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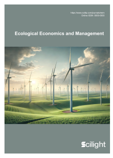

Article

How Does the Low-Altitude Economy Drive Total Factor Productivity in Enterprises?—A Study Based on Machine Learning Methods and a DID Empirical Model

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Abstract: As a new paradigm of productivity, the low-altitude economy (LAE) is increasingly demonstrating its strategic importance. By applying a machine learning dictionary approach to corporate reports and patents, this study finds that LAE significantly enhances firms' total factor productivity (TFP). This effect operates primarily through industrial integration and R&D activities, and is particularly evident in high-tech, manufacturing, and high-pollution firms, as well as in improvements in firm value. Further evidence from the National Big Data Pilot verifies its dynamic impact. The main innovation of this paper lies in quantifying the policy concept of "low-altitude economy" as measurable firm-level TFP gains, thereby filling the gap in micro-level empirical evidence. In addition, the publicly available LAE dictionary and multidimensional indicators provide new research and regulatory tools for academia and policymakers. The results suggest that priority should be given to subsidies and airspace hierarchy reforms in high-tech, manufacturing, and high-pollution industries, fostering synergies between digital infrastructure and airspace liberalization, reducing capital market risk premiums, and accelerating the commercialization of the entire chain of new energy aircraft, urban air mobility, and aerospace information services. Therefore, LAE urgently requires a full-chain, market-oriented policy framework and upgraded airspace regulations.

Keywords: low-altitude economy; total factor productivity of enterprises; integration with green industries; enterprise value

1. Introduction

The report of the 20th National Congress of the Communist Party of China emphasized: "Accelerate the construction of a modern economic system and strive to improve total factor productivity". In March 2024, the low-altitude economy was included in the government work report as a "new growth engine to be actively cultivated." As a comprehensive economic form driven by new productive forces, the low-altitude economy has typical characteristics such as driving new growth in regional economies, expanding new development space for cities, providing new means of social governance, fostering new cross-border integration ecosystems, and integrating new elements of industrial development, which can fully enhance the total factor productivity of relevant enterprises [1].

At the convergence of global carbon neutrality, digital twins and aerospace information infrastructure, the low-altitude economy has leapt from "drone delivery" to a third-dimensional transport backbone encompassing eVTOL urban air mobility, low-altitude logistics, air ambulances, smart agriculture and forestry, border patrols, ocean monitoring, emergency communications, sightseeing, cultural tourism and even defence mobilisation. Technologically, a 40% rise in battery energy density in five years, 30% fall in composite costs and AI flight-control safety down to 10^{-7} have cut the operating cost of electric, autonomous flight to 30% of that of helicopters and only 2.5× that of ride-hailing, opening the commercial window [2]. Financially, the global eVTOL market hit US$12.5 billion in 2023 [3,4]; Morgan Stanley forecasts that combined air-mobility and low-altitude services will exceed US$1 trillion by 2040, creating an "aerospace version of mobile internet". China has written the sector into its strategic emerging industries plan, targeting RMB 3.5 trillion of GDP and 4 million jobs by 2035, with 38 low-altitude corridors and 200 vertiports already planned in the Yangtze River Delta, Greater Bay Area, Chengdu–Chongqing and Hainan FTP, rivalling the U.S. "Agility Prime", EU "SESAR U-space", Singapore "Air Taxi Dubai" and Dubai "Sky Pods" regulatory sandboxes. ICAO is crafting global low-altitude rules (LARPS) while the FAA, EASA and CAAC roll out unmanned traffic management systems for real-time civil–military, air–ground digital-twin airspace control. Socially, UNCTAD estimates that drone logistics could replace 30% of short-haul truck trips, cutting 100 million *t* CO_2 annually; in Africa, the Middle East and ASEAN archipelagos low-altitude grids bypass expensive ground infrastructure, forming an "aerial Silk Road" for vaccines, fertiliser and e-commerce parcels, while in Ukraine swarms are reshaping modern defence logistics. Looking ahead, the low-altitude economy will interweave 5G/6G, BeiDou + GPS, remote-sensing big data, carbon trading and digital finance, becoming a core variable for green recovery, urban renewal, regional rebalancing and the rewriting of global aviation-governance rules [5], as well as a new high ground for great-power industrial competition and cross-border standard-setting cooperation.

Different regions have varying policies toward the low-altitude industry, and the development of low-altitude economy enterprises also varies across regions. Therefore, this study focuses on the Chinese top ten low-altitude economy industries nationwide, combining their local policies with the DID model for empirical research. The policies fully incorporate guidance and planning for the low-altitude industry. Additionally, enterprise data is utilized to assess their total factor productivity, thereby fully exploring the relationship between the low-altitude economy and enterprise total factor productivity [6].

The main innovations of this paper are as follows: First, from the perspective of text analysis, machine learning methods are used to generate a low-altitude economy dictionary and construct low-altitude economy-related enterprise indicators, providing an effective tool and measurement method for subsequent micro-level enterprise-related research on the low-altitude economy, and validating the effectiveness of the constructed low-altitude economy indicators. Second, from a micro level, we select enterprise innovation and R&D capabilities and enterprise industrial integration as two angles to conduct a more specific and in-depth analysis of the mechanism by which the low-altitude economy affects total factor productivity. Third, we construct a double difference model of low-altitude industry enterprise policies and study the dynamic characteristics of enterprises, using parallel trend tests and placebo tests to verify the reliability and validity of the results. Fourth, we study the enterprise value effect of the low-altitude economy to verify the economic effects of the low-altitude industry.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature and develops the research hypotheses. Section 3 presents the research design, including data sources, variable construction, and empirical strategies. Section 4 reports the baseline results using a difference-in-differences (DID) framework. Section 5 conducts a series of further analyses to test the robustness and explore the underlying mechanisms. Finally, Section 6 concludes with a summary of the main findings and discusses their policy implications and recommendations.

2. Literature Review and Research Hypotheses

2.1. Literature Review

In recent years, the low-altitude economy has attracted widespread scholarly attention as an emerging form of industrial development. Existing studies cluster around three main themes.

First, industrial-chain and supply-chain construction. The multi-dimensional integration path of the modern low-altitude industrial system from an industry-building perspective, while the economy's role in strengthening the resilience of both chains.

Second, technological innovation and productivity gains. A significant positive correlation between the development of the low-altitude economy and firms' technological-innovation capacity; and how meteorological-technology advances propel the economy from a technology-driven standpoint.

Third, industrial convergence and application-scenario expansion. A synergistic mechanism for integrating the low-altitude economy with tourism; a using Hainan Province as a case, analyzes the economy's capacity to optimize regional industrial structure through multi-sector integration.

Although these contributions deepen our understanding of the low-altitude economy's characteristics and development paths, two gaps remain. First, most studies stay at the macro level, leaving micro-level empirical evidence on firm performance scarce. Second, the precise channels through which the low-altitude economy affects firm productivity—especially the mediating roles of technological innovation and industrial convergence—have not been systematically explored. This paper therefore empirically investigates whether and how the low-altitude economy influences total factor productivity (TFP) at the firm level to fill these gaps.

2.2. Research Hypotheses

2.2.1. Low-Altitude Economy and Firm Productivity

Existing literature highlights the construction of the industrial and supply chains of the low-altitude economy and its contribution to high-quality development. For instance, the development trends of the modern low-altitude industrial system, emphasizing multi-dimensional integration and advantage-driven leadership. The low-altitude economy strengthens the resilience of industrial and supply chains. Discussing the full-cycle industry based on low-altitude intelligent connectivity pilot bases, calling for broader enterprise and public participation.Building an open and cooperative industrial ecosystem to promote high-quality development. The application of "low-altitude economy +" to form new industrial models, while how high knowledge density and R&D collaboration drive corporate growth in this sector.

Taken together, these studies suggest that the rapid growth of the low-altitude economy injects vitality into firm development. Accordingly, this paper proposes:

Hypothesis 1 (H1): *The low-altitude economy is conducive to enhancing enterprise total factor productivity (TFP).*

2.2.2. Low-Altitude Economy and R&D Innovation

The low-altitude economy, as a new productive force, offers ample opportunities for enterprise innovation. A positive and growing correlation between technological innovation capacity and the development of the low-altitude economy. From a meteorological technology perspective, Advancements in meteorological innovation accelerate the development of the low-altitude economy. From a policy perspective, the low-altitude economy cultivates new industries and stimulates digital innovation among enterprises.

In summary, the low-altitude economy can significantly improve firms' R&D capacity, thereby driving productivity growth. Hence, this paper proposes:

Hypothesis 2 (H2): *The low-altitude economy enhances TFP by improving firms' R&D innovation capabilities*.

2.2.3. Low-Altitude Economy and Industrial Integration

The low-altitude economy spans multiple sectors, including logistics, tourism, aviation, and batteries. It not only inherits traditional general aviation models but also integrates new production service methods supported by low-altitude aircraft.Synergies between the low-altitude economy and tourism, demonstrating their coordinated development. Using Hainan Province as a case, and how the low-altitude economy fosters industrial structure optimization and multi-sector integration.

These findings imply that industrial integration is an important channel through which the low-altitude economy affects firm productivity. Therefore, this paper proposes:

Hypothesis 3 (H3): *The low-altitude economy enhances TFP by increasing the degree of industrial integration within firms*.

3. Research Design

3.1. Data Sources

This study covers the period from 2012 to 2023, focusing on enterprises involved in the low-altitude economy sector. The reasons for selecting the 2012–2023 time period are as follows: First, in terms of policy promotion and industry development, after 2012, with the rapid economic growth and continuous upgrading of the industrial structure in China, the government began to increasingly prioritise the development of the low-altitude economy and introduced a series of policies to support its initial development and growth.

The company data used in this study were obtained from Mark Data Network, Tonghuashun platform, etc.; patent data were sourced from the National Intellectual Property Administration; other data were obtained from the China Industrial Enterprise Database, National Bureau of Statistics, etc. Additionally, based on the stock codes and years of companies related to the low-altitude economy, machine learning techniques were employed to match and merge the data into the final panel dataset.

3.2. Construction of Low-Altitude Economy Indicators

Recent years have witnessed the rapid expansion of the low-altitude economy and its spin-off industries, prompting scholars to leverage large language models for micro-level analysis. Yet the core challenge remains how to measure LAE exposure at the firm level. Instead of building a composite index, we adopt a text-mining rationale that aligns with the following requirements: Firstly, Directness: we want a proxy that is extracted directly from corporate disclosures rather than aggregated across multiple, potentially heterogeneous indicators. Secondly, Scalability: the measure must be replicable across 5000+ annual reports and 150,000+ patents without manual coding. Thirdly, Sensitivity: it should capture nuanced changes in LAE engagement year by year. Fourthly, Robustness: it must tolerate sparse keywords and extreme outliers.

We therefore construct an LAE dictionary with an LLM [7], count relevant occurrences in patent titles and abstracts—the only two text fields consistently available—and apply ln (1 + count) to stabilise variance and avoid zero-count issues. This approach supplies a transparent, high-frequency gauge of firm-level LAE intensity, enabling clean identification of its impact on total factor productivity and strategic decisions. Through this method provides a rigorous framework for evaluating the integration of the low-altitude economy within enterprises, facilitating a detailed analysis of its impact on organisational performance and strategic decision-making. Due to differences in the format and technical limitations of patent information disclosed by companies in the low-altitude economy sector, we only obtained two main types of text data during the data collection process: patent abstracts and titles [8]. Additionally, we performed smoothing on the low-altitude economy dictionary to ensure data stability and avoid situations where certain keywords might have a count of 0. Taking the natural logarithm of 0 directly would cause mathematical issues, so we added 1 to avoid this. The logarithmic transformation also makes the data distribution closer to a normal distribution, reducing the impact of outliers (such as keywords with extremely high counts) on the analysis and making the data more stable.

3.2.1. Data Collection and Text Data Extraction

Mark Data Network, Giant Tide Information Network, and Sina Finance are the information retrieval websites we commonly used to search for company annual report information. However, during manual verification, we found that the annual report texts on these three platforms each had varying degrees of missing values [9]. Therefore, this study synchronously extracted and organised annual reports from 2012 to 2023, and carefully removed duplicate data. A total of over 50,000 annual reports from companies related to the low-altitude economy were obtained, and after screening, a merged corpus containing 5185 annual reports from low-altitude economy companies was finally obtained. Patent texts were obtained from the official government website of the National Intellectual Property Administration, which is the primary repository for information dissemination and services. This study utilised the China Patent Database provided by the Intellectual Property Press, obtaining a total of 150,975 Chinese patents spanning the period from 2011 to 2022.

During the data extraction phase, Python software was used to extract keywords related to low-altitude economy and drones from various sources, including company annual reports, patent abstracts, and titles. Subsequently, the keywords were systematically screened to identify patents related to the low-altitude economy. It is worth noting that the low-altitude economy data in the annual reports is summarised here by quantifying five key indicators: drone test zones, scientific research and innovation technologies, eVTOL technology, market policies, and social benefits. This framework emphasises the commitment of this study to rigorous data collection and analysis, which helps to comprehensively explore the cross-relationships between market policies, social benefits, and technological innovation in the low-altitude economy.

3.2.2. Composition of the Low-Altitude Economy Dictionary

The construction of the low-altitude economy dictionary involves the following steps: (1) Utilising authoritative sources: Reports on the low-altitude economy published by United Nations-related organisations (such as the International Civil Aviation Organisation [ICAO]), such as the "2024 Global Low-Altitude Economy Development Trends White Paper"; reports on technology trends related to the low-altitude economy published by the World Intellectual Property Organisation (WIPO), such as the "2023 Low-Altitude Aircraft Technology

Patent Analysis Report"; Reports published by domestic authoritative research institutions (such as the China Low-Altitude Economy Research Centre), such as the "2024 China Low-Altitude Economy Industry Panorama Map." Manually screen the seed words closely related to the low-altitude economy from the above authoritative sources, and preliminarily select 60–70 seed words based on the main fields and application scenarios of the low-altitude economy; (2) Use the Skip-gram model in Word2vec technology to train the corpus text, set the size parameter to 300, and determine the 10 words most closely related to the meaning of each seed word by calculating the cosine similarity between the candidate output words and the seed words; (3) The vocabulary was then processed to remove duplicate words, irrelevant words, and words with low frequency to ensure the accuracy and relevance of the vocabulary. After rigorous screening and sorting, 80 words closely related to the low-altitude economy were retained, forming the low-altitude economy dictionary used in this paper.

3.2.3. Construction of Low-Altitude Economy Indicators

(1) Based on annual reports of low-altitude economy companies

This study meticulously processed data extracted from low-altitude economy company annual reports, utilising the widely recognised Python open-source tool "jieba" for precise Chinese word processing. However, actual Chinese text analysis faces three main challenges: selecting an appropriate segmentation granularity, accurately disambiguating words, and effectively identifying new words. To avoid the loss of the complete semantic meaning of the word due to traditional segmentation, we pre-constructed a low-altitude economy dictionary and incorporated it into the "jieba" segmentation module as a proper noun dictionary to improve segmentation accuracy. To accurately measure a company's low-altitude economy development level, we adopted the number of low-altitude economy keywords in the annual reports of companies across all low-altitude economy sectors, added 1, and took the natural logarithm (Words) as the core low-altitude economy indicator. Additionally, we have further constructed an alternative indicator for the low-altitude economy. This indicator is based on the number of low-altitude economy keywords in the relevant reports and announcements of the company's management discussion and analysis sections. The same method of adding 1 and taking the natural logarithm (Words_MD&A) is used to quantify the company's investment and attention in the low-altitude industry sector. Additionally, this study sums the number of times five indicators—unmanned aerial vehicle (UAV) test zones, scientific research and innovation technology, eVTOL technology, market policies, and social benefits—are disclosed in the annual reports of low-altitude economy companies, adds 1, and takes the natural logarithm (Words_Indicator) to further measure these indicators. This three-tiered indicator design aims to provide companies with a more comprehensive and accurate assessment perspective.

(2) Based on the abstract text of low-altitude economy company patents

The number of low-altitude economy patents a company holds not only signifies its current technological output in the low-altitude industry but also reflects its R&D achievements and technological capabilities in the low-altitude economy sector. In this study, we obtained patent data from the National Intellectual Property Administration, including patent names, abstracts, application numbers, years, and corresponding company stock codes. We then matched these data with the corresponding listed companies based on their stock codes. By analysing the titles and abstracts of the patent texts, we successfully identified and confirmed over 50,000 patent texts closely related to low-altitude economy technology. To more accurately measure the innovation capabilities of low-altitude economy-related companies in the low-altitude industry sector, we recalibrated the number of patents they hold. Specifically, we added 1 to the number of patents and then took the natural logarithm (Lnpatents) as a new indicator for evaluating companies' low-altitude industry capabilities. This indicator not only considers the number of patents held by a company but also smooths the data through logarithmic transformation, thereby enhancing the accuracy and reliability of the assessment.

(3) Policy documents of the regions where low-altitude economy companies are located

Table 1 shows that the proportion of low-altitude economy-related companies disclosing information related to the low-altitude economy in their annual reports was quite high during the period from 2012 to 2023, reaching 91.37%. Further analysis shows that in the "Management Discussion and Analysis" (MD&A) section of these annual reports, 39.37% of companies mentioned the low-altitude economy, and approximately 21.05% of companies have applied for patents in the low-altitude economy field. Additionally, disclosures related to drone test zones, scientific research and innovation technologies, eVTOL technology, market policies, and social benefits averaged 765 times per year. These data comprehensively reflect the application and patent of the low-altitude economy within relevant companies.

Table 1. Overview of low-altitude economy-related companies.

Year	Number of Companies Whose Business Scope Includes Drones	Number of Companies Disclosing Low-Altitude Economy in Annual Reports Number of Listed Companies	Number of Companies Disclosing Low-Altitude Economy in the MD&A Section of Annual Reports	Number of Disclosures Related to Drone Test Zones, Scientific Research and Innovation Technologies, eVTOL Technology, Market Policies, and Social Benefits	Number of Companies Applying for Low-Altitude Economy Patents
2012	4248	3881	0	426	892
2013	4871	4451	0	706	1023
2014	7262	6635	1	786	1525
2015	9395	8584	21	1522	1973
2016	10,986	10,038	1003	994	2307
2017	10,033	9167	3712	921	2107
2018	9686	8850	3584	835	2034
2019	8138	7436	3011	828	1709
2020	8133	7431	3009	711	1708
2021	6657	6083	2463	792	1398
2022	3705	3385	1371	327	778
2023	1786	1632	661	333	375

3.2.4. Validation of the Effectiveness of Low-Altitude Economic Indicators

(1) Mean Difference Test

To validate the effectiveness of the low-altitude economy indicators constructed in this paper, we employed machine learning methods to explore the potential association between the frequency of low-altitude economy-related terms in the annual reports of companies engaged in low-altitude economy activities and their actual low-altitude economy activities. Specifically, this study selected the top 10 companies based on multiple sources, including the "China Low-Altitude Economy Development Research Report (2024)" and the list of low-altitude economy concept stocks on the Tonghuashun website, and conducted a comprehensive examination of the companies' low-altitude economy levels (Words). By analysing the frequency of low-altitude economy-related terms in the companies' annual reports, the study found significant differences between the top 10 companies and the remaining companies. The results are shown in Table 2.

Furthermore, the analysis was extended to companies specialising in the low-altitude economy. Compared with non-specialised companies, the frequency of low-altitude economy-related terms in the annual reports of specialised companies also increased. These findings emphasise the importance of low-altitude economy-related disclosures, indicating the relevant technical capabilities and strategic orientation of companies. Further research on the frequency of low-altitude economy-related terms in the "Management Discussion and Analysis" (Words_MD& A) section of annual reports reaffirmed the trends observed in the broader analysis, reinforcing the link between robust low-altitude economy information disclosure and a company's low-altitude technology capabilities. The frequency of low-altitude economy-related terms in company annual reports is an important indicator of a company's low-altitude technology capabilities, highlighting the importance of transparent disclosure in assessing a company's low-altitude economy strategy and capabilities.

(2) Pearson correlation test

This paper employs multiple indicators to comprehensively measure and evaluate a company's level of involvement in the low-altitude economy. These indicators include: the frequency of low-altitude economy-related words extracted from company annual reports (Words), the frequency of low-altitude economy-related words in the "Management Discussion and Analysis" (MD&A) section of company annual reports (Words_MD&A), the frequency of low-altitude economy-related words in five company sector indicators (Words_Indicator), and the number of low-altitude economy-related patents applied for by the company (Lnpatents). These indicators provide a multi-dimensional perspective for studying a company's low-altitude economy-related capabilities through text data.

To gain a deeper understanding of the relationships between the indicators, Pearson correlation analysis was conducted, yielding the results presented in Table 3. In this table, we can see that the word frequency of low-altitude economy-related terms in company annual reports (Words) is positively correlated with Words_MD&A, Words_Indicator, and Lnpatents, with correlation coefficients of 0.739, 0.714, and 0.451, respectively. These values indicate a significant positive correlation at the 1% significance level. This finding suggests that these three carefully designed indicators demonstrate varying degrees of effectiveness in measuring and reflecting the level of development related to the low-altitude economy in enterprises.

Table 2. Descriptive statistics and mean difference tests.

Panel A: Descriptive Statistics of Words							
Variable	**Sample**	**Sample Size**	**Mean**	**Sd**	**Min**	**Median**	**Max**
Words	Total sample	324	31.592	55.973	0	31	873
Words	China Business Ranking List Company	2	156.731	108.652	17	87	479
Words	Non-China Business Listed Companies	322	29.417	43.116	0	10	731
Words	Low-altitude economy specialised sector companies	42	64.882	90.251	0	32	639
Words	Non-specialised low-altitude economy sector companies	282	19.393	31.729	0	8.1	317

Panel B: Mean Differences in Words					
Variable	Sample1	Mean	Sample2	Mean	MeanDiff
Words	China Business Ranking List Company ($n = 2$)	156.731	Non-Zhongshang List Companies ($n = 322$)	29.417	127.314
Words	Low-altitude economy specialised sector companies ($n = 42$)	64.882	Non-China Business low-altitude economy sector companies ($n = 282$)	19.393	45.489

Panel C: Words_MD&A							
Variable	Sample	Sample Size	Mean	Sd	Min	Median	Max
Words_MD&A	Total sample	324	29.641	53.278	0	21	649
Words_MD&A	China Business Ranking List Company	2	139.417	87.992	13	69	477
Words_MD&A	Non-China Business List Companies	322	27.643	47.318	0	11	651
Words_MD&A	Low-altitude economy specialised sector companies	42	69.418	91.153	0	27	413
Words_MD&A	Non-specialised low-altitude economy sector companies	282	21.528	29.417	0	3	172

Panel D: Mean Differences in Words_MD&A					
Variable	Sample1	Mean	Sample2	Mean	MeanDiff
Words_MD&A	China Business Ranking List Company ($n = 2$)	139.417	Non-Zhongshang List Companies ($n = 322$)	27.643	111.774
Words_MD&A	Low-altitude economy specialised sector companies ($n = 42$)	69.418	Non-China Business low-altitude economy sector companies ($n = 282$)	21.528	47.89

Table 3. Pearson correlation test.

Variable	**Words**	**Words_MDA**	**Words_Indicator**	**Lnpatents**
Words	1			
Words_MDA	0.739 ***	1		
Words_Indicator	0.714 ***	0.532 ***	1	
Lnpatents	0.451 ***	0.483 ***	0.526 ***	1

Note: This table presents Pearson correlation coefficients between variables. *** indicates statistical significance at the 1% level ($p < 0.01$).

3.3. Total Factor Productivity (TFP)

Total Factor Productivity (TFP) refers to the additional productivity achieved under fixed levels of input factors, serving as a key indicator of the quality of economic growth. When calculating TFP, it is necessary to first define the production function of the enterprise, which describes the relationship between inputs (such as labour and capital) and outputs. Defining the appropriate production function form clarifies how various input factors contribute to output, thereby isolating the TFP contribution. Production functions include various forms such as linear, Leontief, CD, CES, VES, and Trans-log. Here, we adopt the CD method, which has a relatively simple functional structure and clearer economic implications.

$$Y_{it} = A_{it} {L_{it}}^{\alpha} {K_{it}}^{\beta} \tag{1}$$

$$A_{it} = \gamma^t A_{io} \tag{2}$$

where Y_{it} represents output, L_{it} represents labour input, K_{it} represents capital input; A_{it} represents TFP, which is divided into two parts: γ_t represents the growth of TFP in period *t*, and A_{io} represents the TFP in the base period. Substituting model (2) into model (1) and taking the logarithm, we obtain the linearised form:

$$ln\, Y_{it} = \alpha\, ln\, L_{it} + \beta\, ln\, K_{it} + t\, ln\, \gamma + ln\, A_{io} \tag{3}$$

To address the inherent issues of simultaneous non-identity and sample selection bias in traditional ordinary least squares (OLS) estimation of total factor productivity (TFP), this study adopts the method proposed by Wang Guidong (2018): in indicator selection, the natural logarithm of total sales is used to represent firm output, and the natural logarithm of the number of employees is used to reflect labour input.

This study employed the projection tracing algorithm to calculate the average and median values of various indicators for each year from the perspective of enterprises, thereby presenting the general level and trends of these indicators. The specific results are shown in Figure 1.

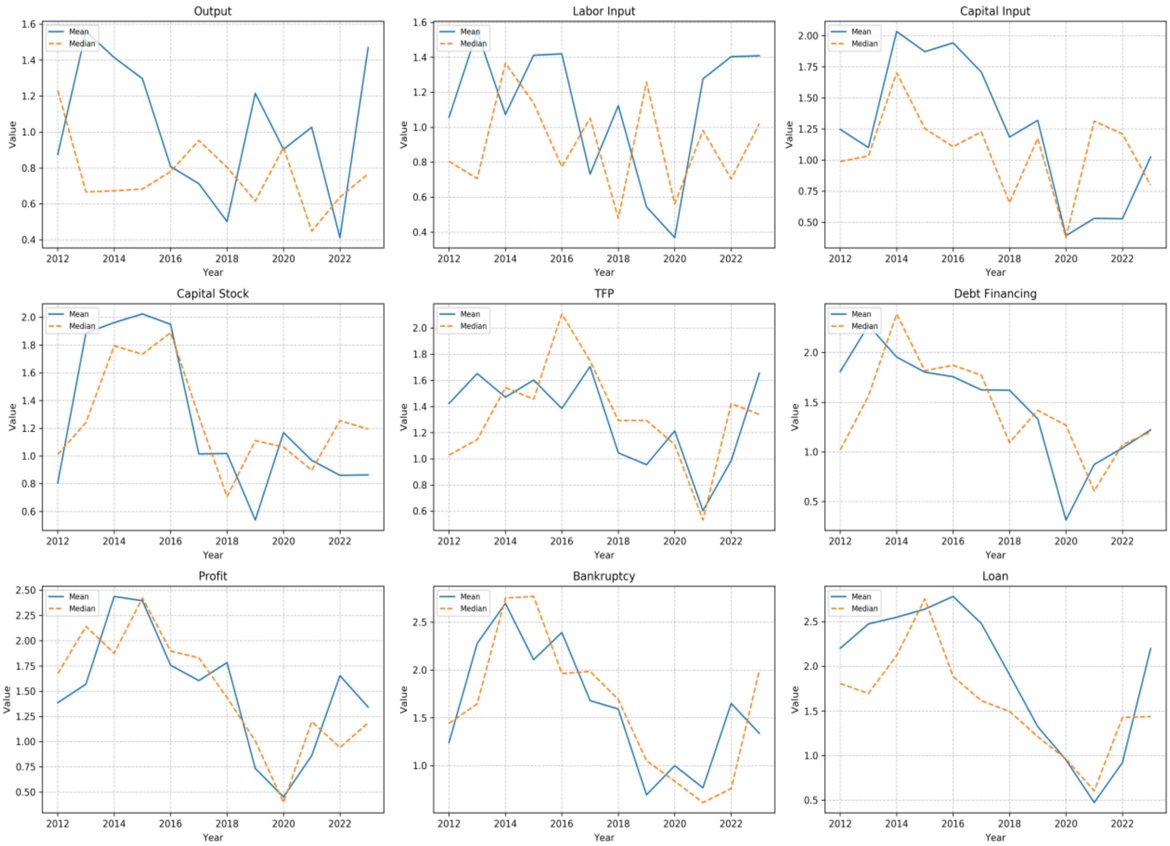

Figure 1. Descriptive statistical analysis of the mean and median values of indicators.

3.4. Research Model on the Impact of the Low-Altitude Economy on Enterprise Total Factor Productivity

To examine the impact of the low-altitude economy on enterprise total factor productivity, the following regression model was established:

$$TFP_{it} = \alpha + \beta\, LA_{it} + \gamma\, Controls_{it} + year + id + \varepsilon_{it} \tag{4}$$

Among these, TFP_{it} represents the total factor productivity of the i th company in t; α is the intercept term of the model, indicating the expected value of total factor productivity when all explanatory variables are zero except for the intercept; *LA* stands for Low-Altitude Economy, β represents the impact of the Low-Altitude Economy on a company's total factor productivity. In the baseline regression analysis, we used the keyword frequency (Words) of the Low-Altitude Economy in the company's annual report as the measurement standard; $Controls$ is a control variable used to control other factors that may influence total factor productivity, such as company size, age, industry characteristics, etc.; $year\ and\ id$ are dummy variables representing the year, used to control for the potential effects of different years, such as economic cycles or policy changes; are dummy variables representing company identity, used to control for inherent characteristics of different companies, such as corporate culture or management style;ε_{it} is the error term, representing the unexplained portion of the model, i.e., the influence of all other factors on total factor productivity that are not included in the model.

Additionally, during the alternative indicator testing process, to more comprehensively assess the company's low-altitude technology level, we shifted to selecting the "Management Discussion and Analysis" (MD&A) section of company annual reports as an alternative indicator for (Words), and combined it with the natural logarithm of the number of low-altitude economy-related patents applied for by the company (Lnpatents) as an additional evaluation indicator to comprehensively examine the effect of low-altitude economy on enterprise total factor productivity.

Based on Hypothesis 1, this study predicts that the regression coefficient β is significantly positive. Referring to Zhao Jianyu and Lu Zhengfei (2018) and Ye Kangtao and Sun Weihang (2019), the following control variables are included: company size (Size), company age (Age), debt-to-equity ratio (Leverage), firm growth (Growth), board size (BoardSize), equity concentration (Top1), technological innovation (Lnallpats), and firm value (Tobing). Additionally, a 0–1 variable indicating whether the chairman and general manager positions are combined is included. To address potential heteroskedasticity across industries, this study performs industry-level cluster adjustments on the standard errors of regression coefficients during model estimation. Variable definitions are shown in Table 4.

Table 4. Variable definitions.

Variable	Standard Deviation	Minimum
Total Factor Productivity	TFP	Calculated according to the method of Lu Xiaodong and Lian Yujun (2012)
Annual report low-altitude economy keyword frequency	Words	The number of low-altitude economy keywords in the company's annual report is increased by 1, and the natural logarithm is taken
Frequency of low-altitude economy-related keywords in the M&A section of annual reports	Words_MD&A	Number of low-altitude economy-related keywords in the MD&A section of company annual reports, plus 1, and take the natural logarithm
Level of the five key indicators in the annual report	Words_Indicator	Add 1 to the total number of disclosures of the five indicators (unmanned aerial vehicle test zones, scientific research and innovation technology, eVTOL technology, market policies, and social benefits) in the company's annual report, then take the natural logarithm
Number of patents related to the low-altitude economy	Lnpatents	The number of low-altitude economy-related patents applied for by the company in the current year is increased by 1, and the natural logarithm is taken
Conventional low-skilled labour force	Routine	The number of employees in production, marketing, and finance, divided by the total number of employees in the company
Non-routine high-skilled labour	Non-routine	The number of technical and R&D personnel in the company, divided by the total number of employees in the company
Company R&D innovation capability	R&D	Enterprise R&D expenditure divided by total assets
Company output	lnSale	Natural logarithm of total sales
Enterprise labour force	Labour	Labour input per company/company size
Enterprise capital input	Input	Natural logarithm of net fixed assets
Enterprise investment indicators	Investment	Natural logarithm of cash paid for the acquisition and construction of fixed assets, intangible assets, and other long-term assets
Company size	Size	The natural logarithm of the company's total assets or operating revenue
Company age	Age	Company age, taken as the natural logarithm
Asset-liability ratio	Leverage	Total liabilities divided by total assets
Business growth	Growth	Sales revenue growth rate, taking the natural logarithm
Board size	BoardSize	Number of board members, taking the natural logarithm
Technology innovation	Lnallpats	Total number of patents applied for by the company plus 1, taking the natural logarithm
Equity concentration	Top 1	Shareholding ratio of the largest shareholder
Enterprise value	Tobing	Enterprise market value (market capitalisation) / (total assets—net intangible assets—net goodwill)
Combined role	Daul	When the positions of Chairman and General Manager are combined, enter 1; otherwise, enter 0

4. DID Empirical Analysis

Employing a difference-in-differences (DID) framework, this study uses the policy shock of National Big-Data Pilot Zones as a plausibly exogenous treatment that accelerates the low-altitude economy. By contrasting firms inside and outside these zones, the design strips out macro cycles and sector trends, cleanly identifying the causal impact of LAE expansion on total factor productivity. Parallel-trend and dynamic-effect tests further safeguard the validity, yielding a coherent and credible narrative that links national strategy, digital infrastructure, and firm-level performance.

4.1. Descriptive Statistics

The results of the descriptive statistics are shown in Table 5. The average total factor productivity (TFP) of selected enterprises in the low-altitude economy sector from 2012 to 2023 was 8.85, with all variables exhibiting normal descriptive results. Among these, the average values for routine low-skilled labour and non-routine high-skilled labour are 0.72 and 0.23, respectively, indicating significant differences in the labour skill structure among listed companies. The minimum value for R&D is 0, and the maximum value is 0.2, indicating significant differences in R&D innovation capabilities among listed companies, with considerable room for improvement.

Table 5. Descriptive statistics of main variables.

Variable	Sample Size	Mean	Standard Deviation	Minimum	Maximum Value
TFP	3500	8.85	0.95	6.5	13.5
Words	3500	2.3	1.3	0	6.5
Words_MD&A	3500	1.05	1.35	0	6.2
Words_Indicator	3500	1.7	1.3	0	5.8
Lnpatents	3500	0.38	0.85	0	6
Routine	3500	0.72	0.22	0	1
Non-routine	3500	0.23	0.2	0	0.9
R&D	3500	0.025	0.022	0	0.2
lnSales	3500	21.3	1.4	17.5	27
Labour	3500	7.4	1.25	3	12.5
Input	3500	19.6	1.65	13	25.5
Investment	3500	18.3	1.7	0	24.5
Size	3500	21.2	1.45	17.2	27.2
Age	3500	1.8	0.9	0	3.2
Leverage	3500	0.38	0.18	0.01	0.95
Growth	3500	0.3	2.2	−10.5	125
Board Size	3500	2.8	0.06	2.5	3.1
Lnallpats	3500	1.75	2.3	0	10
Top 1	3500	0.32	0.14	0.02	0.85
Tobing	3500	2.2	2.2	0	90
Daul	3500	0.38	0.48	0	1

4.2. The Total Factor Productivity Effects of the Low-Altitude Economy

Table 6 provides an in-depth analysis of the potential impact of the low-altitude economy on total factor productivity (TFP). First, as shown in column (1), under the specified 1% significance level, the regression coefficient of the low-altitude economy (Words) is 0.030. When control variables are further included, as shown in column (2), this significant positive impact remains robust. From an economic perspective, ignoring other potential influencing factors, an increase of one standard deviation in the level of the low-altitude economy is expected to lead to a significant 4.89% growth in TFP (1.632 × 0.030). This is a result of major strategic significance. Under unchanged conditions, these findings emphasize the significant contribution of the low-altitude economy to enhancing enterprise TFP, thereby confirming Hypothesis 1.

Table 6. Regression results of low-altitude economy and enterprise total factor productivity.

Variable	(1) With Control Variables	(2) No Control Variables
	TFP	TFP
Words	0.028 *** (7.530)	0.030 *** (3.016)
Controls	Yes	No
_cons	43.127 *** (158.231)	9.463 *** (305.894)
N	3500	3500
R^2	0.84	0.28
Adj. R^2	0.835	0.275

Note: *** indicates significance at the 1% level; the values in parentheses are the cluster standard errors at the industry level.

4.3. Robustness Test

4.3.1. Propensity Score Matching Method

To effectively avoid potential sample self-selection bias, this study employs propensity score matching (PSM) to enhance the precision and reliability of the research. Specifically, based on whether the annual reports of listed companies contain keywords related to the low-altitude economy, the samples were precisely divided into an experimental group and a control group. Subsequently, using the control variables in Model (3) as the matching benchmark, we employed a precise 1:1 nearest neighbour matching method to perform sample replacement.

Before implementing PSM regression, to ensure the rigour of the experimental design and data quality, we first conducted a rigorous balancing test to assess the balance of covariates between the experimental group and the control group. The test results showed that the standard error of enterprise characteristics between the two groups was significantly reduced, from 46.13% to 88.63%, a significant change that fully demonstrated the effectiveness of the matching method. After matching, it was found that the standardised deviations of most covariates were below 5%, and this low deviation level further verified the accuracy of the matching process. Further detailed analysis using t-tests showed that there were no significant coefficient differences between the experimental group and the control group in statistical terms. This finding not only enhanced the credibility of the study but also laid a solid foundation for subsequent in-depth analysis. Table 7, column (3), presents the test results for the matched samples, confirming the robustness of the study findings and alleviating concerns about self-selection bias. These results affirm the effectiveness of PSM in addressing endogeneity issues and enhance the credibility of the study conclusions.

Table 7. Low-altitude economy and enterprise total factor productivity—Regression results after PSM.

Variables		**(2)**	**(3)**	**(4)**
	Post-PSM Regression	**DID Test**	**Dynamic Effects**	**DID After PSM**
	TFP	**TFP**	**TFP**	**TFP**
Words		0.005 *** −0.711		
Treatment × Post		0.018 *** −0.007		0.010 −0.009
Treat × Post (−1)			0.011 −0.005	
Treatment × Post (0)			0.018 -	
Treatment × Post (1)			0.036 -	
Control	1.236 *** −61.002		0.506 ** −35.911	0.671 *** −21.98
_cons	0.850 *** −45		0.480 ** −28	0.650 *** −22
N	550	3500	3500	1600
R^2	0.86	0.4	0.2	0.38
Adjusted R-squared	0.85	0.35	0.19	0.36

Note: ***and ** indicate significance at the 1% and 5% levels, respectively.

4.3.2. DID Test and Dynamic Effects

This study uses listed companies within the "National-level Big Data Comprehensive Pilot Zones" as the treatment group and listed companies outside these zones as the control group to establish a difference-in-differences (DID) model:

$$TFP_{it} = \alpha + \beta\, Treat_i \times Post_{it} + \gamma\, Controls_{it} + year + id + \varepsilon_{it} \quad (5)$$

where Treat indicates whether a firm belongs to the treatment group (1 for treatment group, 0 for non-treatment group); Post is 1 for the year when the firm first became part of the "National Big Data Comprehensive Pilot Zone" and subsequent years, and 0 otherwise; other variables are defined consistently with the baseline regression. The regression results are presented in Table 7, Column (2). The coefficient of the interaction term Treat × Post is significantly positive, indicating that becoming a "national-level big data comprehensive pilot zone".

First, we introduce a variable Treat to identify whether a firm belongs to a specific treatment group. Specifically, if a firm belongs to the treatment group, Treat is 1; otherwise, it is 0. Furthermore, another key variable Post is used to mark the status of firms in the treatment group at a specific point in time (i.e., the year in which the firm first became a "national-level big data comprehensive pilot zone" and subsequent years). At this point in time and thereafter, Post is set to 1; otherwise, it is 0. All other variables are defined consistently with the baseline regression. When conducting an in-depth analysis of the regression results, the coefficient of the interaction term Treat × Post in column (2) of Table 7 is significantly positive, indicating that after becoming a "national-level big data comprehensive pilot zone," the relevant indicators or performance of firms have significantly improved or changed. This further validates the positive role and significant influence of treatment group firms in the construction of big data comprehensive pilot zones, as well as their significant positive impact on enhancing firms' total factor productivity.

Furthermore, the following model is established to study its dynamic characteristics:

$$TFP_{it} = \alpha + \beta\ Treat_i \times Post(n)_{it} + \gamma\ Controls_{it} + year + id + \varepsilon_{it} \tag{6}$$

where, for the treatment group and control group enterprises, we introduce a variable Post(n), which specifically represents the status of these enterprises in the nth time period before and after the treatment group enterprises were first recognised as "national-level big data comprehensive pilot zones." Here, n represents the specific period or time span, which is used to quantify the time span before and after this critical event. This study sets one year before and one year after the decision, totaling three years, with the estimation results shown in Table 7, column (3). The results show that the coefficient of Treat × Post (−1) in the year before the policy is insignificant, while the coefficients of Treat × Post (0) and Treat × Post (1) in the years after the policy are significant, further confirming that becoming a "national-level big data comprehensive pilot zone" and the implementation of the policy are conducive to improving the total factor productivity of enterprises.

Finally, to further validate this promotional effect, this study controlled for consistency in other firm characteristics between the treatment and control groups before and after the policy, and conducted a DID test after propensity score matching (PSM). Specifically, we used enterprise characteristics as control variables to perform propensity score matching across all samples for mixed years. The treatment group was matched with the control group using the nearest neighbour matching method with a 0.1 standardised score, and a 1:1 match was achieved. Subsequently, DID estimation was conducted based on Model (5), with the results presented in Column (4) of Table 7. The results show that the coefficient of Treat × Post is significantly positive, which still indicates that being designated as a "national-level big data comprehensive pilot zone" is beneficial for improving a firm's total factor productivity.

(1) Parallel Trend Test (ParallelTrendTest)

A double difference model was employed to assess the impact of the low-altitude economy (AI) on total factor productivity (TFP). The prerequisite for the validity of this model is that there should be no significant differences between the experimental group and the control group prior to the intervention. Therefore, a parallel trend test was conducted, with the results shown in the figure below. The results indicate that the policy had no significant effect prior to its implementation. After the policy implementation, the policy effect was significant and exhibited a growth effect, indicating that being designated as a "national-level big data comprehensive pilot zone" has a significant positive impact on improving enterprise total factor productivity.

(2) Placebo Test

The parallel trend test preliminarily validated the robustness of the baseline regression results. However, considering that there may still be some unobservable competing factors that could introduce bias in the results, this study arbitrarily selected 50 listed companies as the experimental group. During the estimation process of Model (6), a virtual policy variable was constructed to simulate the potential impact of the policy on the study variable. To further validate the stability and reliability of this variable, we conducted up to 500 repeated regression analyses on the extracted dataset. After each regression, we recorded the regression coefficients of the pilot policy and systematically analysed the coefficients of the 500 regressions. The kernel density plots are shown in Figure 2. The results indicate that randomising the policy shock time the regression coefficients of the pilot policy and systematically analysed the coefficients from the 500 regressions. A kernel density plot is shown in Figure 2. The results indicate that after randomising the policy shock time, the distribution of the 500 regression estimates is concentrated around zero and follows a normal distribution trend, fully demonstrating that the causal effect of a company becoming a "national-level big data comprehensive pilot zone" does not stem from other unobservable factors, indicating that the conclusions of this study are robust.

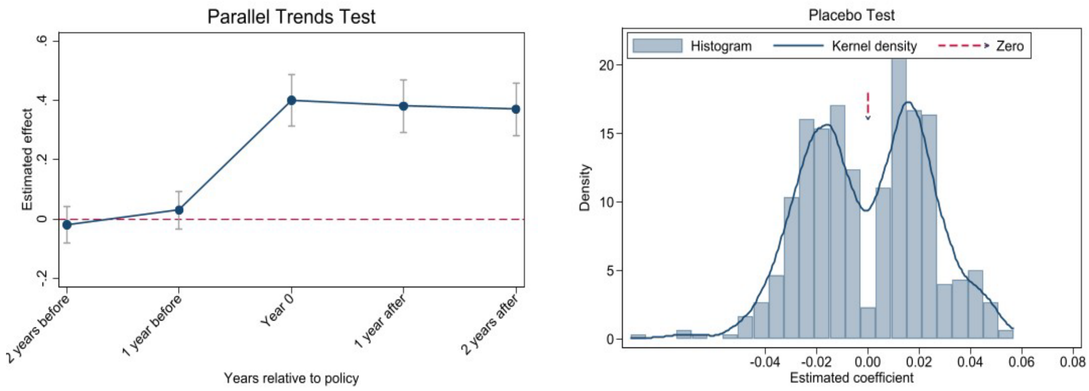

Figure 2. Parallel trend test and Placebo test.

4.3.3. Mitigating Endogeneity Using Instrumental Variables

To address potential endogeneity issues, this study employed multiple strategies in three aspects:

First, a propensity score matching (PSM) model was constructed to address sample self-selection issues. Using control variables, propensity scores were calculated via a Logit regression model to achieve 1:1 neighbour matching. The empirical results in Column (1) of Table 8 indicate that even after accounting for sample self-selection bias, the low-altitude economy still has a significant positive impact on total factor productivity.

To address sample selection bias, we further employed a Heckman two-stage model. In the first stage of the Heckman model, we defined a dummy variable related to a firm's low-altitude economic development level. This variable was defined based on the comparison of a firm's low-altitude economic development level with the sample mean. Specifically, when a firm's low-altitude economic development level exceeds the average level of the overall sample, the dummy variable is assigned a value of 1; otherwise, it takes a value of 0. Using a Probit model, we calculated the inverse Mills ratio (IMR) in the first stage and included it as a control variable in the regression model. These empirical results are presented in column (2) of Table 8. By introducing IMR, we found that the significance of the coefficient of low-altitude economic development level was significantly improved, which further verified the possible sample selection bias in the original model.

Finally, we constructed instrumental variables to address potential reverse causality. Following the method , we used the average low-altitude economy application level of enterprises in the same industry and city as an instrumental variable. And we used the optical cable density of each province as another instrumental variable and included its interaction with the low-altitude economy application level of enterprises in the same industry and city in the analysis [10]. The empirical results shown in columns (3) and (4) of Table 8 highlight the validity of the instrumental variables. Through statistical tests such as the Kleibergen-Paap rk LM Statistic and the Kleibergen-Paap Waldrk F Statistic, we further validate the robustness of this conclusion. These results reduce endogeneity interference, and the adjusted coefficients remain significantly positive, enhancing reliability and confirming their high consistency with the conclusions obtained from the baseline regression model.

Table 8. Endogeneity issues.

Dependent Variable	(1) PSM	(2) Heckman	(3) IV1	(4) IV2
	TFP			
Words	0.120 *** (0.003)	0.193 *** (0.018)	0.140 *** (0.035)	0.292 *** (0.032)
Control variables	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
Individual fixed	Yes	Yes	Yes	Yes
IMR		−0.0076 *** (0.002)		
Kleibergen-Paaprk LM Statistic			180.879	200.278
Kleibergen-Paa WaldrkF Statistic			95.231	25.017
Cragg-Donald Wald F-statistic			900.926	350.267
n	1387	1200	1900.165	1900.378
R^2	0.650		0.162	0.070

Note: *** indicate significance at the 1% levels.

4.3.4. Testing Other Low-Altitude Economy Indicators

To further validate the robustness of the results, the Tobit model was re-estimated, and the regression coefficients for the low-altitude economy showed a significant positive effect, as shown in Column (1) of Table 9. Given the significant attention scholars have paid to the Management Discussion and Analysis (MD&A) section of annual reports, which typically includes discussions on operations, finances, and R&D investments, including initiatives related to the low-altitude economy, this study included the natural logarithm of low-altitude economy keywords in MD&A (Words_MD&A). Regardless of whether control variables were included, the coefficients were significantly positive, as shown in columns (2) and (3) of Table 9, enhancing the reliability of the conclusions. To conduct a comprehensive analysis, we also explored the impact of the low-altitude economy from a technological output perspective, using the number of low-altitude economy-related patents held by listed companies (Patents) as a proxy indicator. Regardless of whether control variables were included, the coefficient of Patents was significantly positive, as shown in columns (3) and (4) of Table 9, supporting the positive role of the low-altitude economy in corporate development.

Additionally, we assessed the level of low-altitude economy data elements (Words_Element) by aggregating disclosures related to low-altitude economy, blockchain, cloud computing, and other topics from annual reports. The results show that the coefficient of Words_Element is significantly positive regardless of whether control variables are included (columns (6) and (7) of Table 9), further confirming the positive impact of the low-altitude economy on corporate development.

Table 9. Robustness test results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Tobit	**Add Control**	**No Control**	**Add Control**	**No Control**	**Add Control**	**No Control**
	Model	**Variable**	**Variable**	**Control Variable**	**Variable**	**Variable**	**Variable**
	TFP	**TFP**	**TFP**	**TFP**	**TFP**	**TFP**	**TFP**
Words	−0.067 *** (−4.516)						
Words MD&A		0.045 *** (7.034)	0.062 *** (14.016)				
Patents				0.051 *** (5.378)	0.045 *** (6.267)		
Words_ Element						0.068 *** (7.165)	0.041 *** (4.526)
Constant	10.524 *** (75.36)	10.20 1*** (85.84)	11.015 *** (650.19)	10.097 *** (80.68)	11.211 *** (350.16)	10.568 *** (85.27)	10.862 *** (600.84)
N	3500	3500	3500	3500	3500	3500	3500
R^2	0.5	0.13	0.025	0.13	0.3	0.135	0.004
Adjusted R^2	0.48	0.125	0.025	0.125	0.23	0.13	0.003

Note: *** indicate significance at the 1% levels.

4.4. Mechanism Study on the Effects of Low-Altitude Economy and Total Factor Productivity

4.4.1. The Mediating Effect of Industrial Integration and Adjustment in Enterprises

Low-altitude economy significantly substitutes traditional repetitive jobs while complementing non-traditional jobs. When enterprises adopt innovative technologies, they often reduce their demand for high-energy-consuming inputs and increase their demand for low-energy-consuming inputs to enhance total factor productivity. This study constructs the following model:

$$TFP_{it} = y_0 + y_1 Tech_{it} + y_i Controls_{it} + \varepsilon_{it} \tag{7}$$

$$Energy_{it} = \delta_0 + \delta_1 Tech_{it} + \delta_i Controls_{it} + \varepsilon_{it} \tag{8}$$

$$TFP_{it} = \theta_0 + \theta_1 Tech_{it} + \theta_2 Labor_{it} + \theta_i Controls_{it} + \varepsilon_{it} \tag{9}$$

where represents the enterprise energy input indicator, is the random error term capturing unobserved variation factors, and are control variables set consistent with the preceding text. This study examines the impact of the low-altitude economy on enterprise industrial integration, particularly high-energy and low-energy inputs. Model (7) directly assesses the overall effect of the low-altitude economy on enterprise total factor productivity, while Model

(8) further analyses the differentiated impact of the low-altitude economy on these two types of energy inputs (high-energy and low-energy inputs). In Model (9), we incorporate enterprise labour indicators into Model (7) to reveal the direct effect of the low-altitude economy on enterprise total factor productivity, while simultaneously examining the specific effects of different types of energy inputs on enterprise total factor productivity after controlling for other variables.

Table 10 presents the stepwise regression results of the mediation effect model. In Panel A, Column (1), we observe that the low-altitude economy has a significant positive effect on the total factor productivity of enterprises, with a total effect of 0.029. Furthermore, Column (2) reveals that the low-altitude economy significantly reduces enterprises' dependence on high-energy-consuming inputs, confirming the existence of a substitution effect. Additionally, Panel A, Column (3) shows that the coefficient of low-energy input is positive, while that of high-energy input is negative, further validating that the low-altitude economy reduces reliance on high-energy input while promoting demand for low-energy input. A deeper exploration of the mediating effect reveals that partial mediation does indeed exist, a conclusion supported by both the Sobel test and Goodman's test. Through calculations, we determine that the proportion of the mediating effect is 16.23%, which strongly demonstrates that the low-altitude economy effectively enhances enterprises' total factor productivity by substituting traditional high-energy-consuming inputs and supplementing low-energy-consuming inputs.

Table10. Regression results of low-altitude economy and industrial integration structural adjustment.

	Panel A: Low-Altitude Economy and High-Energy-Consuming Energy Input Substitution			**Panel B: Complementarity between Low-Altitude Economy and Low-Energy Energy Inputs**		
Variables	**(1) TFP**	**(2) Routine**	**(3) TFP**	**(4) TFP**	**(5) Routine**	**(6) TFP**
Words	0.029 *** (7.634)	−0.033 *** (−14.892)	0.024 (7.231)	0.029 *** (7.634)	0.036 *** (17.981)	0.024 *** (7.231)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Routine			−0.118 *** (−4.987)			
Non-routine						0.112 *** (4.321)
_cons	39.850 *** (158.765)	−0.821 *** (−4.892)	40.123 *** (160.123)	39.850 *** (158.765)	2.031 *** (13.210)	40.234 *** (159.456)
N	4061	4061	4061	4061	4061	4061
R^2	0.869	0.098	0.871	0.869	0.147	0.871
Adjusted R-squared	0.869	0.095	0.871	0.869	0.147	0.871
Sobel			0.003 ***			0.004 ***
Aroian			0.003 ***			0.004 ***
Goodman			0.003 ***			0.004 ***
Mediation effect Proportion			16.23			16.57

Note: *** indicate significance at the 1% levels.

4.4.2. Mediating Effect of Enterprise Innovation and R&D Capabilities

Low-altitude economy not only optimises and improves R&D innovation processes but also significantly enhances enterprises' R&D capabilities, thereby exerting a positive promotional effect on total factor productivity. To further analyse this mechanism, this section focuses on examining the intrinsic relationship between the development level of low-altitude economy and enterprise costs and R&D capabilities, and conducts empirical analysis based on theoretical mechanisms. We use enterprise R&D investment as the measure of R&D capability (abbreviated as R&D), while maintaining the same variable settings as the baseline model in the preceding section. The empirical analysis results are shown in Table 11. The specific research model is constructed as follows:

$$R\&D_{it} = \xi_0 + \xi_1 Tech_{it} + \xi_i Controls_{it} + \varepsilon_{it} \quad (10)$$

$$TFP_{it} = \delta_0 + \delta_1 Tech_{it} + \delta_2 R\&D_{it} + \delta_i Controls_{it} + \varepsilon_{it} \quad (11)$$

The coefficient δ_1 in Model (10) reflects the impact of the low-altitude economy on corporate innovation and R&D capabilities. Based on theoretical analysis, when enterprises possess innovation and R&D capabilities, the expected coefficient ξ_1 significantly increases, indicating the role of the low-altitude economy in enhancing the demand for corporate technological innovation capabilities. To deepen our research framework, we designed Model (11), which incorporates the key indicator of corporate innovation and R&D capabilities into the previous

Model (7). With this setup, we can more comprehensively analyse the direct impact of the low-altitude economy on enterprise total factor productivity. The coefficient 8_1 reveals the direct effect of the low-altitude economy on enterprise total factor productivity, while the coefficient 8_2 of R&D indicates the specific impact of the presence or absence of innovation and R&D capabilities on enterprise total factor productivity after controlling for other factors.

Table 11. Substitution between the low-altitude economy and enterprise innovation and R&D capabilities.

Variables	**(1) TFP**	**(2) R&D**	**(3) TFP**
Words	0.028 *** (7.563)	0.035 *** (17.342)	0.024 *** (6.891)
Control	Yes	Yes	Yes
Non-routine			0.105 *** (3.987)
_cons	39.875 *** (155.234)	1.982 *** (12.897)	40.123 *** (153.456)
N	4061	4061	4061
R^2	0.867	0.148	0.869
Adjusted R-squared	0.865	0.146	0.869
Sobel			0.010 ***
Aroian			0.010 ***
Goodman			0.010 ***
Proportion of mediating effect			40.23%

Note: *** indicate significance at the 1% levels.

Table 11 presents the results of the stepwise regression analysis of the mediation effect model. First, the low-altitude economy has a significant positive impact on firms' total factor productivity, with a total effect of 0.028. Next, in Column (2) of Table 11, we find that the low-altitude economy significantly enhances firms' R&D innovation capabilities, further validating the positive role of the low-altitude economy in promoting firms' R&D innovation. Finally, in column (3), through Sobel tests and Goodman tests, we confirmed the existence of partial mediation effects, with the proportion of mediation effects reaching 40.23%. This finding fully validates that the low-altitude economy enhances enterprise R&D innovation capabilities, thereby improving enterprise total factor productivity.

5. Further Analysis

The impact of the low-altitude economy varies across different types of enterprises, with high-tech industries being more significantly affected, while manufacturing and polluting industries also face specific impacts. For example, leading companies in the drone industry such as DJI, aviation-background companies like EHang and Volocopter, as well as large aircraft and automobile manufacturers such as Volkswagen, Xpeng, and Geely are all paying attention to this emerging field. The development of the low-altitude economy also involves the application of drones in agriculture, logistics, urban management, and other fields, and the development of these application scenarios will similarly impact enterprises in related industries.

5.1. Industry Heterogeneity Analysis

The impact of the low-altitude economy on enterprises in different industries varies significantly, particularly in industries with high R&D and innovation requirements, where the impact is more pronounced. In high-tech industries, the introduction of the low-altitude economy has significantly enhanced enterprises' innovation and R&D capabilities, thereby improving their total factor productivity. For example, new low-altitude aircraft such as drones and eVTOLs are accelerating their integration into various industries, becoming important drivers for improving agricultural efficiency, upgrading manufacturing, and innovating service industry models. Conversely, although the impact of the low-altitude economy may be relatively weaker in non-high-tech industries, it still plays a positive role in improving enterprise productivity. After classifying enterprises into high-tech and non-high-tech industries, it was found that the regression coefficient for high-tech industries was significantly larger, confirming the conclusion that the impact of the low-altitude economy varies greatly between these industries. The results are shown in Table 12.

The low-altitude economy demonstrates significant potential in promoting sustainable development, particularly in reducing pollution emission intensity and improving environmental performance. By applying technologies such as drones, the low-altitude economy not only enhances the efficiency of economic factor mobility but also facilitates precise environmental management and protection. For example, the application of drone technology in environmental monitoring can monitor emission sources such as factory chimneys, ensuring that enterprises comply with emission standards and reduce their impact on the environment, thereby lowering pollution emission intensity. Additionally, the development of the low-altitude economy involves new transportation modes such as electric vertical take-off and landing (eVTOL) aircraft, which offer advantages over traditional fossil-fuel-powered aircraft in reducing greenhouse gas emissions, thereby enhancing environmental performance. In industries with high pollution levels, the return coefficient of the low-altitude economy is significantly lower than that of non-high-pollution industries, highlighting its effectiveness in suppressing pollution emissions.

Table 12. Heterogeneity test.

Variables	(1) Non-High-Tech Industries	(2) High-Tech Industry	(3) Non-Manufacturing	(4) Manufacturing	(5) Non-Heavily Polluting Industries	(6) Heavily Polluting Industries
Words	0.031 ***	0.048 ***	0.035 ***	0.047 ***	0.025 ***	0.007
	−3	−12	−3.2	−10	−4.8	−0.7
Control	Yes	Yes	Yes	Yes	Yes	Yes
_cons	45.000 ***	42.000 ***	45.000 ***	40.000 ***	45.000 ***	38.000 ***
−100	−150	−90	−140	−180	−60	
N	1300	2800	1200	2900	3600	600
R^2	0.89	0.87	0.88	0.875	0.895	0.86
Adjusted R^2	0.888	0.868	0.878	0.873	0.893	0.858

Note: *** indicate significance at the 1% levels.

5.2. Low-Altitude Economy and Corporate Value

The previous section delved into the impact of the low-altitude economy on total factor productivity, emphasising its role in promoting industrial integration and enhancing internal innovation and R&D capabilities within enterprises. This analysis raises a fundamental question regarding the efficacy of the low-altitude economy in enhancing enterprise value, offering insights into the comprehensive economic effects of adopting the low-altitude economy. As an emerging economic model, the low-altitude economy is emerging as a new engine for economic growth, enabling R&D personnel to focus more on creative work and achieve a balance between efficiency and innovation, thereby enhancing a company's market value. Research findings indicate that the low-altitude economy positively impacts a company's total factor productivity by promoting industrial integration and strengthening R&D and innovation capabilities. Market investors should therefore assign higher valuations to companies with advanced low-altitude industry technologies. To this end, we propose a model aimed at examining how the low-altitude economy influences corporate value:

$$Tobinq_{it} = \alpha + \beta\ LA_{it} + \gamma\ Controls_{it} + year + id + \varepsilon_{it} \tag{12}$$

where *Tobinq* represents firm value; *LA* denotes the firm's low-altitude economy level, measured using Words; year and id represent annual fixed effects and industry fixed effects, respectively; other variables are defined as in the preceding text. The regression results shown in Table 13 indicate a significant positive correlation between the low-altitude economy and firm value. Notably, even after controlling for other relevant factors, a one-standard-deviation increase in a company's low-altitude economy level leads to a significant 12.56% increase in firm value. This finding highlights the insight of market investors, who recognise the favourable role of the low-altitude economy in promoting long-term corporate development. This can be achieved by fostering industrial integration within firms, enhancing their R&D and innovation capabilities, and improving total factor productivity, making low-altitude industry technology a key driver of value enhancement for this type of firm.

Table 13. Low-altitude economy and enterprise value.

Variables	(1) No Control Variables	(2) With Control Variables
Words	0.028 ***	0.029 ***
	(9.500)	(4.000)
Constant	45.000 ***	10.000 ***
	(200,000)	(400,000)
Control	No	Yes
year	Yes	Yes
id	Yes	Yes
N	4100	4100
R^2	0.89	0.3
Adjusted R^2	0.888	0.29

Note: *** indicate significance at the 1% levels.

6. Conclusions and Recommendations

As a new type of productive force, the low-altitude economy plays a dual role in adding new capital elements and enhancing total factor productivity. Its potential to drive the growth of enterprise total factor productivity and socio-economic development is significant and should not be overlooked. This study, based on an in-depth analysis of annual reports and patent text data from companies related to the low-altitude economy, has identified the following key findings: (1) From 2012 to 2023, 91.37% of companies were related to the low-altitude economy, with 21.05% of these companies having applied for relevant patents, reflecting the widespread application of the low-altitude industry and technological differences among enterprises; (2)The low-altitude economy significantly improved enterprise total factor productivity, with each standard deviation increase resulting in a 4.89% increase in productivity, demonstrating its enormous potential for enhancing production efficiency; (3)Companies designated as "National-level Big Data Comprehensive Pilot Zones" have experienced significant growth in total factor productivity, highlighting the synergistic effects of policy support and technological innovation; (4) As the low-altitude industry is further applied, companies are actively integrating into the industry and enhancing their innovation capabilities; (5) The application of low-altitude technology yields varying results across different industries, with high-tech industries, manufacturing, and heavily polluting industries benefiting significantly; (6) The low-altitude economy not only enhances companies' total factor productivity but also increases their market value, with each standard deviation increase leading to a 12.56% growth in company value, demonstrating its comprehensive value in driving overall corporate development.

Finally, placing these findings in a global context reveals three ways in which this study can inform the worldwide debate on sustainable growth and productivity.

Firstly, A transferable policy blueprint. The Chinese experiment—using national big-data pilot zones as an exogenous catalyst for the low-altitude economy—provides a quasi-natural laboratory that other countries can emulate. Whether it is the EU's "Green Deal" corridors, the U.S. "Advanced Air Mobility National Campaign", or the African Union's plan for medical-drone networks, regulators can adopt the same DID logic to isolate the TFP effect of low-altitude policies and calibrate subsidies, airspace rules and infrastructure investments accordingly.

Secondly, A common green-productivity metric. By converting textual disclosures (patents, annual reports) into a machine-learning LAE dictionary, we offer an open-source tool that is language- and jurisdiction-agnostic. This allows cross-country comparisons of how quickly firms absorb green aviation technologies and how much productivity they gain, moving the global conversation from output-based to technology-diffusion-based benchmarks.

Thirdly, A North–South bridge for inclusive growth. The evidence that high-tech, manufacturing and heavy-pollution sectors gain most implies that developing economies with nascent aerospace industries can leapfrog directly into high-value segments—bypassing the carbon-intensive path taken by earlier industrialisers. By coupling our TFP estimates with global carbon-price scenarios, policymakers can quantify the social return of leapfrog investments and prioritise concessional finance for low-altitude infrastructure in low-income regions.

In short, the study demonstrates that low-altitude economies can deliver both a measurable TFP dividend and a verifiable carbon dividend, providing the international community with a concrete example of how targeted digital-airspace reforms can simultaneously raise productivity and accelerate the transition to sustainable development.

Author Contributions

J.W.: conceptualization, data curation, formal analysis, writing—original draft; Z.W.: methodology, software, writing—review & editing; J.R.-S.: investigation, resources, writing—review & editing; G.M.: supervision, project administration, writing—review & editing. All authors have read and approved the final manuscript.

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Use of AI and AI-Assisted Technologies

During the preparation of this work the author(s) used ChatGPT to recommend and describe appropriate statistical methods; the author(s) reviewed and edited the content and take full responsibility for the published article.

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