you know matters: venture capital networks and investment performance. J Finance 62(1):251–301.
Hoenen S, Kolympiris C, Schoenmakers W, Kalaitzandonakes N (2014) The diminishing signaling value of patents between early rounds of venture capital financing. Res Policy 43(6):956–989.
Hoppe HC (2000) Second-mover advantages in the strategic adoption of new technology under uncertainty. Int J Ind Organ 18(2):315–338.
Hsu DH (2006) Venture capitalists and cooperative start-up commercialization strategy. Manag Sci 52(2):204–219.
Hsu DH, Ziedonis RH (2013) Resources as dual sources of advantage: implications for valuing entrepreneurial-firm patents. Strateg Manag J 34(7):761–781.
Hu S, Gu Q, Xia J (2021) Problemistic search of the embedded firm: the joint effects of performance feedback and network positions on venture capital firms' risk taking. Organ Sci 33(5):1889–1908.
Huang DX, Chan RCK (2018) On 'land finance' in urban China: theory and practice. Habitat Int 82:96–104.
Gartner (2010) Gartner's 2009 hype cycle special report evaluates maturity of 1,650 technologies. Gartner Research Report.
Ireland RD, Hitt MA, Sirmon DG (2003) A model of strategic entrepreneurship: the construct and its dimensions. J Manag 29(6):963–989.
Kaplan S (2008) Cognition, capabilities, and incentives: assessing firm response to the fiber-optic revolution. Acad Manag J 51(4):672–695.
Kaplan SN, Strömberg P (2001) Venture capitalists as principals: contracting, screening, and monitoring. Am Econ Rev 91(2):426–430.
Kapoor R, Klueter T (2021) Unbundling and managing uncertainty surrounding emerging technologies. Strategy Sci 6(1):62–74.
Katila R, Ahuja G (2002) Something old, something new: a longitudinal study of search behavior and new product introduction. Acad Manag J 45(6):1183–1194.
Kogan L, Papanikolaou D, Seru A, Stoffman N (2017) Technological innovation, resource allocation, and growth. Q J Econ 132(2):665–712.
Koh PS, Reeb DM (2015) Missing R&D. J Account Econ 60(1):73–94.

Kostova T, Zaheer S (1999) Organizational legitimacy under conditions of complexity: the case of the multinational enterprise. Acad Manag Rev 24(1):64–81.
Lahr H, Mina A (2016) Venture capital investments and the technological performance of portfolio firms. Res Policy 45(1):303–318.
Lee J, Collar J (2003) Information technology fashions: lifecycle phase analysis. In: Proceedings of the 36th Hawaii international conference on systems sciences. IEEE Computer Society, Los Alamitos, pp 1–8.
Lerner J (2000) Assessing the contribution of venture capital. Rand J Econ 31(4):674–692.
Lerner J (2002) When bureaucrats meet entrepreneurs: the design of effective 'public venture capital' programmes. Econ J 112(477):F73–F84.
Li J, Chen L, Chen Y, He J (2022) Digital economy, technological innovation, and green economic efficiency—empirical evidence from 277 cities in China. Manag Decis Econ 43(3):616–629.
Luo S, Yimamu N, Li Y, Wu H, Irfan M, Hao Y (2023) Digitalization and sustainable development: how could digital economy development improve green innovation in China? Bus Strategy Environ 32(4):1847–1871.
Madsen D, Stenheim T (2016) Big data viewed through the lens of management fashion theory. Cogent Bus Manag 3(1):1165074.
Maroto A, Gallego J, Rubalcaba L (2016) Publicly funded R&D for public sector performance and efficiency: evidence from Europe. R&D Manag 46(S2):564–578.
Matusik SF, Fitza MA (2012) Diversification in the venture capital industry: leveraging knowledge under uncertainty. Strateg Manag J 33(4):407–426.
Melville N, Kraemer K, Gurbaxani V (2004) Review: information technology and organizational performance: an integrative model of IT business value. MIS Q 28(2):283–322.
Meyer JW, Rowan B (1977) Institutionalized organizations: formal structure as myth and ceremony. Am J Sociol 83(2):340–363.
Miller D, Hartwick J (2002) Spotting management fads. Harv Bus Rev 80(10):26–27.
Minola T, Vismara S, Hahn D (2017) Screening model for the support of governmental venture capital. J Technol Transf 42:59–77.
Miric M, Jia N, Huang KG (2023) Using supervised machine learning for large-scale classification in management research: the case for identifying artificial intelligence patents. Strateg Manag J 44(2):491–519.
Nilsson NJ (2009) The quest for artificial intelligence. Cambridge University Press, Cambridge.
North DC (1990) Institutions, institutional change and economic performance. Cambridge University Press, Cambridge.
Pahnke EC, Katila R, Eisenhardt KM (2015) Who takes you to the dance? How funding partners influence innovative activity in young firms. Adm Sci Q 60(4):596–633.
Peng MW, Sun SL, Pinkham B, Chen H (2009) The institution-based view as a third leg for a strategy tripod. Acad Manag Perspect 23(3):63–81.
Pesaran MH, Smith RJ (1994) A generalized R^2 criterion for regression models estimated by the instrumental variables method. Econometrica 62(3):705–710.
Puri M, Zarutskie R (2012) On the life cycle dynamics of venture-capital-and non-venture-capital-financed firms. J Finance 67(6):2247–2293.
Ramiller E (2004) Innovating mindfully with information technology. MIS Q 28(4):553–583.
Ramiller P (2009) Community learning in information technology innovation. MIS Q 33(4):709–734.
Scott WR (1995) Institutions and organizations. Sage, Thousand Oaks.
Seru A (2014) Firm boundaries matter: evidence from conglomerates and R&D activity. J Financ Econ 111(2):381–405.

Seymour S (2008) Fashionable technology: the intersection of design. Fashion Sci Technol 1:689–692.
Smith DA, Lohrke FT (2008) Entrepreneurial network development: trusting in the process. J Bus Res 61(4):315–322.
Snee RD, Marquardt DW (1984) Comment collinearity diagnostics depend on the domain of prediction, the model, and the data. Am Stat 38(2):83–87.
Sobel RS (2008) Testing Baumol: institutional quality and the productivity of entrepreneurship. J Bus Venturing 23(6):641–655.
Sorenson O, Stuart TE (2001) Syndication networks and the spatial distribution of venture capital investments. Am J Sociol 106(6):1546–1588.
Stratopoulos TC, Lim JH (2010) IT innovation persistence. Commun ACM 53(5):142–160.
Stock JH, Yogo M (2005) Testing for weak instruments in linear IV regression. In: Andrews DWK, Stock JH (eds) Identification and inference for econometric models: essays in honor of Thomas J. Rothenberg. Cambridge University Press, Cambridge, pp 80–108.
Suchman MC (1995) Managing legitimacy: strategic and institutional approaches. Acad Manag Rev 20(3):571–610.
Sun H, Luo F, London J, Li J (2014) Fashionable technology, fashion waves, and post-adoption regret and satisfaction. J Consum Behav 13(5):339–347.
Shleifer A, Vishny RW (1993) Corruption. Q J Econ 108(3):599–617.
Tian J, Haleblian J, Rajagopalan N (2011) The effects of board human and social capital on investor reactions to new CEO selection. Strateg Manag J 32(7):731–747.
Tian X, Wang TY (2014) Tolerance for failure and corporate innovation. Rev Financ Stud 27(1):211–255.
Urban B, Kujinga L (2017) The institutional environment and social entrepreneurship intentions. Int J Entrep Behav Res 23(4):638–655.
Vasudeva G, Spencer JW, Teegen HJ (2013) Bringing the institutional context back in: a cross-national comparison of alliance partner selection and knowledge acquisition. Organ Sci 24(2):319–338.
Wang P (2010) Chasing the hottest IT: effects of information technology fashion on organizations. MIS Q 34(1):63–85.
White S, Gao J, Zhang W (2005) Financing new ventures in China: system antecedents and institutionalization. Res Policy 34(6):894–913.
Wright RMK (1998) Venture capital and private equity: a review and synthesis. J Bus Finance Account 25(5-6):521–570.
Wu L, Brynjolfsson E (2014) The future of prediction: how Google searches foreshadow housing prices and sales. Am Econ Rev 104(5):579–583.
Yang S, Ma S, Lu J (2022) Can government venture capital guidance funds promote urban innovation? Evidence from China. Growth Change 53(2):753–770.
Yoganarasimhan H (2016) Identifying the presence and cause of fashion cycles in data. J Mark Res 53(5):669–682.
Zhang J, Fan Y, Liu Y (2024) The effects of government venture capital: new evidence from China based on a two-sided matching structural model. J Corp Finance 84:102521.
Zhang Y, Mayes DG (2018) The performance of governmental venture capital firms: a life cycle perspective and evidence from China. Pac Basin Finance J 48:162–185.
Zheng C, Wang BX (2012) Innovative or imitative? Technology firms in China. Prometheus 30(2):169–178.
Zoltan A, Estrin S, Mickiewicz TM, Szerb L (2018) Entrepreneurship, institutional economics and economic growth: a systems perspective. Acad Manag Ann Meet Proc 2018(1):1–6.

Figure

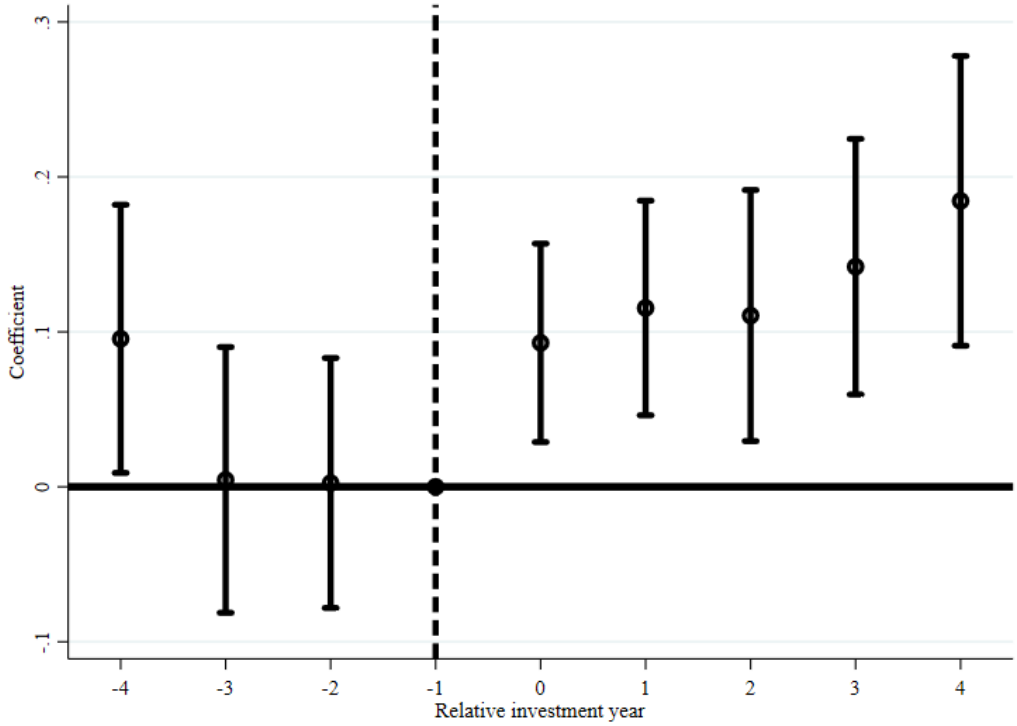


Figure 1. Parallel trend test for the PSM-DID sample. It plots the dynamic impact of GVC infusion on startups AI innovation. The vertical axis reports the estimated coefficients derived from our dynamic event-study specification (Eq.3), with $AI_Innovation_{i,t}$ as the dependent variable. The horizontal axis indicates event time relative to the initial GVC investment year ($t = 0$).

Tables

Table 1. Descriptive statistics

Variables	N	Mean	Std. Dev.	Max	Min
AI_Innovation	6,206	0.262	0.821	6.809	0.000
GVC_Treated	6,206	0.145	0.352	1.000	0.000
State_Owned_Asset	6,206	0.561	0.202	0.923	0.216
Regional_Corruption	6,206	0.173	0.081	0.463	0.007
VC_Age	6,206	5.826	5.119	46.360	0.000
Joint_VC	6,206	0.038	0.191	1.000	0.000
VC_Reputation	6,206	0.074	0.262	1.000	0.000
IPO_Experience	6,206	0.046	0.138	1.000	0.000
VC_Network_Centrality	6,206	0.048	0.091	1.000	0.000
Industry_Focus	6,206	0.444	0.226	1.000	0.000
Industry_Capital_Intensity	6,206	0.904	0.104	0.963	0.092
Investment_Diversification	6,206	0.202	0.316	1.000	0.003
Early_Stage	6,206	0.696	0.460	1.000	0.000
Market_Competition	6,206	6.174	1.014	7.210	0.000

This table presents descriptive statistics for the main variables used in this study. The final sample consists of 6,206 firm-year observations from 1,345 distinct startups spanning the 2010–2019 period, constructed through propensity score matching to approximate the counterfactual of non-GVC-funded firms. Detailed variable definitions are provided in Appendix A.

Table 2. Correlation matrix

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	*AI_Innovation*	1.000						
(2)	*GVC_Treated*	0.261***	1.000					
(3)	*State_Owned_Asset*	0.074***	0.026**	1.000				
(4)	*Regional_Corruption*	−0.140***	−0.099***	−0.398***	1.000			
(5)	*VC_Age*	0.001	0.200***	−0.028**	−0.086***	1.000		
(6)	*Joint_VC*	−0.009	0.086***	−0.013	0.014	0.332***	1.000	
(7)	*VC_Reputation*	−0.032**	0.163***	−0.149***	0.101***	0.453***	0.327***	1.000
(8)	*IPO_Experience*	−0.043***	0.099***	−0.069***	0.047***	0.314***	0.672***	0.529***
(9)	*VC_Network_Centrality*	−0.055***	−0.087***	−0.018	0.066***	0.136***	0.368***	0.219***
(10)	*Industry_Focus*	−0.001	0.109***	−0.051***	−0.079***	0.514***	0.298***	0.337***
(11)	*Industry_Capital_Intensity*	−0.028**	−0.282***	0.099***	−0.016	−0.349***	−0.374***	−0.618***
(12)	*Investment_Diversification*	−0.051***	−0.136***	0.002	0.142***	−0.445***	−0.108***	−0.142***
(13)	*Early_Stage*	−0.124***	−0.246***	−0.043***	0.039***	0.189***	0.059***	0.093***
(14)	*Market_Competition*	0.019	0.127***	−0.061***	0.029**	0.075***	0.073***	0.089***
		(8)	(9)	(10)	(11)	(12)	(13)	(14)
(8)	*IPO_Experience*	1.000						
(9)	*VC_Network_Centrality*	0.519***	1.000					
(10)	*Industry_Focus*	0.444***	0.479***	1.000				
(11)	*Industry_Capital_Intensity*	−0.583***	−0.299***	−0.412***	1.000			
(12)	*Investment_Diversification*	−0.178***	−0.273***	−0.876***	0.217***	1.000		
(13)	*Early_Stage*	0.113***	0.247***	0.439***	−0.054***	−0.423***	1.000	
(14)	*Market_Competition*	0.072***	−0.052***	−0.025*	−0.087***	−0.018	−0.094***	1.000

This table presents the pairwise correlation matrix for the principal variables used in this study. The sample comprises firm-year observations from Chinese startups over the 2010–2019 period. The matched dataset consists of 6,206 observations from 1,345 distinct firms. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Detailed variable definitions are provided in Appendix A.

Table 3. Baseline regression: governmental venture capital and startup AI innovation

Variables	(1)	(2)	(3)
GVC_Treated	0.067***	0.567***	0.059**
	(0.024)	(0.052)	(0.024)
VC_Age		−0.006***	0.023
		(0.002)	(0.015)
Joint_VC		0.161***	−0.141
		(0.056)	(0.332)
VC_Reputation		−0.094**	−0.154**
		(0.038)	(0.077)
IPO_Experience		−0.298***	−0.169
		(0.105)	(0.138)
VC_Network_Centrality		0.116	0.016
		(0.090)	(0.042)
Industry_Focus		−0.445***	0.099
		(0.129)	(0.113)
Industry_Capital_Intensity		−0.167	−0.089
		(0.133)	(0.072)
Investment_Diversification		−0.460***	0.053
		(0.079)	(0.059)
Early_Stage		−0.139***	−0.025
		(0.028)	(0.018)
Market_Competition		−0.016*	0.019
		(0.010)	(0.015)
Constant	0.253***	0.863***	0.070
	(0.005)	(0.159)	(0.152)
Firm FE	Yes	No	Yes
Year FE	Yes	No	Yes
Observations	6,206	6,206	6,206
Adjusted R^2	0.890	0.083	0.891

This table presents the baseline regression results testing the impact of governmental venture capital (GVC) on startup AI innovation. The dependent variable is *AI_Innovation*. Column (1) includes firm and year fixed effects. Column (2) introduces the full set of control variables without fixed effects. Column (3) is the preferred specification, which includes both the control variables and firm and year fixed effects. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The analysis uses firm-year observations of Chinese startups from 2010 to 2019. The matched sample consists of 6,206 firm-year observations from 1,345 unique firms. Detailed variable definitions are provided in Appendix A.

Table 4. Regional institutional environment interaction

Variables	(1)	(2)	(3)
GVC_Treated	0.055**	0.057**	0.054**
	(0.024)	(0.024)	(0.024)
GVC × State_Owned_Asset	0.053**		0.043*
	(0.024)		(0.024)
GVC × Regional_Corruption		−0.049***	−0.039**
		(0.018)	(0.018)
State_Owned_Asset	0.200*		0.120
	(0.114)		(0.118)
Regional_Corruption		−0.236**	−0.238**
		(0.095)	(0.098)
VC_Age	0.025*	0.024*	0.026*
	(0.015)	(0.014)	(0.015)
Joint_VC	−0.172	−0.128	−0.151
	(0.335)	(0.321)	(0.325)
VC_Reputation	−0.155**	−0.157**	−0.156**
	(0.077)	(0.080)	(0.079)
IPO_Experience	−0.155	−0.164	−0.156
	(0.137)	(0.136)	(0.136)
VC_Network_Centrality	0.015	0.007	0.009
	(0.041)	(0.041)	(0.040)
Industry_Focus	0.052	0.084	0.050
	(0.112)	(0.113)	(0.112)
Industry_Capital_Intensity	−0.116*	−0.073	−0.099
	(0.068)	(0.071)	(0.067)
Investment_Diversification	0.036	0.050	0.037
	(0.059)	(0.059)	(0.059)
Early_Stage	−0.025	−0.024	−0.024
	(0.018)	(0.018)	(0.018)
Market_Competition	0.017	0.019	0.018
	(0.015)	(0.015)	(0.015)
Constant	0.002	0.092	0.063
	(0.165)	(0.151)	(0.165)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	6,206	6,206	6,206
Adjusted R^2	0.891	0.891	0.891

This table presents regression estimates examining the interaction effects between GVC and two contextual moderators—state-owned asset share (*State_Owned_Asset*) and provincial regional corruption (*Regional_Corruption*). The dependent variable is *AI_Innovation*. All specifications include firm and year fixed effects. Column (1) introduces the interaction between GVC and state-owned assets. Column (2) introduces the interaction between GVC and regional corruption. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample consists of 6,206 firm-year observations from 1,345 unique Chinese startups spanning the period 2010–2019. Detailed variable definitions are provided in Appendix A.

Table 5. Placebo test

Variables	(1)	(2)
GVC_Treated (1-Year Lead)	0.009	
	(0.025)	
GVC_Treated (2-Year Lead)		−0.032
		(0.027)
VC_Age	0.021	0.021
	(0.015)	(0.015)
Joint_VC	−0.149	−0.171
	(0.336)	(0.332)
VC_Reputation	−0.158**	−0.159**
	(0.080)	(0.081)
IPO_Experience	−0.175	−0.185
	(0.137)	(0.137)
VC_Network_Centrality	0.005	−0.005
	(0.043)	(0.043)
Industry_Focus	0.115	0.122
	(0.113)	(0.112)
Industry_Capital_Intensity	−0.108	−0.116
	(0.074)	(0.074)
Investment_Diversification	0.069	0.079
	(0.059)	(0.059)
Early_Stage	−0.030	−0.033*
	(0.019)	(0.019)
Market_Competition	0.018	0.017
	(0.015)	(0.015)
Constant	0.104	0.122
	(0.154)	(0.153)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	6,206	6,206
Adjusted R^2	0.890	0.890

This table presents results from a lead-lag analysis assessing the timing and persistence of the relationship between GVC investment and subsequent startup AI innovation. The dependent variable is *AI_Innovation*. Column (1) reports the effect of GVC treatment on AI innovation one year after the investment (*GVC_Treated (1-Year Lead)*). Column (2) examines the effect two years after the investment (*GVC_Treated (2-Year Lead)*). Both specifications include the full set of control variables as well as firm and year fixed effects. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample consists of 6,206 firm-year observations from 1,345 unique Chinese startups over the period 2010–2019. Detailed variable definitions are provided in Appendix A.

Table 6. Instrumental variable analysis

Variables	(1) First Stage *GVC_Treated*	(2) Second Stage *AI_Innovation*
GVC_Treated		3.255***
		(0.819)
GVC_Fund_Count	0.004***	
	(0.001)	
VC_Age	0.003***	−0.021***
	(0.001)	(0.004)
Joint_VC	0.063**	−0.020
	(0.028)	(0.121)
VC_Reputation	0.095***	−0.223*
	(0.022)	(0.116)
IPO_Experience	0.114**	−0.448**
	(0.051)	(0.215)
VC_Network_Centrality	−0.568***	1.677***
	(0.057)	(0.507)
Industry_Focus	−0.229***	0.309
	(0.053)	(0.284)
Industry_Capital_Intensity	−0.802***	2.264***
	(0.053)	(0.690)
Investment_Diversification	−0.173***	0.327
	(0.037)	(0.204)
Early_Stage	−0.230***	0.524***
	(0.010)	(0.195)
Market_Competition	0.008**	−0.042**
	(0.004)	(0.016)
Constant	0.843***	−2.022***
	(0.071)	(0.782)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Cragg-Donald F-statistic		21.61
Observations	6,206	6,206
Centered R^2		−0.894

This table presents 2SLS regression estimates using *GVC_Fund_Count* as an instrumental variable for the endogenous treatment variable *GVC_Treated*. The sample comprises 6,206 firm-year observations from Chinese startups spanning the 2010–2019 period and is constructed via propensity score matching to approximate the counterfactual outcomes of non-GVC-funded firms. The dependent variable in the second stage is *AI_Innovation*, a measure of startups' artificial intelligence innovation output. *GVC_Treated* is a binary indicator for whether a startup received GVC funding, and *GVC_Fund_Count* measures the count of GVC funds in startups' home province and serves as the excluded instrument. All specifications include controls, industry and year fixed effects. The *Cragg–Donald Wald F-statistic* for weak instrument testing is reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Detailed variable definitions are provided in Appendix A.

Table 7. Alternative models with negative binomial and logistic regressions

	(1) Negative Binomial *AI_Innovation_Count*	(2) Logistic *AI_Innovator*
GVC Treated	1.619***	0.556***
	(0.227)	(0.118)
GVC Treated × State Owned Asset	0.437**	0.317***
	(0.195)	(0.100)
GVC Treated × Regional Corruption	−0.808***	−0.118
	(0.158)	(0.106)
State Owned Asset	−0.208	−0.483**
	(0.369)	(0.227)
Regional Corruption	−6.105***	−2.335***
	(1.182)	(0.630)
VC Age	−0.020	−0.006
	(0.015)	(0.013)
Joint VC	−1.864***	0.360
	(0.520)	(0.220)
VC Reputation	0.281	−0.182
	(0.508)	(0.234)
IPO Experience	0.953	−0.243
	(0.964)	(0.447)
VC Network Centrality	0.617	−0.215
	(0.996)	(0.742)
Industry Focus	−2.496***	−0.878
	(0.854)	(0.569)
Industry Capital Intensity	−0.939	−1.069**
	(0.888)	(0.487)
Investment Diversification	−0.985*	0.387
	(0.592)	(0.388)
Early Stage	−0.478**	−0.175*
	(0.225)	(0.095)
Market Competition	−0.272***	−0.174***
	(0.056)	(0.038)
Constant	2.620**	−0.750
	(1.199)	(0.740)
lnAlpha	2.800***	
	(0.047)	
Year FE	Yes	Yes
Observations	6,206	6,206
Log likelihood	−5133.23	−2403.45
Pseudo R²	0.082	0.074

This table presents results from alternative model specifications assessing the robustness of the baseline findings. Column (1) reports estimates from a negative binomial regression, with the dependent variable being the raw count of AI patents (*AI_Innovation_Count*). Column (2) reports estimates from a logistic regression, where the dependent variable is a binary indicator that equals 1 if a startup is filed one or more AI patents within the five-year window following potential GVC funding, and 0 otherwise (*AI_Innovator*). Both models include the full set of interaction terms and controls, as well as year fixed effects. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample consists of 6,206 firm-year observations from 1,345 unique Chinese startups over the period 2010–2019. Detailed variable definitions are provided in Appendix A.

Table 8. Heterogeneity analysis

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	High Focus	Low Focus	High IPO Exp.	Low IPO Exp.	2010-2014	2015-2019
GVC_Treated	0.031	0.153***	0.008	0.094**	0.030	0.100***
	(0.034)	(0.047)	(0.040)	(0.036)	(0.043)	(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,694	1,798	1,916	3,999	560	4,896
Adjusted R2	0.888	0.952	0.826	0.905	0.845	0.937

This table presents the heterogeneous effects of GVC on startup AI innovation across different VC characteristics and sample periods. Each column reports estimates from separate subsample regressions using the *reghdfe* estimator with firm and year fixed effects. Singleton observations (those that are the only observation within a firm or year group) are automatically dropped (Correia, 2015). Columns (1)-(2) split the sample by VC industry focus (*Industry_Focus*). Columns (3)-(4) distinguish between VCs with above- and below-median IPO experience (*IPO_Experience*). Columns (5)-(6) examine temporal differences between 2010-2014 and 2015-2019 periods. All specifications include firm and year fixed effects and the full set of control variables from Table 3, excluding the respective grouping variable in columns (1)-(6) to avoid collinearity. Robust standard errors in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix A. Description of the Main Variables

Variables	Definitions
AI_Innovation	The natural logarithm of one plus the cumulative number of AI patents filed by startup *i* over the five-year window [*t*, *t*+4]. AI patents are identified using a supervised random forest algorithm applied to patent titles and abstracts (Miric et al., 2023; Cockburn et al., 2018).
GVC_Treated	A binary indicator that equals 1 if startup *i* has received an investment from GVC fund by year *t*, and 0 otherwise. For treated firms, the indicator switches from 0 to 1 in the year of the first GVC investment and remains 1 thereafter (Chen et al., 2021).
State_Owned_Asset	The proportion of total fixed asset investment in a province contributed by state-owned and state-holding enterprises. Measures the dominance of the state-owned sector in the regional economy. Data was obtained from the National Bureau of Statistics of China
Regional_Corruption	A proxy for regional governance quality, calculated as the number of duty-related crime cases per 100 public officials in a province. A higher value indicates higher regional corruption (weaker governance quality). We hand-coded data on the anti-corruption campaign from the website of the Central Commission for Discipline Inspection and the Procuratorial Yearbooks of China.
VC_Age	The VC firm's experience, measured as the number of years between its founding year and the year of the focal investment event. We address potential measurement error in the founding years of VC firms by recoding negative values of *VC_Age*. This adjustment accounts for documented data limitations in commercial VC databases, which may arise from: (i) institutional retrospection, where founding teams incorporate pre-fund experience; (ii) brand consolidation, in which merged entities adopt the earlier founding date of a predecessor; or (iii) conflation of a founder's angel investment history with the formal establishment of the VC firm.
VC_Network_Centrality	The prominence of the VC firm within the syndication network, measured as its normalized Bonacich centrality in a directed syndication network over a rolling five-year window. Reflects strategic access and influence.
Industry_Focus	The VC's experiential depth in the focal startup's industry. Measured as the natural logarithm of one plus the ratio of the number of deals the VC completed in the startup's industry to the number of deals in all other industries over the past five years.
Industry_Capital_Intensity	The VC's financial commitment to the focal startup's industry. Measured as the proportion of the VC's total historical investment amount allocated to that specific industry.
Investment_Diversification	The degree of industry diversification within the VC's overall portfolio. Measured by a Herfindahl-Hirschman Index (HHI) based on the industry distribution of its total investment amount over the past five years. A higher HHI indicates a more concentrated (less diversified) portfolio.
Joint_VC	A dummy variable that equals 1 if the venture capital firm is a Sino-foreign joint venture, and 0 otherwise.
VC_Reputation	A dummy variable that equals 1 if the VC firm was ranked among the top 50 in the annual Zero2IPO China Venture Capital & Private Equity Ranking for that year, and 0 otherwise. Captures the VC's market status and certification effect.
IPO_Experience	The VC's track record of successful exits in the relevant sector, calculated as the natural logarithm of one plus the cumulative number of successful IPOs achieved by the VC in the investee firm's 2-digit industry over the five years preceding the investment.
Early_Stage	The VC's propensity for investing in early-stage ventures. A dummy variable that equals 1 if 50% or more of the VC's investments over the three years preceding the focal investment were in early-stage companies (seed, angel, or Series A rounds), and 0 otherwise (Guler, 2007).
Market_Competition	The degree of competition in the startup's operating environment, measured by the Herfindahl-Hirschman Index (HHI) at the industry-province level. Higher values indicate less competition.

AI_Innovation_Count	The cumulative number of AI patents filed to startup *i* over the five-year window [*t*, *t*+4]. AI patents are identified using a supervised random forest algorithm applied to patent titles and abstracts (Miric et al., 2023; Cockburn et al., 2018).
AI_Innovator	A dummy variable that equals 1 if a startup is filed one or more AI patents within the five-year window following potential GVC funding, and 0 otherwise.

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Declarations We declare that we have no relevant or material financial interests that relate to the research described in this paper.