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Multi-Perspective Research on the Mechanism of Venture Capital in Driving Innovation Development

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Abstract: This study empirically examines the impact and mechanisms of venture capital on innovation-driven development using a Panel Vector Autoregressive (PVAR) model with three proxy variables: total factor productivity (TFP), industrial upgrading, and technological progress. The findings demonstrate that venture capital significantly promotes innovation-driven economic development overall. Specifically, while the scale of venture capital investment shows a significant positive correlation with industrial upgrading, it fails to significantly enhance either TFP growth or technological advancement. In contrast, increasing the proportion of venture capital in aggregate social financing significantly drives technological progress. These results suggest that to fully realize high-quality, innovation-driven development through venture capital, policymakers must simultaneously expand the scale of venture capital investment and restructure regional financing systems by increasing the share of direct financing. Based on these conclusions, the study proposes policy recommendations including reforming the social financing structure, improving the multi-tier capital market system, and optimizing exit mechanisms for venture capital funds.

Keywords: venture capital; innovation-driven development; industrial upgrading; financing structure; technological progress

1. Introduction

With the advent of the digital era, major economies such as the United States, Europe, and China are transitioning from factor-driven to innovation-driven economic models. Innovation development has become a key indicator for measuring economic growth quality across major countries and regions. Given that venture capital plays a crucial role in fostering innovation incubation, optimizing resource allocation, and accelerating factor mobility, many nations and regions have introduced or established venture capital mechanisms as a catalyst for economic innovation.

However, despite the rapid expansion of venture capital, existing research on its mechanisms in driving innovation remains relatively narrow in perspective. Innovation development manifests at three levels: (1) macro-level, as an improvement in total factor productivity (TFP); (2) meso-level, as industrial structure upgrading; and (3) micro-level, as technological progress and innovation output [1]. Yet, most studies focus solely on the relationship between venture capital and firm-level innovation output [2], with only a few recent works touching upon venture capital's role in industrial structure advancement [3]. Notably, there is a lack of theoretical research examining the impact of venture capital on total factor productivity.

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To address this gap, this study incorporates proxy variables for economic innovation—total factor productivity (TFP), industrial upgrading, and technological progress—into a unified analytical framework. By adopting a multi-dimensional perspective, we systematically investigate the mechanisms and pathways through which venture capital influences economic innovation development.

2. Literature Review

The theoretical foundation of venture capital's role in accelerating innovation-driven growth originates from research on the relationship between industrial upgrading and economic growth. Variations in productivity growth rates and demand expansion across industries imply that resource allocation cannot remain optimally efficient across sectors indefinitely. When industrial upgrading aligns with shifts in demand and improvements in technological utilization efficiency, production factors (e. g., labor and capital) flow toward sectors with higher productivity or productivity growth rates, thereby enhancing economic growth [4]. Peneder's (2003) research further demonstrates that technological progress drives industrial upgrading, and the resulting factor reallocation elevates societal productivity, sustaining economic growth [5]. Thus, technological progress serves as the primary pathway through which industrial upgrading spurs economic growth—a process summarized as technological progress → industrial upgrading → economic growth [6].

However, technological progress itself depends on capital-driven mechanisms. A defining feature of global technological advancement is that "innovation begins with technology but thrives through capital" [7]. Venture capital facilitates rapid profitability for innovative firms [8] and mitigates pervasive underinvestment in corporate innovation [9]. In this process, venture capital promotes industrial upgrading by accelerating technological progress, ultimately driving economic growth—a causal chain encapsulated as "venture capital → technological progress → industrial upgrading → economic growth".

Given venture capital's direct impact on technological progress, much theoretical research focuses on its relationship with firm-level innovation output. Empirical studies globally confirm that equity-based financing instruments like venture capital constitute the most critical external funding source for corporate R&D [10]. Scholars have also identified a significant positive correlation between venture capital investment and patent grants [11]. Analyses of China's earliest major venture capital initiative—the Innovation Fund for Technology-based SMEs—reveal its substantial effects on firm-level innovation output, with economic growth further amplifying these effects [12].

Early theoretical frameworks posit that venture capital indirectly drives industrial upgrading through technological progress, prompting later scholars to expand their focus from innovation output to structural economic transformation. Chen Feiqiong et al. (2015) employed empirical models to investigate venture capital's mechanisms in industrial restructuring, using multi-group structural equation modeling (SEM). Their findings indicate that venture capital significantly enhances value creation and R&D investment at the micro level but exhibits negligible effects on macro-level capital accumulation or employment [13]. Subsequent studies introduced heterogeneity analyses of venture capital's role in industrial upgrading. For instance, Zijing Wu et al. (2019) applied PVAR regression to provincial panel data, concluding that venture capital lacks an initiation mechanism but possesses an acceleration mechanism for industrial upgrading [14].

Existing research predominantly examines venture capital's effects on technological progress and industrial upgrading, with scant attention to its role in total factor productivity (TFP) growth. Levine and Zervos (1998) pioneered this inquiry through financial development theory, empirically demonstrating that direct financing instruments (including venture capital) significantly boost TFP despite limited impacts on aggregate economic growth [15]. Notably, China-specific studies rarely address venture capital's TFP mechanisms, and none integrate TFP, industrial upgrading, and technological progress into a unified analytical framework.

To address these gaps, this study employs panel vector autoregression (PVAR) models to empirically analyze venture capital's innovation-driving mechanisms across three dimensions: total factor productivity, industrial upgrading, and technological progress.

3. Measurement and Indicator Decomposition of TFP

Total Factor Productivity (TFP) refers to the ratio of total output to total input factors in an economic system, serving as a crucial tool for analyzing the sources and pathways of economic growth. It helps identify whether current economic growth is input-driven or efficiency-driven, thereby assessing the sustainability of economic system growth.

The measurement approaches for TFP primarily include parametric and non-parametric methods: (1) parametric methods, mainly based on Solow residual theory, estimate production functions and derive results by calculating the residual value after deducting factor input growth from output growth; (2) non-parametric methods, primarily employing Data Envelopment Analysis (DEA model), compute production frontiers through linear programming. This approach offers the advantage of being unaffected by the measurement units of input-output indicators since it doesn't require constructing specific production function models.

In this study, we adopt the DEA approach to measure TFP and decompose its indicators by calculating the Malmquist-Luenberger index (ML index).

3.1. Methodology and Variables

The Malmquist index constructs the production possibility frontier of an economic system and employs directional distance functions to measure the distance between each decision-making unit (DMU) and this frontier, thereby calculating the input-output efficiency of DMUs. The ML productivity index can be decomposed into an efficiency index (*Effch*) and a technological progress index (*Techch*), indicating that TFP growth stems from both efficiency improvement and technological advancement. The model specifications are as follows:

$$ML_i^{t+1}(x_i^{t+1},y_i^{t+1},x_i^t,y_i^t)=\frac{d_i^{t+1}(x_i^{t+1},y_i^{t+1})}{d_i^t(x_i^t,y_i^t)}\times\sqrt{\frac{d_i^t(x_i^{t+1},y_i^{t+1})}{d_i^{t+1}(x_i^{t+1},y_i^{t+1})}\times\frac{d_i^t(x_i^t,y_i^t)}{d_i^{t+1}(x_i^t,y_i^t)}} \tag{1}$$

$$Effch_i^{t+1}=\frac{d_i^{t+1}(x_i^{t+1},y_i^{t+1})}{d_i^t(x_i^t,y_i^t)} \tag{2}$$

$$Techch_i^{t+1}=\sqrt{\frac{d_i^t(x_i^{t+1},y_i^{t+1})}{d_i^{t+1}(x_i^{t+1},y_i^{t+1})}\times\frac{d_i^t(x_i^t,y_i^t)}{d_i^{t+1}(x_i^t,y_i^t)}} \tag{3}$$

where i and t denote the DMU and time period respectively, while x and y represent inputs and outputs. Thus, d_t^i (x_t^i, y_t^i) and d_t^i (x_{t+1}^i, y_{t+1}^i) represent the distance functions for DMU i at periods t and $t+1$ relative to the period t production frontier. In Equations (2) and (3), *Effch* measures efficiency change and *Techch* captures technological progress change for DMU i between t and $t+1$.

However, under real-world conditions of variable returns to scale (VRS), efficiency changes may not solely reflect pure technical efficiency changes but could also include scale efficiency effects. Therefore, the Malmquist-Luenberger productivity index under VRS can be reformulated as:

$$ML_i^{t+1}(x_i^{t+1},y_i^{t+1},x_i^t,y_i^t)=Pech_{\mathrm{i}}^{t+1}\times Sech_i^{t+1}\times Techch_i^{t+1} \tag{4}$$

$$Pech_i^{t+1}=\frac{d_i^{t+1}(x_i^{t+1},y_i^{t+1})_{/VRS}}{d_i^t(x_i^t,y_i^t)_{/VRS}} \tag{5}$$

$$Sech_i^{t+1}=\frac{d_i^t(x_i^t,y_i^t)_{/VRS}}{d_i^t(x_i^t,y_i^t)_{/CRS}}\bigg/\frac{d_i^{t+1}(x_i^{t+1},y_i^{t+1})_{/VRS}}{d_i^{t+1}(x_i^{t+1},y_i^{t+1})_{/CRS}} \tag{6}$$

$$Techch_i^{t+1}=\frac{d_i^t(x_i^t,y_i^t)_{/CRS}}{d_i^{t+1}(x_i^t,y_i^t)_{/CRS}}\times\frac{d_i^t(x_i^{t+1},y_i^{t+1})_{/CRS}}{d_i^{t+1}(x_i^{t+1},y_i^{t+1})_{/CRS}} \tag{7}$$

Equation (4) decomposes efficiency change into pure technical efficiency change (*Pech*) and scale efficiency change (*Sech*). The notations VRS and CRS distinguish between variable and constant returns to scale scenarios.

This DEA framework demonstrates that TFP growth (*TFPch*) derives from three components: technological progress (*Techch*), pure technical efficiency improvement (*Pech*), and scale efficiency change (*Sech*). While TFP growth broadly captures new drivers of macroeconomic growth, technological progress (*Techch*) more precisely reflects the micro-level "innovation-driven" development paradigm.

For ML index measurement, input factors primarily include capital and labor:

Capital input: Calculated using perpetual inventory method with fixed asset investment data: $C_{it} = I_{it} + (1 - \delta)$ Ci_{t-1}, where C_{it} is capital stock for province i in quarter t, I_{it} is fixed asset investment, and δ is the depreciation rate (annual 6%, quarterly 1.5%).

Labor input: Total employment, summing registered urban employees and private/individual workers.

The output measure is regional GDP. This study examines venture capital's impact on TFP using Chinese provincial data. Since regional statistics on venture capital became more complete post-2020, we employ 16 quarters of data (2021–2024) for panel VAR analysis. GDP and fixed asset investment data come from CEIC, while labor data is sourced from China Economic Net.

3.2. Results and Analysis

Using DEAP 2.1 software, we measured the total factor productivity (TFP) index and decomposed its components for panel data covering 30 Chinese provinces over 16 quarters by employing the DEA-Malmquist index model under variable returns to scale (VRS). The results are presented in Table 1.

Table 1. TFP of China: Measurement and Component Analysis.

Time (Quarter)	*Effch*	*Techch*	*Pech*	*Sech*	*TFPch*
2021-Q2	1.0070	0.9850	0.9900	1.0160	0.9920
2021-Q3	1.0500	0.8200	1.0530	0.9970	0.8610
2021-Q4	0.8780	1.1630	0.9430	0.9300	1.0210
2022-Q1	0.8790	0.7400	0.8400	1.0460	0.6510
2022-Q2	1.0010	1.0340	1.0150	0.9860	1.0360
2022-Q3	1.0440	0.9470	1.0530	0.9910	0.9880
2022-Q4	0.9150	1.1450	0.9740	0.9400	1.0480
2023-Q1	0.8680	0.8320	0.8660	1.0030	0.7220
2023-Q2	1.1030	0.9900	1.0740	1.0270	1.0920
2023-Q3	0.9820	1.0790	1.0310	0.9520	1.0590
2023-Q4	0.9550	1.0820	0.9850	0.9700	1.0340
2024-Q1	0.8750	0.8620	0.8800	0.9950	0.7550
2024-Q2	1.1200	0.9880	1.0870	1.0300	1.1070
2024-Q3	1.0080	1.0180	1.0320	0.9760	1.0260
2024-Q4	0.9920	1.1140	1.0200	0.9720	1.1040
Mean	0.9750	0.9790	0.9870	0.9880	0.9550

The mean value of TFP growth rate changes was 0.955, indicating an average quarterly decline of 4.5% in TFP growth between 2021 and 2024 (16 quarters). Decomposition analysis reveals that when TFP growth is disaggregated into efficiency change (*Effch*) and technological progress (*Techch*), the year-on-year TFP growth rate remained consistently above 5% from 2022 through Q3 2023. However, beginning in Q4 2023, TFP growth approached zero, with occasional quarters showing negative growth. This phenomenon can be partially attributed to: the lagged scarring effects of COVID-19 pandemic-induced economic contraction in 2023 and systemic contraction in China's real estate market leading to reduced aggregate social financing.

Notably, the observed TFP fluctuations were primarily driven by technological progress rather than efficiency changes, suggesting that: (1) the productivity slowdown reflected innovation capacity constraints rather than operational inefficiencies; (2) the economic shocks disproportionately affected frontier technology adoption rather than existing production practices.

4. Empirical Analysis by PVAR

4.1. Data and Variables

This study examines the impact of venture capital on innovation-driven development, which is measured through three dimensions: total factor productivity (TFP) growth, industrial upgrading, and technological progress. To analyze the dynamic mechanisms, we employ a Panel Vector Autoregressive (PVAR) model to investigate how venture capital influences these three pathways.

While existing studies predominantly use venture capital investment size as the proxy variable, we recognize that aggregate social financing also significantly drives regional industrial upgrading. To distinguish venture capital's unique effects from other financial instruments, we additionally introduce venture capital weight (the ratio of venture capital investment to total social financing) as a complementary proxy variable.

(1) **Venture Capital Investment Size** (denoted as $Fund_{it}$). Common measures include investment amount, number of investees, and investment frequency. The distinction between investees and frequency arises because multiple funds may invest in the same project or a single fund may invest in the same project multiple times. For model parsimony, we select investment amount (denoted as $Fund_{it}$) as the primary proxy, as internal fund allocation structures do not affect our aggregate conclusions.

(2) **Venture Capital Weight** (denoted as $FundEntropy_{it}$). Empirical evidence confirms that equity-based direct financing instruments (like venture capital) contribute more substantially to industrial upgrading than indirect instruments (e.g., medium/long-term credit). As venture capital represents the dominant form of equity investment, its weight in total social financing reflects regional capital structure efficiency:

$$FundEntropy_{it} = Fund_{it}/SocFinance_{it} \tag{8}$$

where $Fund_{it}$ is the size of venture capital investment and $SocFinance_{it}$ denotes total social financing.

(3) **Industrial Upgrading** (denoted as Ser_{it}). Industrial upgrading manifests as the transition from lower- to higher-value-added sectors. Early studies used the non-primary industry share of GDP, but this fails to capture China's current transition from manufacturing to service-oriented industries [16]. We instead adopt the service-industrialization ratio:

$$Ser_{it} = S_{it}/I_{it} \tag{9}$$

where S_{it} and I_{it} represent output values of tertiary and secondary sectors, respectively, for province i at time t.

(4) **TFP Growth Rate** (denoted as $TFPch_{it}$). As a macroeconomic proxy for innovation-driven development, TFP measures output growth unexplained by labor or capital inputs. We focus on TFP growth rate ($TFPch_{it}$) rather than its absolute level to assess dynamic improvements.

(5) **Technological Progress** (denoted as $Techch_{it}$) and **Scale Efficiency Change** (denoted as $Sech_{it}$). TFP decomposition reveals two components: (1) Technological progress ($Techch_{it}$) is our proxy for innovation capacity because that innovation output stems from technological progress at the micro level; (2) Scale efficiency change*,* further split into pure technical efficiency and scale efficiency change ($Sech_{it}$) including which in the PVAR model controls for non-technological factors affecting TFP [17] (as shown in Table 2).

Table 2. Variable Definitions and Descriptive Statistics.

Variable	Definition	Min	Max	Mean	St. Dev
TFPch	TFP Growth Rate	−0.707	1.163	−0.018	0.222
Techch	Technological Progress Rate	−1.000	0.230	−0.014	0.137
Sech	Scale Efficiency Change	−0.203	0.194	−0.009	0.054
Ser	Industrial Upgrading Level	0.615	4.762	1.308	0.746
Fund	VC Investment Scale	0.000	1907.31	52.772	173.512
FundEntropy	VC Investment Weight	0.000	0.816	0.025	0.080

The industrial upgrading variables in the model are sourced from the CEIC database, while venture capital related data and aggregate social financing figures are obtained from the WIND database and China Economic

Net. To ensure stationarity in the PVAR model, all variables except VC investment scale ($Fund_{it}$) are ratio-based measures, so we apply a natural logarithm transformation (denoted as ln $Fund_{it}$) for the empirical analysis.

4.2. Methodology and Empirical Analysis

To investigate the mechanism through which venture capital affects total factor productivity (TFP), industrial upgrading, and technological progress, we construct a Panel Vector Autoregressive (PVAR) model using quarterly data from 30 provinces spanning 2021 to 2024. The PVAR framework combines the advantages of both time-series and panel data approaches, enabling a multidimensional analysis of the dynamic evolution of venture capital's impact on industrial upgrading. The empirical model is specified as follows:

$$Y_{it} = \alpha_{it} + \gamma_t + \sum_{t=1}^{n} \prod_{nt} Y_{i,t-n} + \varepsilon_{it} \tag{10}$$

where Y_{it} represents the vector of endogenous variables, comprising six dimensions as $TFPch_{it}$, $Techch_{it}$, $Sech_{it}$, Ser_{it}, $Fund_{it}$, and $FundEntropy_{it}$. $\{Y_{it}\}^{i}_{t=1}$ represents cross-sectional data for province i across all quarters and $\{Y_{it}\}^{t}_{i=1}$ represents time-series data for all provinces in quarter t. Π_{it} is the parameter matrix to be estimated, n denotes the lag order, ε represents random disturbances with identical distribution and no serial correlation, α captures province fixed effects accounting for cross-sectional heterogeneity and γ represents time effects reflecting common temporal trends.

Our dataset consists of 16 quarterly observations across 30 provinces, characteristic of "wide panel, short time series" data that can be treated as stationary. Stationarity tests confirm this property, with all variables' characteristic roots lying within the unit circle (Figure 1), satisfying the PVAR model's stability conditions.

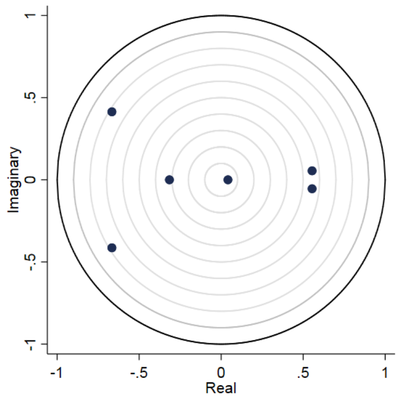

Figure 1. Inverse Roots of the Companion Matrix Test (Unit Circle Test).

Prior to PVAR estimation, we determine the optimal lag length using Hansen's J statistic and three information criteria: MAIC, MBIC, and MQIC. As shown in Table 3, all criteria (AIC, BIC, and HQIC) unanimously select one lag as optimal. Consequently, we specify a first-order lag structure for our PVAR model examining the initiation mechanism of venture capital's impact on industrial upgrading.

Table 3. Determination of Optimal Lags in PVAR Model.

Lags	MBIC	MAIC	MQIC
1	−412.5754	−85.9963	−218.6641
2	−258.6806	−40.9612	−129.4064
3	−121.7665	−12.90678	−57.12938

The PVAR model offers distinct advantages by enabling the decomposition of each shock's effect on endogenous variables through orthogonalized impulse responses, while holding other variables constant. However, the presence of fixed effects in the model violates the strict exogeneity assumption of classical linear regression. To address this, we employ forward mean differencing (Helmert transformation) to eliminate the mean of future observations for each individual, thereby preventing correlation between explanatory variables and the error term.

To mitigate endogeneity concerns, we utilize first-order lagged terms as instrumental variables (IVs) in system generalized method of moments (GMM) estimation. This approach yields consistent and efficient estimates for the parameter matrix Π. While additional time periods provide supplementary moment conditions and instruments, they may also lead to instrument proliferation. Consequently, we conduct an overidentification test using Hansen's J-statistic after GMM estimation to verify the orthogonality of instruments and ensure the validity of the IV set.

Using the system GMM estimation approach, in Table 4 we obtain the PVAR model estimates for the relationships among TFP growth rate (*TFPch*), technological progress (*Techch*), scale efficiency change (*Sech*), industrial upgrading (*Ser*), venture capital investment scale (ln*Fund*), and venture capital investment weight (*FundEntropy*). The Hansen's J statistic fails to reject the null hypothesis, indicating no overidentification issues with the instrumental variables and validating the estimation results.

The PVAR model reveals divergent patterns among the three key variables characterizing innovation-driven development: industrial upgrading (*Ser*) shows a significantly positive correlation with technological progress (*Techch*), however, TFP growth (*TFPch*) exhibits negative correlations with both industrial upgrading (*Ser*) and technological progress (*Techch*), suggesting that TFP—which incorporates scale efficiency effects—may not be the optimal proxy for "innovation-driven" development due to its composite nature.

Table 4. PVAR-GMM Estimation Results.

Variables	*TFPch*	*Techch*	*Sech*	*Ser*	ln*Fund*	*FundEntropy*
$TFPch_{t-1}$	−0.475*** (0.092)	−0.376*** (0.057)	0.058 (0.059)	−0.139*** (0.036)	0.120 (0.174)	0.094 (0.095)
$Techch_{t-1}$	0.120 (0.106)	−0.011 (0.090)	−0.314*** (0.067)	0.258*** (0.089)	−2.411*** (0.512)	−0.156 (0.160)
$Sech_{t-1}$	−0.088 (0.210)	1.347*** (0.290)	−0.926*** (0.145)	0.091 (0.163)	2.169* (1.155)	−0.220 (0.304)
Ser_{t-1}	0.422*** (0.138)	1.118*** (0.095)	−0.012 (0.063)	0.353*** (0.088)	6.959*** (0.927)	−0.197* (0.115)
$\ln Fund_{t-1}$	−0.011* (0.007)	−0.024*** (0.008)	0.008* (0.004)	0.019*** (0.006)	0.095* (0.051)	−0.003 (0.006)
$FundEntropy_{t-1}$	0.437*** (0.157)	0.512** (0.202)	0.001 (0.167)	0.064 (0.170)	0.080 (0.805)	0.467** (0.186)
Hansen's J	84.144118 (p Value = 0.244)					

Note: ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard deviation in parentheses.

The results in Table 4 also show the key findings on venture capital effects:

VC investment scale (ln*Fund*): (1) positive correlation with industrial upgrading (*Ser*), confirming that venture capital accelerates industrial upgrading and advanced industrial structures attract more venture capital; (2) negative correlation with *TFPch*, as increased capital inputs mechanically reduce TFP's relative contribution; (3) positive correlation with scale efficiency change (*Sech*), indicating improved returns-to-scale.

VC investment weight (*FundEntropy*): (1) significantly promotes both TFP growth and technological progress (*Techch*); (2) highlights the importance of capital structure optimization beyond mere scale expansion.

The above results demonstrate that while industrial upgrading attracts venture capital, simply expanding fund investments without rebalancing regional capital structures (e.g., reducing indirect financing ratio) proves insufficient for fostering genuine innovation-driven development.

4.3. Granger Causality Tests, Impulse Response and Variance Decomposition

The Granger causality tests (in Table 5) on the PVAR model reveal a bidirectional causal relationship between industrial upgrading and venture capital investment. Specifically:

(1) Mutual Reinforcement Effect: Increased venture capital investment accelerates industrial upgrading. Meanwhile, the advanced industrial structures simultaneously attract more venture capital (reverse causality).

(2) Differential Effects on Productivity Growth: Both venture capital scale (ln*Fund*) and weight (*FundEntropy*) demonstrate Granger causality with TFP growth (*TFPch*) and technological progress (*Techch*). However, their coefficients in the PVAR model show opposite signs, indicating that mere increases in VC investment volume may crowd out other productivity-enhancing factors but also by rebalancing regional financing structures (reducing indirect financing ratio while increasing VC scale) can venture capital effectively drive innovation-led development.

The impulse response functions (IRFs) trace the dynamic effects of a one-standard-deviation shock to the stochastic disturbance term on current and future values of variables in the VAR system, effectively capturing the temporal relationships and interaction intensities among variables. Figure 2 shows the venture capital's impact on innovation-driven development, examining how the shocks of VC scale (ln*Fund*) and weight (*FundEntropy*) affect the TFP growth (*TFPch*), technological progress (*Techch*) and industrial upgrading (*Ser*) over a 10-period horizon. The left-side variables represent shock sources, while the right-side variables show responses, with the X-axis indicating time periods and Y-axis response magnitudes.

The impulse response analysis in Figure 2 reveals distinct dynamic patterns:

(1) Capital Structure Effects (Row 1): The response of TFP growth (*TFPch*) and technological progress (*Techch*) to a one-standard-deviation shock in venture capital investment weight (*FundEntropy*) reaches its peak positive effect at 2–3 quarters before gradually converging to zero by quarter 5. This indicates that rebalancing the social financing structure by increasing direct financing ratio generates that the strong innovation-driven effects emerging within 2–3 quarters (half year) and the persistent impacts lasting approximately 5 quarters (over one year).

(2) Investment Scale Effects (Row 2): The industrial upgrading (*Ser*) response to venture capital scale (ln*Fund*) shocks shows that the significant positive effects during quarters 1–4 and the gradual dissipation by quarter 5. However, technological progress (*Techch*) exhibits the initial negative impact in quarter 1 and positive turnaround from quarter 2 onward, peaking subsequently.

This dual pattern suggests that: (a) Venture capital predominantly invests in emerging tertiary industries through equity financing, leading to the immediate increases in tertiary sector share (industrial upgrading) and short-term capital deepening effects that initially crowd out R&D inputs (negative *Techch* in Q1; (b) The equity investment mechanism subsequently enhances firm innovation capacity through governance and resource allocation and generates delayed but sustained technological progress (positive *Techch* from Q2).

Through forecast error variance decomposition (FEVD), we quantify the relative contribution of orthogonalized shocks from all variables to the forecast mean squared error of each individual variable, thereby providing deeper insights into their interrelationships [18]. Table 6 presents the FEVD results based on 300 Monte Carlo simulations of shocks to innovation-related proxy variables, showing decomposition outcomes for periods 5 and 10.

The variance decomposition analysis reveals three key findings: First, industrial upgrading (*Ser*) and technological progress (*Techch*) exhibit significant bidirectional interactions, with variance contribution rates of 20.1% and 11.5% respectively, confirming their dual role as primary proxies for innovation-driven development. Second, venture capital demonstrates differential impacts, with investment scale (ln*Fund*) contributing 3.7% to technological progress (*Techch*) and 5.2% to industrial upgrading (*Ser*), while investment weight (*FundEntropy*) accounts for approximately 2.4% to both TFP growth (*TFPch*) and technological progress (*Techch*). Third, while venture capital shows statistically significant effects on innovation development, the results suggest it operates as a secondary driver rather than the dominant force, as structural factors (embodied in *Ser*-*Techch* interactions) account for greater variance, though capital structure optimization (*FundEntropy*) demonstrates comparable importance to absolute investment volume (ln*Fund*).

Table 5. Granger Causality Test.

Variable	χ^2 Value	DF	*p*-Value	Test Conclusion
TFPch ← *Techch*	1.270	1	0.260	Do not reject H_0: No Granger causation
TFPch ← *Sech*	0.178	1	0.673	Do not reject H_0: No Granger causation
TFPch ← *Ser*	9.365	1	0.002	Reject H_0: Significant Granger causation
TFPch ← ln*Fund*	2.998	1	0.083	Reject H_0: Significant Granger causation
TFPch ← *FundEntropy*	7.733	1	0.005	Reject H_0: Significant Granger causation
TFPch ← *All*	21.970	5	0.001	Reject H_0: Significant Granger causation
Techch ← *TFPch*	43.924	1	0.000	Reject H_0: Significant Granger causation
Techch ← *Sech*	21.571	1	0.000	Reject H_0: Significant Granger causation
Techch ← *Ser*	137.547	1	0.000	Reject H_0: Significant Granger causation
Techch ← ln*Fund*	9.460	1	0.002	Reject H_0: Significant Granger causation
Techch ← *FundEntropy*	6.395	1	0.011	Reject H_0: Significant Granger causation
Techch ← *All*	248.191	5	0.000	Reject H_0: Significant Granger causation
Sech ← *TFPch*	0.960	1	0.327	Do not reject H_0: No Granger causation
Sech ← *Techch*	22.295	1	0.000	Reject H_0: Significant Granger causation
Sech ← *Ser*	0.037	1	0.847	Do not reject H_0: No Granger causation
Sech ← ln*Fund*	2.997	1	0.083	Reject H_0: Significant Granger causation
Sech ← *FundEntropy*	0.000	1	0.996	Do not reject H_0: No Granger causation
Sech ← *All*	85.242	5	0.022	Reject H_0: Significant Granger causation
Ser ← *TFPch*	15.265	1	0.000	Reject H_0: Significant Granger causation
Ser ← *Techch*	8.492	1	0.004	Reject H_0: Significant Granger causation
Ser ← *Sech*	0.311	1	0.577	Do not reject H_0: No Granger causation
Ser ← ln*Fund*	9.822	1	0.002	Reject H_0: Significant Granger causation
Ser ← *FundEntropy*	0.142	1	0.707	Do not reject H_0: No Granger causation
Ser ← *All*	39.528	5	0.000	Reject H_0: Significant Granger causation
ln*Fund* ← *TFPch*	0.481	1	0.488	Do not reject H_0: No Granger causation
ln*Fund* ← *Techch*	22.189	1	0.000	Reject H_0: Significant Granger causation
ln*Fund* ← *Sech*	3.527	1	0.060	Reject H_0: Significant Granger causation
ln*Fund* ← *Ser*	56.402	1	0.000	Reject H_0: Significant Granger causation
ln*Fund* ← *FundEntropy*	0.010	1	0.921	Do not reject H_0: No Granger causation
ln*Fund* ← *All*	118.759	5	0.000	Reject H_0: Significant Granger causation
FundEntropy ← *TFPch*	0.970	1	0.325	Do not reject H_0: No Granger causation
FundEntropy ← *Techch*	0.953	1	0.329	Do not reject H_0: No Granger causation
FundEntropy ← *Sech*	0.524	1	0.469	Do not reject H_0: No Granger causation
FundEntropy ← *Ser*	2.923	1	0.087	Reject H_0: Significant Granger causation
FundEntropy ← ln*Fund*	0.245	1	0.621	Do not reject H_0: No Granger causation
FundEntropy ← *All*	9.961	5	0.076	Reject H_0: Significant Granger causation

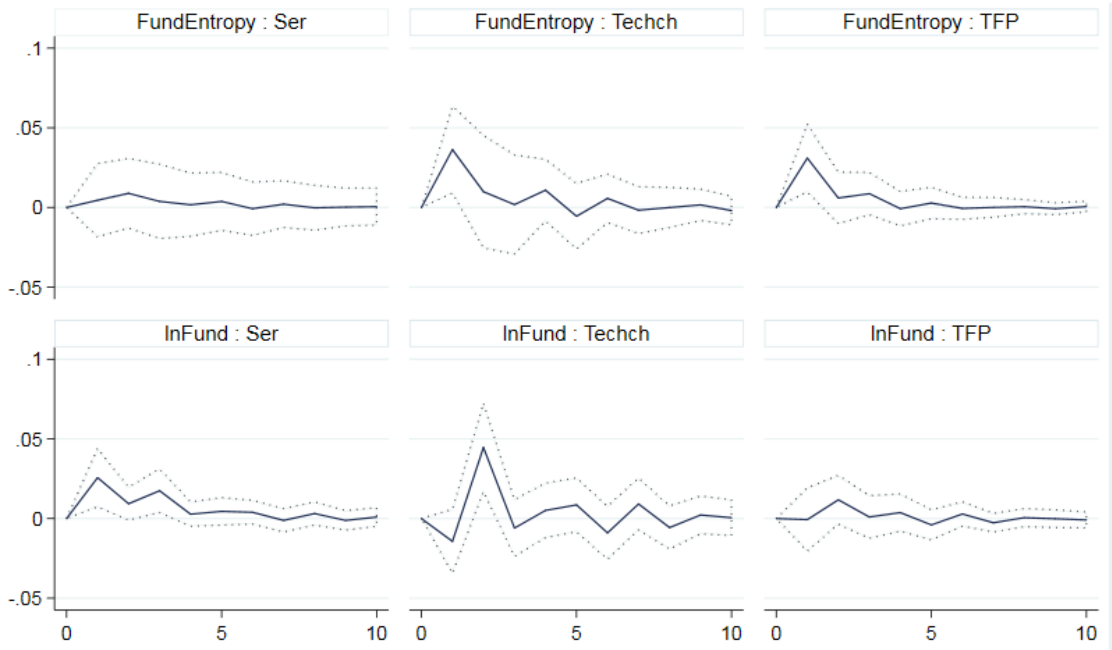

Figure 2. Impulse Response of the PVAR Model.

Table 6. Variance Decomposition Results of the PVAR Model.

Variable	S	*TFPch*	*Techch*	*Sech*	*Ser*
TFPch	5	0.909	0.097	0.058	0.031
Techch	5	0.009	0.505	0.311	0.110
Sech	5	0.136	0.142	0.464	0.035
Ser	5	0.039	0.196	0.134	0.768
ln*Fund*	5	0.003	0.036	0.019	0.051
FundEntropy	5	0.024	0.024	0.011	0.006
TFPch	10	0.903	0.101	0.063	0.033
Techch	10	0.012	0.495	0.302	0.115
Sech	10	0.015	0.142	0.459	0.039
Ser	10	0.041	0.201	0.138	0.756
ln*Fund*	10	0.004	0.037	0.021	0.052
FundEntropy	10	0.024	0.025	0.012	0.006

5. Conclusions and Implications

The empirical analysis employing provincial quarterly panel data from 2021 to 2024 within a panel vector autoregressive (PVAR) framework demonstrates that venture capital exerts significant positive effects on innovation-driven economic development overall. When decomposing venture capital into investment scale and investment weight while using total factor productivity, industrial upgrading and technological progress as distinct proxies for innovation development, the results reveal a bidirectional relationship between industrial upgrading and venture capital: industrial upgrading attracts venture capital while increased venture capital scale simultaneously drives industrial upgrading. However, the analysis shows that merely expanding investment scale without improving the proportion of direct financing in the social financing structure fails to significantly promote technological progress. These findings suggest that comprehensive promotion of innovation-driven development requires coordinated policies that simultaneously increase venture capital investment scale and optimize regional financing structures by enhancing direct financing ratio.

Based on the theoretical framework and empirical findings of this study, the following policy implications are proposed:

(1) Promote venture capital development and restructure social financing channels. The results demonstrate that while expanding venture capital investment scale significantly drives industrial upgrading, it shows limited effects on enhancing total factor productivity (TFP) or technological progress. Conversely, increasing the proportion of direct financing in social financing structures exerts significantly positive impacts on TFP growth, industrial upgrading, and technological advancement. Therefore, policymakers should not merely focus on scaling up venture capital funds, but rather prioritize restructuring the social financing system through institutional development, policy guidance, and investment incentives. This includes encouraging enterprises to increase direct financing ratio and motivating financial institutions to innovate diversified, flexible direct financing instruments, thereby gradually reducing indirect financing ratio while meeting corporate financing needs.

(2) Improve the multi-tier capital market system to enhance exit flexibility for venture capital. As the primary platform for direct financing and crucial exit channel for venture capital, the capital market system's development is essential [19]. Given that venture capital primarily realizes returns through exit mechanisms, insufficient or narrow exit options significantly dampen investment incentives. We recommend deepening capital market reforms beyond stock market expansion, including developing innovative market mechanisms and strengthening alternative exit channels such as mergers and acquisitions. These measures would accelerate capital recycling towards promising enterprises, generating synergistic effects between industrial and financial development.

(3) Implement coordinated policies to foster innovation-driven growth. The study reveals that although venture capital significantly contributes to innovation development, it alone cannot serve as the primary driving force. Regional innovation requires comprehensive strategies combining talent recruitment, business environment optimization, and technology commercialization, complemented by venture capital investments. Furthermore, the research identifies a virtuous cycle wherein industrial upgrading attracts venture capital, which in turn accelerates further upgrading—creating a reinforcing feedback mechanism. This dynamic consolidates regional industrial transformation by sustaining upgrading processes and maintaining structural advantages.

(4) Establish differentiated policies based on regional characteristics. The effectiveness of venture capital varies significantly across regions with different financial development levels and industrial structures. Policymakers should adopt tailored approaches: developed regions should focus on optimizing capital structures and exit mechanisms, while developing regions may prioritize basic scale expansion and market infrastructure building. This spatial differentiation ensures optimal resource allocation and maximizes policy impacts according to local conditions.

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Conflicts of Interest

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