

Research on the Impact of Lean Startup Methodology on Corporate Labor Investment Efficiency

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Abstract. Against the dual background of deep digital economy penetration and continuous rises in macro labor costs, optimizing the efficiency of labor resource allocation has become a core issue for the transformation, upgrading and high-quality development of micro-enterprises. Taking Shanghai and Shenzhen A-share listed companies in China from 2007 to 2024 as research samples, this paper systematically examines the effect of the lean startup method on corporate labor investment efficiency and its internal working mechanism. The study finds that the lean startup method can significantly improve corporate labor investment efficiency. This conclusion remains valid after a series of robustness tests, including changing the measurement of explanatory variables, controlling high-order fixed effects, and excluding municipality samples. Mechanism tests show that the lean startup method indirectly boosts labor investment efficiency mainly through three paths: improving information transparency, accelerating digital transformation, and stimulating corporate innovation vitality. Further heterogeneity analysis finds that the improvement effect of the lean startup method on labor investment efficiency is more prominent in enterprises in eastern regions, enterprises in non-regulated industries, and high-tech enterprises. This research not only expands the theoretical boundary of the economic consequences of the lean startup method, but also provides an innovative micro-management perspective for enterprises to optimize human capital allocation in an uncertain environment.

Keywords: Lean Startup Method, Labor Investment Efficiency, Information Transparency, Digital Transformation, Corporate Innovation

1. Introduction

Against the complex background of deep penetration of the digital economy and mounting macroeconomic downward pressure, how to restructure and optimize the allocation of corporate labor resources has become the key to the transformation and upgrading of China's manufacturing industry and its escape from the low-cost trap. As the most dynamic core production factor of enterprises, the investment efficiency of labor directly determines enterprises' operational performance and long-term risk resistance capacity. However, with the fading demographic dividend and rigid rise in labor costs, Chinese enterprises face a dilemma in employment decision-making: on the one hand, constrained by the bounded rationality of management information or agency motives, some enterprises tend to blindly expand their workforce to "build personal empires", which gives

rise to severe labor redundancy and resource manipulation; on the other hand, restricted by external financing constraints or short-term performance pressure, some enterprises tend to downsize excessively, resulting in underemployment and missed opportunities for market expansion [1]. In addition, while the in-depth implementation of the *Labor Contract Law of the People's Republic of China* protects workers' rights and interests, it also objectively raises enterprises' dismissal costs and employment rigidity [2]. Therefore, in a highly uncertain market environment, how to find a micro-management paradigm that balances decision-making agility and risk control to optimize labor investment efficiency has become a practical issue that urgently needs to be addressed by both academia and the industrial sector.

Meanwhile, as an emerging management paradigm to cope with uncertainty, the Lean Startup Method (LSM) has triggered a wave of transformation in modern corporate management since it was proposed by Ries [3]. Different from the "plan-driven" static management mode under the traditional system, lean startup takes "minimum viable product (MVP)", "rapid iteration", "customer feedback" and "validated learning" as its core logic. It emphasizes verifying market assumptions through a low-cost "build-measure-learn" feedback loop, thus greatly reducing enterprises' trial-and-error costs and improving factor utilization. Existing studies show that the lean startup method can not only significantly empower product innovation [4], but also reshape dynamic business processes [5], and demonstrates strong contextual adaptability in digital scenarios [6]. Bortolini et al. point out [7] that the applicable scope of lean startup has broken the initial label of "startups" and gradually extended to mature enterprises, becoming an important strategic tool for enterprises to resolve external environmental uncertainty.

However, looking at existing research on economic consequences, scholars mostly focus on the driving effect of lean startup on the "output side" such as product innovation or financial performance, while ignoring its governance function on internal resource allocation, especially on the input side of labor, the core production factor. In fact, under the Chinese context where the *Labor Contract Law* is fully implemented, labor investment decisions feature typical high adjustment costs and asymmetric rigidity — enterprises often face institutional constraints that make hiring easier than firing. This requires enterprises to have strong foresight and fault tolerance when assessing future labor demand. This special decision-making scenario fits perfectly with the core features of lean startup: data retention, small-scale trial and error, and strong feedback. On this basis, the restructuring of labor factors by the lean startup method is by no means a simple physical combination. Instead, it realizes indirect empowerment and implicit governance of labor investment efficiency by reshaping enterprises' internal information ecology (improving transparency), technical foundation (deepening digitalization) and action mechanism (stimulating innovation).

On the other hand, academia has accumulated rich findings on the driving factors of labor investment efficiency. At the internal governance level, based on data from US listed companies, Jung et al. first found that high-quality accounting information can significantly improve corporate labor investment efficiency by alleviating information asymmetry and agency problems [1]. Ha and Feng further confirmed that accounting conservatism restrains inefficient investment behavior by providing early warning signals to management [8]. At the external supervision level, Khedmati et al. found that close ties between CEOs and independent directors weaken the supervisory effectiveness of the board of directors [9], leading to lower labor investment efficiency; Liu and Sun, from the perspective of institutional investors, found that institutional ownership can significantly improve corporate labor investment efficiency by reducing two types of agency costs and easing financing constraints [10]. In addition, external market mechanisms such as relaxed short-selling constraints have also been proven to improve labor investment efficiency [11]. The above studies

have laid a solid foundation for understanding the driving factors of labor investment efficiency, but a notable research gap remains: as a management method emphasizing data-driven decision-making and rapid validation, the systematic impact of lean startup on internal labor investment efficiency of enterprises has not been tested.

In addition, regarding the influence mechanism, existing studies generally agree that information asymmetry, agency problems and financing constraints are the three core causes of inefficient labor investment [1, 10]. The lean startup method has potential positive effects in exactly these three aspects. First, lean startup emphasizes "validated learning" and customer data-driven decision-making, which helps reduce management's subjective assumptions in hiring decisions and lower information asymmetry. Second, through MVP and small-batch iteration, lean startup reduces the risk exposure of a single investment decision, thus alleviating the "risk aversion" bias in principal-agent problems. Third, the concept of efficient resource allocation advocated by lean startup can improve the overall operational efficiency of enterprises, and in turn enhance their financing capacity. These mechanism paths theoretically form a complete chain through which lean startup affects labor investment efficiency, but their validity still needs to be verified through rigorous empirical research.

Based on the above analysis, this paper takes Shanghai and Shenzhen A-share listed companies in China from 2007 to 2024 as research samples to systematically examine the impact of the lean startup method on corporate labor investment efficiency. Specifically, this paper attempts to answer three questions: First, can the lean startup method significantly improve corporate labor investment efficiency? Second, if such an effect exists, what is its working mechanism — is it through improving information transparency, accelerating digital transformation, or promoting corporate innovation? Third, does this effect differ significantly across enterprises in different regions, different industries, and with different technical attributes?

The marginal contributions of this paper are mainly reflected in three aspects. First, this paper extends the research on the lean startup method from the fields of innovation management and entrepreneurship management to the level of internal labor allocation. It tests the main effect of the lean startup method on labor investment efficiency, enriches the research scope of the economic consequences of lean startup, and provides a new analytical perspective for research on the driving factors of labor investment efficiency. Second, at the mechanism level, this paper systematically tests three potential mediating paths: information transparency, digital transformation and innovation. It reveals the transmission mechanism of the lean startup method affecting labor investment efficiency from the multi-dimensional perspective of "information-technology-innovation", and provides multi-level empirical evidence for understanding how the lean startup method reshapes internal corporate management. Third, the conclusions of this paper can provide practical and operable references for manufacturing enterprises on how to optimize human capital allocation through lean startup thinking under the dual background of digital transformation and rising labor costs, with clear policy implications.

2. Research hypotheses

As the most dynamic core production factor of micro-enterprises, the investment and allocation efficiency of labor directly determines enterprises' production and operation performance and market competitiveness. As Jung et al. note [1], more than half of the value created by micro-enterprises worldwide comes directly from labor cost input. Against this backdrop, how to address inefficient labor investment has long been a focus of academic attention. Existing literature has conducted useful explorations on the driving factors of labor investment efficiency mainly from the

dimensions of information environment, governance structure and external supervision. For example, Jung et al. first systematically examined the impact of financial reporting quality on labor investment efficiency [1], and confirmed that high-quality accounting information can significantly curb over-employment and under-employment by alleviating information asymmetry and agency conflicts. Khedmati et al. started from internal governance [9] and found that overly close social ties between CEOs and independent directors erode the board's supervisory effectiveness, which in turn aggravates labor misallocation. Under the Chinese institutional context, Liu and Sun confirmed from the perspective of external supervision [10] that institutional ownership can significantly improve corporate labor investment efficiency by reducing two types of agency costs and easing financing constraints. In addition, the improvement effects of external governance mechanisms such as accounting conservatism, analyst coverage and relaxed short-selling constraints have also been widely verified. However, among the above studies, most existing findings focus on finding solutions from external institutions, capital markets or traditional financial governance, while ignoring the restructuring effect of changes in enterprises' micro-level management paradigms on labor factors. As an emerging management paradigm featuring "rapid validation, customer orientation and iterative learning", the systematic impact of the Lean Startup Method (LSM) on labor investment efficiency and its micro-governance function have not been fully tested.

Different from the traditional plan-driven management mode, the core of the lean startup method is to quickly test market assumptions through the minimum viable product (MVP), obtain validated learning through the "build-measure-learn" feedback loop, and realize efficient resource allocation under uncertainty. Through a systematic review of lean startup literature, Bortolini et al. point out [7] that this method has gradually expanded from startups to mature enterprises, becoming an important management tool for coping with uncertain environments. Since labor investment decisions are inherently highly uncertain — enterprises need to judge future labor demand with incomplete information, and face dual constraints of hiring costs and dismissal rigidity — this decision-making scenario aligns well with what the lean startup method excels at: small-step trial and error, rapid feedback, and data-driven operation. Therefore, the lean startup method can not only help enterprises optimize product development processes, but also may exert a positive impact on labor investment efficiency through channels such as improving the information environment and optimizing resource allocation.

Specifically, the positive impact of the lean startup method on labor investment efficiency can be understood from the following three dimensions.

2.1. Information perspective: the path of information transparency

The introduction of the lean startup paradigm can enhance micro-entities' dynamic trial-and-error capacity, thus breaking the "information black box" in labor employment decision-making. A major pain point of human capital allocation is that management often faces a disconnect between external market disruption and internal management cognition, and this lack of forward-looking information can easily trigger blind expansion or conservative contraction. The logic of "minimum viable product (MVP)" advocated by lean startup essentially deconstructs one-time, large-scale factor bets into multiple rounds of small-scale verification. This agile employment mode of "trial first, review second, adjustment third" allows enterprises to precisely calibrate their staffing levels based on real-time business feedback, and curbs labor resource misallocation caused by decision-making blind spots at the source.

2.2. Technology perspective: the path of digital transformation

The practice of the lean startup method accelerates the process of enterprise digital transformation, which in turn promotes the improvement of labor investment efficiency. Digital transformation and the lean startup method share deep logical homology in their core concepts — both emphasize data-driven operation, rapid iteration and customer orientation. Existing studies find that enterprise digital transformation can effectively improve labor investment efficiency. Its working mechanism lies in that digital transformation lays the foundation for the improvement of labor investment efficiency through two key channels: alleviating internal agency conflicts and reducing external financing constraints. Research by Zhou and Wan also shows [12] that digital transformation improves enterprise labor investment efficiency, and this effect is more significant in non-state-owned enterprises and high-tech enterprises. Enterprise digital transformation can enhance enterprises' capacity for resource management and utilization, ease financing constraints and raise total factor productivity, thereby improving labor investment efficiency. The practice of the lean startup method is exactly one of the important driving forces for enterprise digital transformation. To implement the rapid iteration and data validation required by lean startup more effectively, enterprises need corresponding digital infrastructure as support, which forces enterprises to speed up digital transformation. Based on this, this paper proposes hypothesis H1b: the lean startup method improves labor investment efficiency by promoting enterprise digital transformation, that is, the degree of digital transformation plays a mediating role between the lean startup method and labor investment efficiency.

2.3. Innovation perspective: the path of innovation vitality

The practice of the lean startup method can improve labor investment efficiency by promoting corporate innovation activities. The improvement of corporate innovation capacity has a significant positive impact on labor investment efficiency. On the one hand, innovation activities themselves require matching highly skilled talents, which prompts enterprises to adjust their workforce structure more precisely and reduce redundant employment and misallocation. Research by Bu and Sun points out [13] that environmental uncertainty aggravates agency problems and limits managers' capabilities, thereby reducing corporate labor investment efficiency, while innovation activities effectively alleviate the above negative impacts by improving enterprises' information processing capacity and organizational learning capacity. On the other hand, innovation can improve the overall production efficiency of enterprises, and the marginal output of labor rises accordingly, enabling enterprises to allocate labor resources more precisely for the same output. The promoting effect of the lean startup method on innovation activities has been confirmed by a large amount of literature. Taking the digital lean startup KIT-AR as an example, Powell and Oliveira find [5] that the build-measure-learn cycle of lean startup can effectively match production needs in intelligent manufacturing scenarios and significantly improve innovation efficiency. Felin et al. point out [14] that the rapid experimentation and validated learning update emphasized by lean startup can help enterprises identify the optimal path of technological innovation evolution and reduce trial-and-error costs in the innovation process. Based on this, this paper proposes hypothesis H1c: the lean startup method improves labor investment efficiency by promoting corporate innovation activities, that is, the level of corporate innovation plays a mediating role between the lean startup method and labor investment efficiency.

3. Empirical design

3.1. Sample data and data sources

This study selects Shanghai and Shenzhen A-share listed companies in China from 2007 to 2024 as the initial research sample. To ensure data quality and robustness of conclusions, the samples are screened as follows: (1) Exclude financial and insurance enterprises; (2) Exclude enterprises marked as ST, *ST or PT during the sample period; (3) Exclude enterprises with missing data for main variables; (4) To eliminate the influence of extreme values, all continuous variables are winsorized at the 1% and 99% quantiles. Finally, firm-year observations covering multiple industries are obtained. Enterprise financial data, corporate governance data and labor investment efficiency data are mainly sourced from the China Stock Market & Accounting Research (CSMAR) database. The text data of enterprise annual reports are sourced from the official websites of the Shenzhen Stock Exchange and the Shanghai Stock Exchange, which are used to construct the lean startup method index. Patent data are sourced from the China Research Data Services Platform (CNRDS), which serve as the mediating variable of corporate innovation in mechanism tests.

3.2. Model design and variable definition

To test the impact of the lean startup method on labor investment efficiency, this paper constructs the following benchmark regression model:

$$Abhire_{it} = \alpha + \beta LSM_Score_{it} + \gamma Control_{it} + \mu + \delta + \varepsilon$$

Among them, the explained variable *Abhire* is the inefficiency of corporate labor investment; the core explanatory variable *LSM_Score* is the degree of application of the lean startup method in enterprises; *Control* is the set of control variables; μ is the firm fixed effect, used to control the heterogeneous characteristics of enterprises that do not change over time; λ is the year fixed effect, used to control time trend factors such as the macroeconomic environment; ε is the random disturbance term.

3.2.1. Explained variable

The explained variable is labor investment efficiency (*Abhire*). Drawing on the methods of Jung et al. and Liu and Sun [1, 10], this paper measures labor investment efficiency using the absolute value of the residual obtained by regressing the growth rate of enterprise employees (*Nethire*) with relevant economic variables. The absolute value of the residual ε obtained from year-by-year and industry-by-industry regression is labor investment inefficiency (*Abhire*). A smaller value indicates higher labor investment efficiency of the enterprise.

3.2.2. Explanatory variable

The explanatory variable is the intensity of the lean startup method (*LSM_Score*). Drawing on the research method of Wang and Wu [4], this paper measures the implementation level of the lean startup method in enterprises by combining annual report word frequency counting with entropy weight method for weighting. First, a keyword dictionary is constructed based on core lean startup

keywords such as "minimum viable product (MVP)", "rapid iteration", "customer feedback", "build-measure-learn" and "validated learning". Second, the word frequency of the above keywords is extracted from the annual reports of listed companies through Python crawler technology. Finally, the entropy weight method is used to weight the word frequency of various keywords to construct a comprehensive index of the lean startup method (LSM_Score). A larger index value indicates a higher degree of implementation of the lean startup method in the enterprise.

3.2.3. Mediating variables

Mediating variables include information transparency (TRANS), degree of digital transformation (DIGI_text) and corporate innovation level (Innovation). For information transparency, drawing on the method of Xin et al. [15], a comprehensive index (TRANS) is constructed using the average percentile rank of five indicators: earnings quality, information disclosure assessment results of the Shenzhen Stock Exchange, number of analysts following, accuracy of analysts' earnings forecasts, and whether the enterprise is audited by the Big Four international accounting firms. A larger value indicates higher information transparency. For the degree of digital transformation, referring to the method of Wu et al. [16], keywords such as "artificial intelligence", "blockchain", "cloud computing", "big data" and "digital technology application" are extracted from the annual reports of listed companies through Python crawler technology and their word frequencies are counted. A comprehensive index (DIGI_text) is then constructed after weighting with the entropy weight method. The level of corporate innovation is measured by the natural logarithm of the total number of patent applications of the enterprise in the current year plus 1 as the proxy variable.

3.2.4. Control variables

To control for other micro characteristics that may interfere with enterprise employment decisions and factor allocation, this study introduces a series of control variables. Specifically: (1) Firm size (Size), represented by the logarithm of total assets, to control differences in resource endowment under the scale effect; (2) Asset-liability ratio (Lev), to control the financial constraints and risk preferences faced by enterprises; (3) Return on assets (ROA), to capture the basic profitability and operating performance of enterprises; (4) Current ratio (Liquid), to measure short-term debt repayment pressure and capital liquidity; (5) Proportion of fixed assets (Fixed), to reflect the asset-heavy attribute of the asset structure; (6) Operating revenue growth rate (Growth), to control the future expansion space of enterprises. In addition, this paper also controls for corporate governance variables, including board size (Board), proportion of independent directors (Indep), duality of chairman and general manager (Dual), shareholding ratio of the top ten shareholders (Top10) and equity balance degree (Balance2), and adds firm age (FirmAge) to eliminate the life cycle effect. All the above continuous variables are winsorized at both the 1% and 99% quantiles.

Table 1. Descriptive statistics results

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
Abhire	43,104	0.244	0.277	0	3.438
LSM_Score	43,104	0.006	0.012	0.001	0.283
Size	43,104	22.300	1.329	17.641	28.791
Lev	43,104	0.443	0.204	0.008	0.998

Table 1. (continued)

ROA	43,104	0.029	0.081	-2.746	0.974
Liquid	43,104	2.322	2.840	0.026	144.000
Fixed	43,104	0.217	0.163	0.000	0.954
Growth	43,104	3.753	652.371	-1.445	134607.100
Board	43,104	2.124	0.203	1.099	2.890
Indep	43,104	0.376	0.055	0.000	0.818
Dual	43,104	0.275	0.447	0	1
Top10	43,104	0.561	0.155	0.013	1.012
Balance2	43,104	0.726	0.616	0.003	4.000
FirmAge	43,104	2.967	0.337	1.099	4.290

4. Empirical analysis

4.1. Baseline analysis

Table 2 presents the benchmark estimation results. In column (1), which includes no control variables or fixed effects, the estimated coefficient of LSM_Score does not reach statistical significance. In column (2), after controlling for firm fixed effects, the coefficient of the core explanatory variable is significantly negative at the 10% level. Column (3) further excludes the macro impact of time trends on micro-enterprises. Under the two-way fixed effect framework, the coefficient of lean startup intensity (LSM_Score) is -0.295, and is strongly significant at the 1% level. This strongly confirms that deepening the application of the lean startup method can significantly reduce the deviation of corporate labor investment from the optimal level. In terms of economic significance, assuming other control variables remain constant, each standard deviation increase in the level of lean startup reduces labor investment inefficiency (Abhire) by approximately 2.1% (calculated based on the sample mean). The above empirical evidence directly supports the core hypothesis H1 of this paper, that is, the lean startup paradigm can empower micro-entities and improve the allocation efficiency of their human capital.

Table 2. Benchmark regression

	(1)	(2)	(3)
VARIABLES	Abhire	Abhire	Abhire
LSM_Score	-0.029 (-0.327)	-0.227* (-1.896)	-0.295*** (-2.611)
Observations	43,104	43,104	43,104
R-squared	0.009	0.139	0.196
id	NO	YES	YES
year	NO	NO	YES

Note: t-values are in parentheses; ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

4.2. Robustness checks

4.2.1. Changing the explanatory variable

To avoid measurement bias of the index, alternative variables are used for re-regression. The regression results show that the regression coefficient of LSM_Score is -15.473, significant at the 1% level, and the benchmark conclusion is robust.

4.2.2. Adding model fixed effects

On the basis of the original two-way fixed effects of firm and year, city fixed effects and industry fixed effects are further added to control for time-invariant confounding factors at the regional and industry levels. The results show that the regression coefficient of LSM_Score is -0.258, significant at the 5% level, and the benchmark conclusion is robust.

4.2.3. Excluding municipalities

Considering the particularity of the four municipalities directly under the central government — Beijing, Shanghai, Tianjin and Chongqing — in terms of administrative level and policy resources, the conclusions based on these samples may not be universally applicable. After excluding the samples of these four cities, re-regression is conducted. The results show that the regression coefficient of LSM_Score is -0.291, significant at the 5% level, and the benchmark conclusion is robust.

Table 3. Results of robustness tests

	(1)	(2)	(3)
VARIABLES	Abhire	Abhire	Abhire
LSM_Score	-15.473*** (-5.73)	-0.258** (-2.464)	-0.291** (-2.095)
Observations	43,104	41,325	34,673
R-squared	0.227	0.204	0.204
id	YES	YES	YES
year	YES	YES	YES

4.3. Heterogeneity analysis

4.3.1. Regional heterogeneity

The test results of regional heterogeneity show that in the group of enterprises in eastern regions, the regression coefficient of LSM_Score is -0.404, significant at the 1% level; while in the group of enterprises in non-eastern regions, the regression coefficient of LSM_Score is 0.064, which fails the statistical significance test. This indicates that the improvement effect of the lean startup method on labor investment efficiency is more significant in eastern regions, which may benefit from the more developed market environment and more complete institutional guarantees in eastern regions.

4.3.2. Regulated industries

The test results of heterogeneity across regulated industries show that in the group of enterprises in non-regulated industries, the regression coefficient of LSM_Score is -0.448, significant at the 1% level; while in the group of enterprises in regulated industries, the regression coefficient of LSM_Score is 0.526, which fails the statistical significance test (and the coefficient is positive). This indicates that the improvement effect of the lean startup method on labor investment efficiency is more significant in non-regulated industries. A possible reason is that regulated industries are subject to more policy constraints, making it difficult for the flexibility and rapid iteration advantages of the lean startup method to be fully exerted.

4.3.3. High-tech industries

The test results of heterogeneity across technical attributes show that in the group of high-tech enterprises, the regression coefficient of LSM_Score is -0.342, significant at the 5% level; while in the group of non-high-tech enterprises, the regression coefficient of LSM_Score is -0.191, which fails the statistical significance test. This indicates that the improvement effect of the lean startup method on labor investment efficiency is more significant in high-tech enterprises. High-tech enterprises have stronger technology absorption capacity and more mature R&D systems, which can more effectively absorb the knowledge spillover contained in the lean startup method and translate it into optimal decisions for labor resource allocation.

Table 4. Results of heterogeneity analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Eastern Enterprises	Non-Eastern Enterprises	Regulated Industries	Non-Regulated Industries	High-Tech Industries	Non-High-Tech Industries
VARIABLES	Abhire	Abhire	Abhire	Abhire	Abhire	Abhire
LSM_Score	-0.404*** (-3.421)	0.064 (0.226)	0.526 (1.379)	-0.448*** (-4.003)	-0.342** (-2.537)	-0.191 (-0.738)
Observations	30,146	12,946	10,976	32,060	12,946	30,146
R-squared	0.201	0.196	0.210	0.211	0.203	0.194
id	YES	YES	YES	YES	YES	YES
year	YES	YES	YES	YES	YES	YES

5. Mechanism analysis

To test the transmission path through which the lean startup method affects labor investment efficiency, this paper adopts Jiang's two-step method [17]. First, it tests the impact of the lean startup method (LSM_Score) on three mediating variables, and then demonstrates the causal relationship between the mediating variables and labor investment efficiency combined with existing literature.

5.1. Information transparency

The empirical test for the information transparency channel shows that the estimated coefficient of LSM_Score on TRANS is significantly positive at the 1% confidence level (coefficient = 1.030), indicating that the implementation of the lean startup model can effectively enrich an organization's information resources. According to the classic micro-governance theory of Jung et al. and Liu and Sun [1, 10], agency conflicts induced by external uncertainty and the absence of external supervision are the root causes of micro factor misallocation. Improved information transparency can significantly reduce management's self-interested space to hide information or manipulate earnings, thereby curbing over-employment or under-employment. Based on the above logical closed loop, the lean startup method indirectly optimizes the investment boundary of labor resources by fostering a high-quality information ecology, and research hypothesis H1a is verified.

5.2. Degree of digital development

In the digital transformation path, the driving coefficient of LSM_Score on DIGI_text is significantly positive (0.046, $p < 0.01$), meaning that "data retention" and "high-frequency iteration" aligned with lean startup have a strong catalytic effect on the construction of enterprises' digital infrastructure. According to the empirical evidence of Zhou and Wan and Wang et al. [4, 12], the deep penetration of digital transformation at the micro level can greatly enhance enterprises' ability to accurately predict labor supply and demand and achieve real-time dynamic matching, and can substantially ease the financing obstacles faced by enterprises, providing technical dividends for eliminating inefficiency in employment decisions. Accordingly, lean startup opens up the technical path to improve labor investment efficiency by forcing enterprises to accelerate the pace of digital transformation, which verifies research hypothesis H1b.

5.3. Innovation channel

Examining the mechanism of innovation vitality reveals that the impact coefficient of LSM_Score on Innovation is significant at the 1% level (coefficient = 1.977), indicating that the experimental mechanism of lean startup has a significant incubation effect on corporate technological innovation. Combined with the research logic of Bu and Sun [13], environmental uncertainty usually distorts labor investment behavior by weakening management capabilities, while continuous innovation activities can significantly improve organizational learning and information processing capabilities, prompting enterprises to more rationally recruit and optimize the allocation of highly skilled talents in line with technological evolution, and realize the outward shift of the human capital frontier. This closed mechanism loop shows that the release of endogenous innovation vitality constitutes a key transmission channel through which lean startup empowers labor factor allocation, and research hypothesis H1c holds.

Table 5. Results of mechanism analysis

	(1)	(2)	(3)
VARIABLES	TRANS	DIGI_text	Innovation
LSM_Score	1.030*** (10.874)	0.046*** (3.974)	1.977*** (3.004)
Observations	37,149	43,104	19,721

Table 5. (continued)

R-squared	0.696	0.811	0.746
id	YES	YES	YES
year	YES	YES	YES

6. Conclusion

Taking Shanghai and Shenzhen A-share listed companies in China from 2007 to 2024 as research samples, this paper focuses on the employment transformation demands of micro-enterprises under the dual shocks of an uncertain environment and rigidly rising labor costs, and systematically examines the effect, micro transmission mechanism and situational boundaries of the lean startup method on corporate labor investment efficiency. The results of theoretical analysis and large-sample empirical tests show that the lean startup method has a significant "quality improvement and efficiency enhancement" function for micro factor allocation. It can effectively curb inefficient labor investment behaviors (including over-employment and under-employment) where enterprise labor resources deviate from the rational boundary. This core conclusion remains solid after a series of rigorous robustness tests, including changing the measurement method of core explanatory variables, controlling high-order multi-dimensional fixed effects, and excluding municipality samples. In terms of internal transmission paths, the empowerment of lean startup on labor investment efficiency is not a simple, direct physical intervention, but a multi-dimensional "governance combination". Mechanism analysis shows that relying on the "build-measure-learn" feedback loop, the lean startup method first reshapes the internal information ecology of enterprises by reducing management's room for earnings manipulation and self-interest motives, thereby improving information transparency. Second, its endogenous demand for data-driven operation forces and catalyzes the digital transformation process of micro-entities, thus consolidating the technical foundation of data intelligence. Finally, this method significantly activates the endogenous innovation motivation of micro-entities through a small-step, fast-running experimental mechanism. Through the three implicit channels of "improving information transparency, accelerating digital transformation, and releasing endogenous innovation vitality", lean startup indirectly drives the systematic optimization of human capital allocation efficiency. In addition, empirical evidence from heterogeneity analysis further reveals that the factor restructuring effect of the lean startup method is not one-size-fits-all. Instead, it is highly dependent on the inclusiveness of the external institutional environment, the degree of market development, and enterprises' own knowledge and technology absorption capacity. Specifically, the improvement effect of this method on labor investment efficiency shows stronger spillover effects and governance flexibility in enterprises in eastern regions with more mature market-oriented business environments, enterprises in non-regulated industries with fewer rigid policy access constraints, and high-tech enterprises with more mature R&D layouts and technology absorption capacity.

Although this paper provides useful insights for enterprise employment governance in a risk-resistant environment, there are still micro limitations that need to be further explored. First, regarding the measurement of core variables, although combining annual report text word frequency with entropy weight method weighting is a mature practice for quantifying enterprise management paradigms at present, text features often carry the color of management's "forward-looking strategic claims". It is difficult to fully and accurately reflect the depth of lean startup practice at the micro implementation level of enterprises, which may lead to a gap between strategic advocacy and actual practice. Future research can adopt mixed research designs such as in-depth enterprise interviews

and first-hand questionnaire tracking to measure the implementation effect of lean startup more precisely. Second, regarding the exploration of the working mechanism, although this study clarifies and verifies three key transmission links — information transparency, digital foundation and innovation vitality — the restructuring of organizational structure by lean startup is comprehensive. Future research can try to include potential factors such as organizational flexible learning and implicit human capital structure upgrading into the research scope, to further enrich the institutional spillover matrix of lean management. Finally, limited by data availability, the empirical observation scope of this paper focuses on A-share entities in China's capital market. However, lean startup thinking also has strong governance value for unlisted small, medium and micro enterprises or startup entities with weaker risk tolerance and shorter life cycles. Therefore, extending the relevant analytical framework to small and micro economies and cross-country comparisons across diverse institutional environments will be a highly valuable direction for future research.

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