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Inter-Firm Land Optimization and the Advancement of New Quality Productive Forces—Empirical Evidence Based on Micro-Enterprise Data

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Abstract

In the context of advancing new quality productive forces (NQP), the optimization of factor allocation is of critical importance. This study empirically examines how inter-firm land allocation affects the development of NQP and explores the moderating roles of labor, capital, and data factors from a perspective of factor synergy. Combining theoretical analysis with empirical investigation, the findings are as follows: (1) optimizing land allocation across firms significantly enhances the level of urban NQP, and this result remains robust after accounting for endogeneity and a series of robustness checks; (2) capital expansion and the scaling of data resources substantially reinforce the positive effect of land allocation on NQP, whereas the interregional mobility of labor—particularly high-skilled workers—exerts a negative moderating influence. The results suggest that policymakers should promote the rational allocation of land resources while leveraging the synergistic effects of labor, capital, and data to accelerate the development of NQP at the local level.

Keywords: land allocation; new quality productive forces; land management

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1. Introduction

The development of new quality productive forces (NQP) is both an inherent requirement and a central priority for achieving high-quality growth. Unlike traditional productive forces that depend primarily on factor accumulation and scale effects, NQP emphasizes growth driven by efficient factor allocation and technological innovation [1,2]. As a key production factor, land serves not only as the fundamental resource base for NQP but also as the spatial carrier of production activities, with its institutional arrangements embodying core production relations. During the high-growth era, China's "land-driven development" model—characterized by large-scale land inputs—was a major driver of the country's economic miracle [3]. This land-based model, relying on land supply and land finance to stimulate investment, industrial expansion, and fiscal revenue, has now reached its limits. While it was instrumental in earlier stages of rapid growth, it has also generated structural imbalances, resource depletion, and misallocation that increasingly constrain the transition to high-quality development [4,5]. Beyond China, international studies show that factor misallocation is a key source of cross-country productivity gaps [6]. Distortions in large developing economies have led to substantial losses in manufacturing total factor productivity (TFP), underscoring the importance of allocation efficiency beyond simple factor accumulation [6]. Research also highlights the role of land market distortions in

explaining agricultural productivity differences across countries [7], and evidence from advanced economies shows that housing and land-use constraints hinder labor mobility and cause significant aggregate output losses [8]. More recent comparative studies emphasize that land-use is not only an economic issue but also a sustainability concern, as balancing conservation with development remains a central challenge in both EU and non-EU countries [9]. Taken together, this evidence demonstrates that land allocation efficiency is a global productivity concern and provides a comparative foundation for analyzing China's NQP. Against this international background, China's transition to high-quality growth makes its traditional land-intensive model increasingly unsustainable. Correcting land misallocation has therefore become essential to unlock new sources of productivity growth and advance the development of NQP.

Recently, a series of influential publications have theoretically examined the relationship between optimal land allocation and new quality productive forces (NQP). Scholars generally agree that the innovative allocation of land factors can promote the development of NQP. This is crucial for ensuring their spatial realization and represents an important approach to optimizing the spatial configuration of NQP [10–14]. Several studies, grounded in historical, theoretical, and practical logic, posit a mutually reinforcing relationship between the development of NQP and land resource allocation, where the former provides impetus for change and the latter establishes a spatial foundation. Other research emphasizes theoretical logic by exploring fundamental models and mechanisms through which land elements support NQP, distilling their development into four basic patterns. These studies suggest that innovative allocation of land elements requires precise quantitative guarantees for the needs of NQP, spatial coordination of their layout, and dynamic adaptation over time, supported by planning guidance, market-driven mechanisms, and social co-governance [15,16]. Furthermore, some studies focus specifically on land elements, analyzing the core connotations of NQP to dissect the mechanisms and fundamental pathways through which land resources empower their development. These studies identify five key connotations within NQP—"new qualities," "new models," "new formats," "new technologies," and "new drivers"—and further analyze how land resources enable their development by meeting emerging spatial demands, balancing different forms of productive forces, promoting industrial transformation and upgrading, supporting technological innovation, and enhancing adaptive governance. Collectively, these theoretical contributions lay the groundwork for understanding how innovative land allocation can foster the development of NQP, but they also highlight the need for more empirical evidence. At present, there remains a significant lack of empirical research on this issue, particularly a shortage of micro-level analyses. Therefore, this paper quantifies both the level of inter-firm land allocation and the degree of NQP development using a large-scale micro-enterprise database combined with city-level data, and identifies the causal relationship between the two. Furthermore, from a factor synergy perspective, it investigates the moderating roles of labor, capital, and data in shaping this relationship.

The marginal contributions of this paper are as follows: First, drawing on empirical tests with a large-scale micro-enterprise dataset, the study examines the impact of land allocation on the development of new quality productive forces (NQP), thereby providing robust empirical support for existing theoretical research. Second, from a factor synergy perspective, the paper demonstrates how labor, capital, and data factors shape the relationship between land allocation and NQP through their moderating effects, offering new insights and policy implications for understanding how multi-factor synergies drive productivity improvement.

Compared with existing studies, the originality of this paper lies in bringing the concept of new quality productive forces (NQP) into the international debate on productivity

measurement. By combining the Chinese context with global discussions of allocative efficiency, total factor productivity (TFP), and spatial misallocation, the paper not only deepens the understanding of NQP but also offers a novel micro-level empirical perspective on how land allocation efficiency contributes to productivity growth.

2. Theoretical Framework

2.1. Direct Impacts of Optimized Inter-Enterprise Land Allocation on New Quality Productive Forces

In recent years, the Chinese government has been actively working to improve the quality of economic development by continuously optimizing the urban land management system. This includes promoting the marketization of land factor allocation, thereby achieving a more rational supply ratio of industrial and commercial land. This approach not only enhances the efficiency of land resource allocation for enterprises but also helps address market imperfections. Specifically, a more transparent and efficient factor market creates a more stable and equitable competitive environment for businesses, lowering barriers to entry—particularly external transaction costs [17,18]. This optimization of the market environment, by reducing unnecessary friction costs, directly encourages enterprises to participate more actively in competition, thereby enhancing market vitality. Within such an environment, firms can allocate production factors more flexibly and quickly acquire the resources needed to optimize production processes and management practices. By improving resource allocation efficiency, enterprises are able to devote more effort and capital to innovation and productivity enhancement, which in turn has a positive effect on total factor productivity (TFP). Transparent market mechanisms also facilitate the formation of an open pricing system, reducing information asymmetry and market distortions while providing clearer guidance for corporate decision-making [19,20]. This mechanism reduces uncertainty in resource acquisition, enabling firms to make more precise production decisions based on more accurate information and lower costs, thereby enhancing overall efficiency and competitiveness. Conversely, the gradual reduction in the share of land transferred through administrative agreements inevitably raises land costs for enterprises. This shift generates an "exit effect" for less productive firms, making it difficult for them to sustain operations under higher land-use costs and forcing them to withdraw from the market. As a result, land resources are released, creating more opportunities for efficient firms to expand and develop.

Furthermore, market competition plays a crucial selection mechanism in this process. In a more competitive environment, firms must accelerate the optimization of production processes and management practices to improve efficiency in order to survive. Such competition not only compels enterprises to undertake technological and managerial innovations but also encourages them to upgrade workforce skills, strengthen team management, and optimize organizational structures. This internal drive continuously forces firms to reform themselves to meet the demands of intensifying competition, thereby driving efficiency improvements across the industry. Through continuous advancements in technology, management, and market strategies, competition not only enhances the productivity of individual enterprises but also promotes the optimal allocation of resources across the entire market. In addition, the reduction in the share of land allocated through negotiated agreements—driven by market competition—has heightened firms' risk awareness. Companies are compelled to evaluate land costs more carefully and allocate land resources more judiciously. This shift necessitates more refined management practices, with greater emphasis on cost control and efficient production. Under the dual pressures of land scarcity and intensified competition, firms are shifting away from reliance on scale expansion to gain market advantages. Instead, they are adopting intensive land-use strategies, leveraging

technological innovation and managerial optimization to strengthen core competitiveness. This transformation not only raises overall corporate productivity but also lays a solid foundation for the sustainable development of competitive, high-quality enterprises.

2.2. The Regulatory Function of Capital Elements

This paper posits that an increase in the scale of capital factors positively influences the mechanism through which inter-firm land allocation enhances new quality productive forces (NQP). First, a larger capital scale provides firms with more diversified financing channels, thereby improving the accessibility and flexibility of capital acquisition. Through these channels, enterprises can more effectively obtain the funds required for land acquisition or leasing—an effect particularly pronounced among growth-oriented and small- to medium-sized enterprises [21]. Moreover, expanding the scale of capital factors significantly strengthens the effectiveness of land-based mortgage financing, transforming land into a critical instrument for corporate capital flows. For instance, when local governments secure higher financing rates through land mortgage loans, they often rely on such instruments to raise funds while reserving more land for future sales to capture potential appreciation in land values [22]. A similar pattern can be observed at the enterprise level. Specifically, land collateralization provides firms with immediate financial support and enhances their ability to adapt to future market fluctuations. Through land-backed financing, enterprises gain opportunities for broader capital operations, effectively leveraging land assets. This mechanism facilitates a cyclical interaction between land collateralization and utilization, thereby enhancing the efficiency of land-use. Collateralization strategies also increase financing flexibility, particularly in response to market demand shifts or during corporate expansion. Consequently, firms can secure the necessary capital more swiftly by leveraging land assets, thereby alleviating capital constraints [23].

2.3. The Regulatory Function of Labor as a Factor of Production

The labor factor is not only a direct force driving enterprise production and operations but also a key driver of innovation and technological progress. This paper argues that the net inflow of labor across regions exerts a negative influence on the mechanism through which inter-firm land allocation enhances new quality productive forces (NQP). Specifically, due to the inherent attractiveness of economically developed regions, the so-called "talent siphon effect" leads to the concentration of labor in a small number of prosperous coastal and metropolitan areas, resulting in the loss of labor resources in most other regions of China. This effect reflects the uneven distribution of highly skilled workers, who are disproportionately drawn to advanced regions. Consequently, inland and less-developed areas face persistent human-capital shortages, widening regional productivity disparities and constraining balanced growth. Because of these shortages, enterprises in affected regions must raise wages, offer additional benefits, and provide more training opportunities to attract and retain workers. These measures raise local labor costs and alter firms' allocation of funds, diverting capital from other uses. This shift in capital allocation slows land acquisition and expansion initiatives, potentially delaying or canceling projects, thereby reducing investment in land procurement and development [24,25]. Given that land is a fundamental resource for scaling production and enhancing productivity, restricted access—whether in timing or quantity—forces firms to operate within constrained spaces, impeding further development and increasing their vulnerability to market exit.

Similar "talent siphon" effects have also been documented in international contexts. Empirical studies in the European Union show that high-skilled workers tend to cluster disproportionately in a few metropolitan regions, generating persistent regional disparities in innovation capacity and productivity [26,27]. Evidence from the United States simi-

larly indicates that high-skilled labor is increasingly concentrated in large urban centers, reinforcing productivity advantages in these areas while leaving peripheral regions with persistent talent shortages [28]. These findings suggest that the challenges China faces in balancing regional labor distribution are part of a broader international phenomenon, underscoring the need for policies that not only attract talent but also ensure a more balanced spatial distribution.

2.4. The Regulatory Function of Data Elements

This paper posits that the scale of data elements exerts a positive influence on the mechanism through which inter-firm land allocation promotes new quality productive forces (NQP). Specifically, in conventional land allocation, firms typically rely on experience and market intuition for decision-making. While this approach may meet short-term needs, it is often inadequate in complex market environments with uncertain resource demands, which can lead to oversimplified local assessments and suboptimal choices. Such intuition-based decision-making often results in inefficient investment and wasted land resources.

With the widespread adoption of data analytics tools, an increasing number of enterprises can now evaluate the potential and value of land resources more precisely through real-time, comprehensive market information analysis. These technologies allow for more accurate assessments of land potential and value, helping firms promptly identify demand trends across regions, industries, and markets, thereby providing stronger decision-making support [29,30]. Furthermore, the continuous evolution of market demand and environmental conditions requires enterprises to adapt to shifting customer needs. In this dynamic context, real-time monitoring of market fluctuations and rigorous data tracking enable firms to detect changes in supply and demand as well as price volatility in the land market. This capability facilitates timely adjustments in land leasing and acquisition strategies, thereby improving capital allocation efficiency [29].

3. Methodology and Data

3.1. Model Specification

To examine the impact of inter-firm land allocation on the development of new quality productive forces (NQP), the following baseline regression model is specified:

$$\text{Newproductivity}_{ct} = \beta_1 \text{Land}_{ct} + \beta_2 X_{ct} + \mu_c + \gamma_t + \varepsilon_{ct} \quad (1)$$

In this context, with ‘c’ denoting the city and ‘t’ representing the year, represents the level of new quality productive forces. represents the state of land allocation among enterprises. encompasses a series of control variables that potentially influence new quality productive forces, including the level of economic development (Pergdp), population aggregation level (Density), infrastructure conditions (Road), the degree of openness to the outside world (Open), and the extent of government intervention (Government). represents city-fixed effects; represents year-fixed effects; represents the random disturbance term; is the parameter of interest in this study; and represents the parameters of the control variables.

3.2. Variable Definitions

3.2.1. Explanatory Variables

This paper measures inter-firm land allocation through the concept of land allocation efficiency. According to factor allocation theory, a perfectly competitive market achieves the optimal allocation of resources. At this optimum, the factor prices faced by enterprises are equal to the marginal returns of those factors. However, due to various non-market distortions, the equilibrium allocation in the real economy often deviates from this benchmark [31]. Such deviations are reflected in large disparities in firms’ marginal returns to

factors [32–34]. When the deviation is small—meaning the actual allocation is closer to the optimal level—allocation efficiency is higher; conversely, larger deviations imply lower efficiency. Accordingly, inter-firm land allocation efficiency is defined as the degree to which the actual allocation of land among enterprises approaches the optimal allocation in the real economy. When the actual allocation converges toward the optimal benchmark, efficiency improves, as evidenced by smaller differences in marginal returns to land across firms. The measurement of inter-firm land allocation efficiency follows the covariance method proposed by Olley and Pakes. In industries where the productivity of firms is misaligned with the factor shares they command, allocation efficiency is lost. If factors flow from less productive to more productive firms, the overall allocation improves. Olley and Pakes capture this improvement as an increase in the covariance between firms' factor shares and their total factor productivity (TFP), i.e., by calculating the covariance of each firm's factor share with its TFP to represent intra-industry allocation efficiency. Duranton et al. extend this approach to land factors. Building on Olley and Pakes and Duranton et al., this paper constructs a measure of inter-firm land allocation efficiency [35,36].

As shown in Equation (2), the weighted productivity Ω_{cj} of a group of firms in industry j in city c can be split into two parts: First, the arithmetic mean of total factor productivity of firms representing industry productivity levels $\overline{T_j}$; The second is the covariance between firms' total factor productivity, which represents the level of factor allocation in the industry, and firms' land factor stocks. Where T_i denotes the productivity of firm i; W_i denotes the share of land held by firm i in industry j; $\overline{W_j} = 1/n$;

$$\Omega_{cj} = \overline{T_j} + \sum_{i=1}^{n} (W_i - \overline{W_j})(T_i - \overline{T_j}) \quad (2)$$

At this point, the efficiency of land allocation between firms at the city-industry level ($Land_{cj}$) can be expressed as the difference between weighted productivity and arithmetic mean productivity:

$$Land_{cj} = \Omega_{cj} - \overline{T_j} = \sum_{i=1}^{n} (W_i - \overline{W_j})(T_i - \overline{T_j}) \quad (3)$$

In Equation (3), the functional equation for inter-firm land allocation efficiency can be understood as follows: in city c, industry j, inter-firm land allocation efficiency is determined by the correlation between the share of land held by micro-firms and their total factor productivity.

The inter-firm land allocation efficiency at the city-industry level ($\overline{S_j}$) is further aggregated to the city level ($land_{cj}$) through weighted averages based on industry j's share of land in the city as a whole ($land_c$):

$$land_c = \sum_{i=1}^{n} \overline{S_j}\, land_{cj} \quad (4)$$

The above methods need to be adapted to large samples of microenterprise data.

This paper uses a newly available dataset, the National Enterprise Tax Survey Database (2007–2016). This database, jointly managed by China's Ministry of Finance and the State Administration of Taxation (SAT), is collected annually by local tax authorities and covers all industries. It contains basic enterprise information, input–output details, financial status, and tax payments. Most importantly, it provides detailed records on each enterprise's land-use, including land purchases, land holdings, land transfers, and land-related taxes. The survey sample is highly representative, accounting for approximately 65 percent of total national tax payments and 66 percent of national value added. For data cleaning, this study applied the following procedures: (1) In general, the land area of enterprises remains stable over many consecutive years, which was confirmed during data validation.

Therefore, missing floor-space values for certain years were imputed using available data on the same enterprises in other years. (2) While the original dataset typically reports industrial value added, some years (e.g., 2015) contain missing observations. These missing values were estimated following standard accounting methods. (3) Observations with problematic values—such as "net fixed assets," "new fixed asset investment," "industrial value added," "land area of firms," or "number of employees" less than or equal to zero, or missing altogether—were excluded. (4) Enterprises for which city identifiers or ownership type could not be determined were also excluded. After cleaning, the final dataset contains 114,365 usable observations, covering 389,058 enterprises across 92 industries in 261 cities.

While the Olley–Pakes (OP) covariance decomposition was originally developed to measure productivity dynamics in specific manufacturing industries, its application to the Chinese context requires several adaptations. First, given the large number of firms and the substantial industry heterogeneity in China, we implement the OP measure at the city–industry level and then aggregate it to the city level. This approach ensures that the covariance between firms' land shares and productivity captures within-industry allocation efficiency while remaining comparable across regions. Second, because China's land market is characterized by imperfect competition and strong government intervention—factors that often distort the alignment between firm productivity and land-use—the OP covariance method is well suited in this context, as it directly reflects the extent to which more productive firms are able to command a greater share of land resources. Third, by relying on firm-level microdata from a nationally representative survey, we reduce measurement error and better account for the pronounced spatial and institutional heterogeneity of China's economy. Collectively, these adaptations make the OP framework not only valid but also particularly informative for analyzing land allocation efficiency in China's urban economy.

To provide an intuitive illustration of the explanatory variable, Figure 1 presents the national average trend of inter-firm land allocation efficiency from 2007 to 2016. The index shows a steady upward trajectory over this period, reflecting continuous improvements in the alignment between firm-level productivity and land-use. This upward trend provides preliminary evidence that land allocation efficiency has gradually improved over time, with important implications for the development of new quality productive forces.



Figure 1. National Average Trend of Inter-Firm Land Allocation Efficiency, 2007–2016.

3.2.2. Explained Variables

Although the concept of NQP has only recently emerged in Chinese policy and academic discourse, its underlying rationale is consistent with long-standing theories of productivity and growth. Classical growth accounting emphasizes that sustained output ex-

pansion depends primarily on efficiency improvements rather than the mere accumulation of inputs, with TFP serving as the residual measure that captures technological progress and institutional quality. Building on this foundation, integrative studies further highlight the importance of resource allocation, organizational change, and the growing role of intangible and digital assets in shaping modern productivity dynamics. Positioning NQP within this broader framework reinforces that it is not a departure from established international theory but rather a context-specific operationalization aligned with mainstream productivity research. Conceptually, our NQP composite—constructed from innovation, industrial upgrading, and enabling conditions—can be mapped onto conventional productivity notions widely used in international economics. Innovation and industrial sophistication correspond to improvements in technical efficiency and technological progress, while enabling conditions capture the institutional and human-capital environment in which productivity is realized. This design is consistent with the mainstream understanding of TFP, which has been the core residual measure of growth since Solow's seminal contribution [37]. Therefore, NQP should not be regarded as a departure from the established framework of total factor productivity (TFP), but rather as its contextualized extension under China's ongoing structural transformation. Classical TFP focuses on capturing the residual efficiency of factor use once capital and labor inputs are accounted for, thereby serving as the benchmark for international productivity comparisons. In contrast, NQP specifies the channels through which such efficiency gains are realized—namely technological innovation, industrial upgrading, and enabling conditions such as human capital and institutional support. By explicitly incorporating these dimensions, NQP reflects how productivity improvements are increasingly driven by intangible assets, digital infrastructure, and organizational capital, which are often underrepresented in conventional TFP indices. In this sense, NQP remains theoretically consistent with TFP while offering a more fine-grained and policy-relevant measure of productivity in economies undergoing rapid structural change. This design also enhances its comparability and transferability across different contexts, providing a bridge between China's developmental experience and international debates on the sources of sustainable growth. Recent reviews emphasize that productivity measurement depends not only on technological efficiency but also on broader methodological choices, including the incorporation of intangible capital and digital inputs that increasingly shape modern growth dynamics [38,39]. By adopting an entropy–TOPSIS approach, our index offers a transparent and systematic method for weighting multiple drivers of productivity, thereby aligning with these broader international measurement perspectives. In the robustness section, we further examine the correspondence between NQP and alternative productivity proxies, which strengthens its comparability with internationally recognized indicators.

Regarding the measurement of new quality productivity (NQP), existing studies generally proceed from two perspectives: (i) considering the three fundamental production elements, and (ii) examining their optimal combinations [26,40]. This paper argues that the evaluation of NQP should incorporate three dimensions: scientific and technological innovation, industrial upgrading, and enabling conditions.

First, scientific and technological innovation is the core driving force of NQP. Compared with traditional productivity, NQP represents a qualitative leap, with science and technology as its primary driver, higher performance, and a strong reliance on continuous technological advancement [1]. To quantify innovation, this paper employs two indicators: patent R&D intensity, reflecting the intensity of regional innovation activities, and enterprise technological innovation capacity, reflecting firms' performance in technology transformation and innovation practice. Second, industrial upgrading is a key pathway to high-quality economic development. NQP is achieved as enterprises recombine factors of production to advance industrial transformation. To measure industrial upgrading, this

paper uses two indicators: the level of rationalization, reflecting the degree of resource allocation optimization, and the level of sophistication, capturing the extent of industrial structure transformation and upgrading. Finally, enabling conditions provide the necessary social and economic support for the development of NQP. At the early stages of industrialization, state support is essential in terms of finance and policy. Likewise, without sufficient human capital, enterprises cannot sustain technological innovation or industrial upgrading. To capture these conditions, this paper adopts four indicators: human capital level (measured by the share of higher education talent), degree of industrialization, share of education expenditure in total government spending, and share of science and technology expenditure in total government spending. These indicators, respectively, reflect human capital endowment, economic infrastructure development, industrialization level, and government investment in education and science and technology.

In the measurement method, entropy weight-TOPSIS method is used for comprehensive evaluation. The data were obtained from official statistics such as China Statistical Yearbook, China Tertiary Industry Statistical Yearbook, China Industrial Statistical Yearbook, China Science and Technology Statistical Yearbook and China Trade and Foreign Economic Statistics Yearbook. The specific framework for measuring new quality productivity is shown in Table 1 below.

Table 1. New quality productivity measurement framework.

Guideline Level	Indicator Level	Measurement Approach	Indicator Direction
technology and innovation	Patent R&D Intensity	Number of patents obtained/total population at the end of the year	+
	Enterprise Technological Innovation Capability	Number of patents obtained/number of patent applications	+
industrial upgrade	Rationalization Level	Tel index [41]	−
	Advanced level	Value added of tertiary industry/value added of secondary industry	+
Development conditions	Human Capital Level	Number of students enrolled in general undergraduate and tertiary education/total population at the end of the year	+
	Industrialization Level	Value Added of Industry/Gross Regional Product	+
	Emphasis on Education Expenditure	Expenditure on education/general government expenditure	+
	Emphasis on Science and Technology Expenditure	Expenditure on science and technology/general government expenditure	+

As shown in Figure 2, the national average NQP index has exhibited a steady upward trend from 2007 to 2016, reflecting continuous improvements in innovation, industrial upgrading, and enabling conditions.

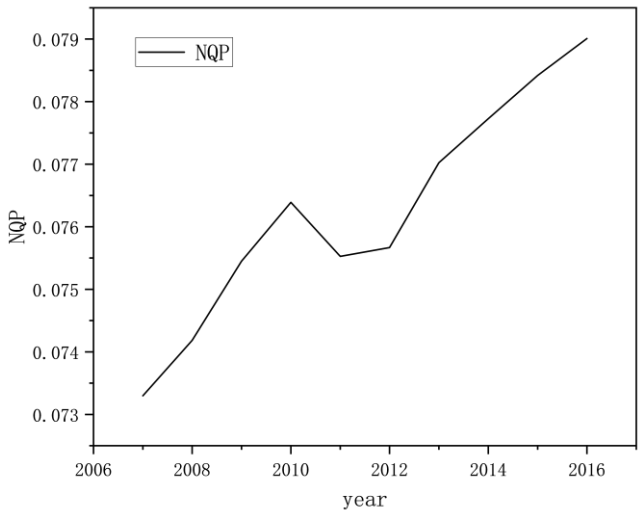


Figure 2. National Average Trend of NQP, 2007–2016.

3.2.3. Control Variables

With reference to existing studies, this paper also incorporates a series of control variables that may affect the development of new quality productivity (NQP): (1) Level of economic development (Pergdp): measured by GDP per capita, adjusted to 2007 constant prices. This variable controls for differences in regional economic development that may influence NQP. (2) Population agglomeration (Density): measured by the logarithm of population density, capturing the effects of economies of scale and knowledge spillovers associated with urban agglomeration. (3) Infrastructure (Road): measured by the ratio of total road area at year-end to total population, controlling for the potential impact of accessibility on productivity. (4) Openness to the outside world (Open): measured by total imports and exports as a share of GDP, capturing the effect of regional economic openness on productivity. (5) Government intervention (Government): measured by government fiscal expenditure as a share of GDP. Through investment and fiscal policy, government activity can directly shape regional economic structures, infrastructure development, and enterprise growth, thereby influencing productivity.

The data for these control variables are mainly drawn from the China Statistical Yearbook, China Tertiary Industry Statistical Yearbook, China Industrial Statistical Yearbook, China Science and Technology Statistical Yearbook, China Trade and Foreign Economy Statistical Yearbook, and various local statistical yearbooks.

3.2.4. Moderating Variables

Scale of capital factors: In the process of promoting high-quality economic development, the flow and allocation of capital are crucial, and the improvement of the financial system provides the foundation for such flows. Therefore, this paper measures the scale of capital factors by the ratio of year-end deposit and loan balances of financial institutions to GDP.

Labor mobility: Following existing studies, this paper measures labor mobility using the ratio of interregional population inflows to outflows, i.e., the net inflow of labor.

High-skilled labor mobility: This paper adopts the method proposed by Hai-Ping Lü, who uses interregional wage levels and economic development levels as attractiveness factors to simulate the scale and direction of innovative talent flows [42]. After calculating the inflows and outflows of innovative talent, high-skilled labor mobility is measured as the ratio of inflow to outflow.

Scale of data factors: Digital infrastructure reflects the capacity for information transmission, data storage, and computing power. By measuring both the inputs and outputs of digital infrastructure, it is possible to obtain a comprehensive assessment of the regional scale of data factors. In this paper, digital infrastructure is divided into input and output indicators, and the overall scale of data factors is calculated using the entropy-weight method.

The data for the moderating variables are mainly drawn from the China Statistical Yearbook, China Urban Statistical Yearbook, and statistical yearbooks and bulletins of provinces and cities. Descriptive statistics for the main variables are presented in Table 2.

Table 2. Descriptive statistics for the main variables.

Variable Name	Variable Symbol	Variable Definition	Sample Size	Mean	Value Standard Deviation	Minimum Value	Maximum Value
new quality productive forces	New productivity	$\text{Newproductivity} = \frac{\text{Newproductivity}_{ct}^{-}}{\text{Newproductivity}_{ct}^{+}+\text{Newproductivity}_{ct}^{-}}$	2272	0.076	0.032	0.045	0.202
inter-firm land allocation efficiency	Land	$land_c = \sum_{i=1}^{n} \overline{S}_g \, land_{cj}$	2557	0.245	0.370	−1.312	1.434
Openness to the outside world	Open	Total exports and imports/GDP	2430	0.207	0.353	0.001	3.384
Level of economic development	Pergdp	Real per capita GDP (million yuan)	2609	2.367	1.581	0.342	10.765
Infrastructure status	Road	Total road area at the end of the year/total population at the end of the year	2398	15.279	6.437	0.390	46.400
Government intervention	Government	Government fiscal expenditure/GDP	2606	0.170	0.083	0.044	0.716
Population agglomeration	Density	ln(population density)	2430	5.836	0.867	−0.446	7.882
Scale of capital factors	Finance	Year-end deposit and loan balances of financial institutions/GDP	2430	2.133	1.044	0.560	8.777
Scale of data factors	Data	Calculated by entropy weight method	2274	0.025	0.014	0.009	0.087
Labor mobility	Labor	Population inflow/outflow	2195	1.006	0.049	0.600	2.157
High-skilled labor mobility	Highlabor	Inflow/outflow of innovative talents	2186	1.141	5.017	0.005	131.147

4. Results

4.1. Baseline Results

Table 3 reports the results of the benchmark regressions on the impact of inter-firm land allocation on new quality productivity (NQP). Across all model specifications, optimizing inter-firm land allocation exerts a significant positive effect on NQP, confirming the theoretical assertions of existing studies and suggesting that the optimal allocation of land resources is an important source of productivity enhancement.

According to the results in column (6) of Table 3, several control variables show noteworthy patterns. First, the degree of openness is significantly negative at the 1% level. While competitive pressure from foreign firms is one factor, it is unlikely to be the sole explanation. A possible mechanism is resource reallocation: the entry of foreign enterprises may divert capital, skilled labor, and policy support toward export-oriented sectors, thereby crowding out domestic firms and weakening their innovation incentives. In addition, the

relocation of low value-added or pollution-intensive industries to less-developed regions may also help explain the observed negative association with NQP.

Table 3. Baseline regression results.

New Productivity	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	**Random Effect**	**Fixed Effect**	**OLS**	**Random Effect**	**Fixed Effect**
Land	0.005 ***	0.002 ***	0.001 **	0.006 ***	0.002 **	0.001 **
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Open				0.017 ***	−0.026 ***	−0.038 ***
				(0.002)	(0.002)	(0.003)
Pergdp				0.012 ***	0.008 ***	0.001
				(0.000)	(0.001)	(0.001)
Road				−0.001 ***	0.000 ***	-0.000
				(0.000)	(0.000)	(0.000)
Government				0.049 ***	0.014 **	−0.054 ***
				(0.009)	(0.007)	(0.009)
Density				0.007 ***	0.005 ***	0.001
				(0.001)	(0.001)	(0.001)
Constant	0.075 ***	0.077 ***	0.071 ***	0.009 *	0.026 ***	0.080 ***
	(0.001)	(0.002)	(0.001)	(0.005)	(0.007)	(0.008)
City fixed	NO	NO	YES	NO	NO	YES
Year fixed	NO	NO	YES	NO	NO	YES
R^2	0.003		0.144	0.414		0.259
N	2227	2227	2227	2203	2203	2203

Note: The models are estimated using ordinary least squares (OLS), fixed effects (FE), and random effects (RE) specifications, as indicated in the column headings. All FE models include city and year fixed effects. R-squared (R^2) represents the proportion of variance explained by the model. Coefficient estimates are reported with standard errors in parentheses. Significance levels are denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Second, the degree of government intervention is also significantly negative at the 1% level, suggesting that excessive government involvement may hinder resource allocation efficiency. This finding highlights the need to reduce administrative intervention and rely more on market mechanisms to promote the optimal allocation of resources and the development of NQP.

The remaining control variables are generally insignificant at conventional levels. However, both economic development and population agglomeration enter with positive coefficients, implying that regional economic development can provide financial support for technological innovation, while population concentration fosters technology diffusion and market expansion.

By contrast, infrastructure shows a negative sign. This may reflect overinvestment or a mismatch between infrastructure expansion and industrial upgrading. In some regions, large-scale road construction has exceeded firms' actual needs, leading to inefficient resource use. In others, infrastructure development has been concentrated in areas with weak industrial bases, preventing accessibility improvements from being effectively translated into productivity gains. These results suggest that the productivity-enhancing role of infrastructure depends critically on its alignment with industrial structure and regional development needs.

4.2. Robustness Tests

(1) Random resampling. In this paper, the bootstrap method is applied to resample the dataset 500 times in order to reduce potential bias caused by extreme values. The results remain consistent across replications, reinforcing the robustness of our findings.

(2) Shortened time window. Because the 2007–2008 global financial crisis caused severe macroeconomic fluctuations, it may have distorted the estimation results. Therefore,

we exclude the 2007–2008 observations and re-estimate the model. The results remain stable, further supporting the robustness of the conclusion.

(3) Alternative measure of NQP. Following Han Wenlong et al. [43], we re-quantify NQP using an alternative index. The results are unaffected, which further strengthens confidence in the conclusions.

(4) Addressing endogeneity. To mitigate potential endogeneity, we employ two instrumental variables: terrain relief and the two-period lag of inter-firm land allocation. Terrain relief is a natural, time-invariant geographic characteristic that influences the cost and feasibility of land development and thus affects land allocation across firms. However, it does not directly determine firms' productivity once economic and institutional factors are controlled for, thereby satisfying the exogeneity condition. In addition, we construct an interaction term between terrain relief and land allocation (Land × Relief) to capture how natural geographic constraints shape the efficiency of land reallocation. The rationale is that in areas with greater relief, reallocating land across firms is inherently more costly and constrained, which systematically affects the observed allocation outcome but does not directly alter firm productivity. In this sense, Land × Relief reflects the mechanism through which geographic conditions influence land-use frictions without conflating with unobserved productivity shocks. While we acknowledge that this instrument is not perfect, statistical diagnostics confirm that it is relevant and valid, thereby reinforcing the robustness of the IV estimation. The two-period lag of land allocation captures the strong path dependence in China's land-use system: past allocation patterns are highly correlated with current ones but are unlikely to be contemporaneously correlated with productivity shocks. This makes the lagged variable a valid predictor of current land allocation while alleviating concerns about reverse causality. Although these instruments may have limitations, we conduct overidentification tests and robustness checks with alternative specifications. The results consistently support the validity of our instruments and confirm the stability of the baseline estimates.

Overall, these robustness exercises consistently confirm our baseline finding that more efficient inter-firm land allocation promotes the development of NQP. Random resampling and the shortened time window mitigate concerns about outliers and macroeconomic shocks, while alternative measures of NQP ensure that the results are not index-specific. The instrumental variable strategy further alleviates endogeneity concerns, and diagnostic tests indicate that the instruments are both relevant and strong. Taken together, these results demonstrate that the positive effect of land allocation efficiency on NQP is not model-specific but robust across different model specifications, measurement approaches, and sample periods. This strengthens confidence that our conclusions reflect an underlying economic mechanism rather than an artifact of estimation.

The results of all robustness tests are presented in Table 4.

Table 4. Robustness tests.

New Productivity	(1)	(2)	(3)	(4)	(5)
	Random Resampling	**Shortened Time Window**	**Alternative Measure of NQP**	**Stage 1**	**Stage 2**
Land	0.001 **	0.001 **	0.001 *		0.002 **
	(0.001)	(0.001)	(0.000)		(2.511)
L2_Land				−0.039 **	
				(−2.113)	

Table 4. *Cont.*

New Productivity	(1)	(2)	(3)	(4)	(5)
	Random Resampling	Shortened Time Window	Alternative Measure of NQP	Stage 1	Stage 2
Land × Relief				0.642 ***	
				(35.428)	
Weak Instrumental Variable Test					635.560
Sargan test					2.033
R^2	0.259	0.186	0.546	0.464	0.181
N	2203	1750	1911	1715	1715

Note: Models (1)–(3) are estimated using fixed effects (FE) regressions with city and year fixed effects. Model (4) is estimated using an instrumental variable (IV) regression with the same set of fixed effects. R-squared (R^2) is reported for the FE models. Coefficient estimates are reported with standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5. Regulatory Mechanisms

5.1. Regulatory Mechanisms of the Capital Factor

In order to explore the mechanism through which the scale of capital factors affects inter-firm land allocation, as well as the heterogeneous moderating effects across regions, this paper centers both capital scale and land allocation variables to test their interaction. According to the results in columns (1) and (2) of Table 5, a larger capital scale significantly strengthens the positive effect of inter-firm land allocation on new quality productivity (NQP) at the national level, indicating a positive moderating role. However, as shown in columns (3)–(8), this positive moderating effect is evident only in the western region. This may be attributed to the region's late development and relatively weak infrastructure, where firms often face limited financing channels and high capital costs, thereby constraining land-use efficiency and overall productivity. By contrast, in other regions with more developed infrastructure and mature market mechanisms, firms face fewer capital constraints and enjoy relatively abundant financing opportunities, which diminishes the prominence of the moderating effect of capital on land allocation. Beyond financing constraints, institutional differences also help explain these heterogeneous effects. In eastern regions, more mature financial systems, stronger property rights protection, and diversified capital markets reduce firms' reliance on land-based financing. In contrast, in the western region, weaker institutional environments make external capital support more critical for sustaining firms' productivity growth.

Industry-integrated cities are those that, with policy support, enhance capital flows and improve resource allocation efficiency by strengthening cooperation between industry and finance. In this paper, and in line with the *Notice on Organising the Declaration of Pilot Cities for Industry–Finance Cooperation* jointly issued by the Ministry of Industry and Information Technology (MIIT), the People's Bank of China (PBOC), and other central ministries and commissions, Chinese cities are divided into two groups: non–industry-integrated cities and industry-integrated cities. According to the results in columns (6)–(7) of Table 5, the efficiency of inter-firm land allocation is significant at the 10% level in both groups. However, the estimated coefficient for non-industry-integrated cities is 0.001, whereas for industry-integrated cities it is 0.005. This indicates that the productivity-enhancing effect of land allocation is more pronounced in industry-integrated cities, thereby further confirming the robustness of our findings.

Table 5. Regression results on the moderating effect of capital factor size.

New Productivity	Capital Factor Size Regulation									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	National		Eastern		Central		Western		Non-Industrial Integration	Industrial Integration
Land	0.001 *	0.001 **	0.001	0.001	−0.000	−0.000	0.002 *	0.002	0.001 *	0.005 *
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Finance	0.004 ***	0.004 ***	0.003 **	0.003 ***	0.002 **	0.002 ***	0.011 ***	0.011 ***		
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		
C_Land × C_Finance		0.003 ***		0.002		0.001		0.003 ***		
		(0.001)		(0.001)		(0.001)		(0.001)		
Constant	0.072 ***	0.071 ***	−0.047	−0.045	0.068 ***	0.068 ***	0.053	0.049	0.079 ***	0.219
	(0.008)	(0.007)	(0.083)	(0.083)	(0.006)	(0.006)	(0.051)	(0.050)	(0.007)	(0.154)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
City fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	2203	2203	886	886	808	808	509	509	1941	262
N	0.277	0.283	0.402	0.403	0.123	0.124	0.288	0.309	0.236	0.424

Note: All models are estimated using fixed effects (FE) regressions with city and year fixed effects. All variables with the prefix C_ are mean-centered for the construction of interaction terms. R-squared (R^2) values are reported for model fit. Coefficient estimates are reported with standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.2. Mechanisms for Regulating the Labor Factor

To examine the regulatory mechanism of labor mobility and the heterogeneous effects across regions, this paper centers both labor mobility and inter-firm land allocation variables to test their interaction. According to the results in columns (1)–(2) of Table 6, greater labor mobility weakens the positive effect of inter-firm land allocation on new quality productivity (NQP), indicating a negative moderating role. However, the results in columns (3)–(8) show that when the country is divided into three regions—eastern, central, and western—interregional labor mobility does not exhibit a statistically significant moderating effect.

Table 6. Regression results on the moderating effect of interregional labor mobility.

New Productivity	Regulation of Interregional Labor Mobility							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	National		Eastern		Central		Western	
Land	0.001 **	0.001 **	0.001	0.001	−0.000	−0.000	0.003 ***	0.003 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Labor	0.010 **	0.008 *	−0.023	−0.018	0.005	0.005	0.039 ***	0.037 ***
	(0.004)	(0.004)	(0.020)	(0.021)	(0.004)	(0.004)	(0.008)	(0.013)
C_Land × C_Labor		−0.052 ***		0.064		−0.045 **		−0.011
		(0.019)		(0.070)		(0.018)		(0.059)
Constant	0.045	0.039	−0.010	−0.016	0.184 ***	0.167 ***	0.019	0.021
	(0.037)	(0.037)	(0.093)	(0.093)	(0.048)	(0.048)	(0.059)	(0.060)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
City fixed	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES	YES	YES
R^2	1971	1971	794	794	724	724	453	453
N	0.228	0.231	0.343	0.344	0.127	0.135	0.234	0.234

Note: All models are estimated using fixed effects (FE) regressions with city and year fixed effects. All variables with the prefix C_ are mean-centered for the construction of interaction terms. R-squared (R^2) values are reported for model fit. Coefficient estimates are reported with standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Labor mobility can be divided into high-skilled and low-skilled flows [44]. To further investigate the mechanism behind the negative moderating effect of labor mobility, this paper centers both high-skilled labor mobility and inter-firm land allocation variables to test their interaction. According to the results in columns (1)–(2) of Table 7, greater high-skilled labor mobility weakens the positive effect of inter-firm land allocation on new quality productivity (NQP) at the national level, indicating a negative moderating role. However, the results in columns (3)–(8) show that when the country is divided into three regions—eastern, central, and western—interregional high-skilled labor mobility does not exhibit a statistically significant moderating effect. While the "talent siphon" effect highlights the uneven distribution of skilled labor, more balanced mobility could be promoted through targeted policy interventions such as fiscal incentives for talent relocation, regional innovation programs, and the development of digital platforms. Moreover, the growing feasibility of teleworking provides opportunities for high-skilled workers to contribute to less-developed regions without physically relocating, thereby potentially mitigating the negative impact of labor concentration in major metropolitan areas.

Table 7. Regression results on the moderating effects of interregional high-skilled labor mobility.

New Productivity	Interregional Regulation of Highly Skilled Labor Mobility							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	National		Eastern		Central		Western	
Land	0.001 **	0.001 *	0.001	0.001	−0.000	−0.003 **	0.003 ***	0.005 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Highlabor	−0.001 ***	−0.001 ***	−0.000 **	−0.001 ***	−0.004 ***	−0.005 ***	0.002	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
C_Land × C_Highlabor		−0.000 *		−0.001 *		−0.003 **		0.002
		(0.000)		(0.000)		(0.001)		(0.002)
Constant	0.062 *	0.062 *	−0.040	−0.038	0.199 ***	0.192 ***	0.101 *	0.102 *
	(0.036)	(0.036)	(0.089)	(0.089)	(0.047)	(0.047)	(0.058)	(0.058)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
City fixed	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES	YES	YES
R^2	1971	1971	794	794	724	724	453	453
N	0.232	0.233	0.347	0.350	0.137	0.144	0.195	0.199

Note: All models are estimated using fixed effects (FE) regressions with city and year fixed effects. All variables with the prefix C_ are mean-centered for the construction of interaction terms. R-squared (R^2) values are reported for model fit. Coefficient estimates are reported with standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.3. Regulatory Mechanisms for Data Elements

To explore the moderating mechanism of data factor scale, this paper examines the heterogeneous effects of data scale both at the national level and across regions. In the analysis, data factor scale and inter-firm land allocation variables are mean-centered to test their interaction. According to the results in columns (1)–(2) of Table 8, a larger data factor scale significantly strengthens the positive effect of inter-firm land allocation on new quality productivity (NQP), indicating a positive moderating role. Furthermore, the results in columns (3)–(8) show that this positive moderating effect is evident in both the eastern and western regions. This may be because these regions lead the country in data circulation and utilization efficiency, supported by richer innovation resources and stronger industrial bases. As a result, the expansion of data factor scale can further unlock the potential of data resources, enabling firms to adjust resource allocation and investment more flexibly. Such data-driven resource optimization not only improves the efficiency of land allocation but also provides robust support for firms' innovation activities.

Table 8. Regression results on the moderating effect of data factor size.

New Productivity	Capital Factor Size Regulation									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	National		Eastern		Central		Western		Non-Data Trading Platforms	Data Trading Platforms
Land	0.001 **	0.002 ***	0.002 *	0.001	−0.000	0.000	0.002 **	0.003 **	0.001	0.006 **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Data	0.339 ***	0.349 ***	0.280 ***	0.294 ***	0.372 ***	0.378 ***	0.298 ***	0.302 ***		
	(0.040)	(0.040)	(0.067)	(0.067)	(0.066)	(0.067)	(0.074)	(0.074)		
C_Land × C_Data		0.200 ***		0.252 ***		0.086		0.149 *		
		(0.047)		(0.081)		(0.090)		(0.085)		
Constant	0.069 ***	0.069 ***	0.065	0.077	0.066 ***	0.065 ***	0.034	0.037	0.019	0.408 ***
	(0.007)	(0.007)	(0.079)	(0.079)	(0.006)	(0.006)	(0.056)	(0.056)	(0.036)	(0.141)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
City fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	2074	2074	840	840	765	765	469	469	1773	198
N	0.264	0.271	0.367	0.376	0.164	0.166	0.222	0.228	0.193	0.531

Note: All models are estimated using fixed effects (FE) regressions with city and year fixed effects. All variables with the prefix C_ are mean-centered for the construction of interaction terms. R-squared (R^2) values are reported for model fit. Coefficient estimates are reported with standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Generally, the larger the scale of data factors, the greater their liquidity and market activity. This process not only promotes the continuous expansion of the data trading market but also contributes to the gradual improvement of data marketization mechanisms. In this paper, based on the distribution of data trading platforms, Chinese cities are divided into two categories: those without data trading platforms and those with such platforms. According to the results in columns (9)–(10), inter-firm land allocation is insignificant in cities without data trading platforms, whereas in cities with such platforms it is significantly positive at the 5% level. This finding indicates that the productivity-enhancing effect of land allocation is more pronounced in cities with data trading platforms, thereby further confirming the robustness of the results. Despite the positive contribution of data factors, potential risks must also be acknowledged. Concerns about data security and privacy may reduce firms' willingness to adopt data-driven strategies, while unequal access to digital infrastructure across regions could exacerbate disparities in the productivity gains from data. These limitations highlight the need for complementary policies to ensure that the benefits of data-driven optimization are distributed more widely and equitably.

6. Conclusions

Based on microenterprise data from prefecture-level cities in China between 2007 and 2016, this paper employs both theoretical and empirical methods to examine the regulatory mechanisms of labor, capital, and data factors from a factor-synergy perspective. The findings can be summarized as follows: (1) Optimizing inter-firm land allocation significantly improves the level of new quality productivity (NQP) at the city level, and this conclusion remains robust across multiple tests. (2) The relationship between land allocation and NQP is moderated by capital, labor, and data factors. For capital, a larger scale amplifies the positive effect of land allocation on NQP. For labor, the concentration of highly skilled workers generates uneven regional distributions, leading to talent loss in most areas and weakening the positive effect of land allocation. For data, an expanded scale significantly enhances the productivity gains from optimized land allocation.

Based on the above findings, this paper derives the following policy implications: (1) Accelerate financial development to strengthen capital supply. Local governments

should deepen financial market reforms, improve credit and financing policies, and facilitate enterprises' access to capital. In particular, financial support for efficient enterprises in the western region should be reinforced. Commercial banks and financial institutions are encouraged to provide funding for firms' technological R&D and resource expansion through innovative financial products and science-and-technology loans, thereby enhancing the positive effect of land allocation on NQP. (2) Guide the rational flow of labor. The uneven distribution of the labor force weakens the productivity-enhancing role of optimized land allocation. It is therefore essential to redirect surplus labor from developed regions—especially highly skilled workers—toward less developed areas. The government should strengthen education and talent cultivation, while introducing targeted incentives to encourage highly skilled workers to relocate, work, and settle in less developed regions, thereby alleviating brain drain and narrowing regional disparities. (3) Promote the expansion of data resources and improve digital infrastructure. Governments should further advance the construction of new digital infrastructure, accelerate the flow of information and technology, and strengthen cross-regional integration and sharing of data resources, thereby unlocking the productivity-enhancing potential of data-driven optimization. While these policy implications are rooted in the Chinese context, they also carry broader international relevance. Many developing and transition economies face similar challenges of misallocation, labor imbalance, and unequal access to digital infrastructure. The Chinese experience thus provides valuable lessons for other countries seeking to improve productivity through more efficient factor allocation and multi-factor interaction.

Beyond its relevance for China, our study also contributes to the broader international debate on productivity measurement and factor allocation. The NQP framework adopted here—emphasizing innovation, industrial upgrading, and enabling conditions—aligns with long-standing concerns that efficiency improvements, rather than mere factor accumulation, are the true drivers of sustainable growth. It also resonates with contemporary discussions on how to measure productivity in economies increasingly shaped by intangible assets, organizational capital, and digital infrastructure. By explicitly situating NQP within these broader perspectives, we demonstrate that the mechanisms observed in China's transition to high-quality growth are not unique to a single national context but instead reflect a global challenge: how to enhance allocative efficiency while addressing land frictions, labor mobility constraints, and the rising importance of digital inputs. Thus, although our empirical focus is on China, the findings provide comparative insights for both emerging and advanced economies confronting similar issues of land allocation, spatial misallocation, and the integration of new drivers of productivity into development strategies.

At the same time, several limitations should be acknowledged. First, the study relies on data from 2007 to 2016, and the rapid transformations in China's digital economy and land market reforms in more recent years may have reshaped some of these relationships. Second, while our analysis provides insights into China's context, further cross-country comparisons would be valuable to assess the extent to which these findings can be generalized. Future research using updated data and international comparisons would therefore help validate and extend our conclusions more comprehensively.

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