Government Attention and AI Industry Development : Evidence from China

ABSTRACT
As artificial intelligence (AI) is increasingly applied across a wide range of industries, the AI sector has become a critical driver of regional economic growth. Due to the considerable positive externalities associated with AI technology, optimal allocation of market resources often requires government intervention. In this context, the intensity of governmental focus on the AI industry—referred to as government AI attention—serves as a key policy lever. This article examines the impact of government AI attention on the development of the AI industry and finds that such attention significantly promotes local AI industry growth. This result remains robust after a series of robustness checks and endogeneity tests. Furthermore, the study investigates the mechanisms through which government AI attention fosters AI industry development, revealing that it primarily works by enhancing the environment for technological innovation and alleviating financing constraints faced by AI enterprises. Finally, the article explores regional heterogeneity and finds that the positive effects of government AI attention are more pronounced in regions with lower fiscal pressure, better government–business relations, higher levels of marketization, and more advanced digital infrastructure.

KEYWORDS
Artificial intelligence; government attention; industry policy

1. Introduction

By the end of 2024, the total scale of China's core artificial intelligence (AI) industry has reached approximately 600 billion yuan, with nearly 5,000 enterprises operating along the industry chain. This underscores the crucial role of the AI sector in China's economic development. As the new generation of the digital economy experiences rapid growth, the AI industry is gradually becoming a key driver of economic advancement, with its impact demonstrating significant regional variability[1].

Therefore, the development of the AI industry has a significant impact on a nation's economic prospects and its position in the global economy. Existing research indicates that the growth of the artificial intelligence industry can facilitate the undertaking of international industrial transfers[2], and, by enhancing efficiency, sustainability, and productivity, drive the transformation of agricultural systems[3] while promoting the overall high-quality development of regional economies[4]. As global trade competition intensifies, the AI industry has become a key battleground for international rivalry. Developing AI capabilities to boost national competitiveness and global influence has become an urgent priority for many countries.

In recent years, China has been rapidly narrowing the gap with the world's leading nation in artificial intelligence (AI) development—the United States. This catch-up is evident in the rise of enterprises with advanced AI technological capabilities. For ex-

ample, prior studies[5] have examined major Chinese internet giants like Tencent and Alibaba, both renowned for their strong technological innovation and deep managerial expertise. More recent research [6] has highlighted the brand Deepseek, which has attracted considerable attention in the past two years and further demonstrates China's pursuit of industrial innovation through AI development. Against this backdrop, China provides an exemplary case for examining the role of government attention in shaping the AI industry's growth.

The concept of attention management was first introduced in management studies. The scholar Herbert A. Simon pointed out that when there is a vast availability of information, attention becomes the more scarce resource as human beings cannot digest all the information. For example, within organizational decision-making processes, attention is regarded as a critical and scarce resource, reflecting the extent to which decision-makers focus on competing issues. Early research[7] recognized that the way managerial attention is allocated within firms influences innovation, firm size, and organizational structure. Extending this concept from firms to governments, we argue that governments—given their access to far greater information resources than individuals—should proactively direct adequate attention toward the potential of the artificial intelligence (AI) industry. Such attention enables governments to mobilize resources that support the sector's development. For example, a research[8] finds that government digital attention can promote the provision of digital subsidies, alleviate financing constraints, and increase R&D investment, thereby driving digital innovation among enterprises.

Literature on government attention research is mainly divided into two categories: government environmental attention and government digital attention. These two themes have different research focuses and provide varying degrees of empirical insights for this paper.

Research on government environmental attention is grounded in environmental issues, exploring the mechanisms through which government attention affects environmental protection. Wang et al. [9] examined the enhancing effect of government environmental attention on urban energy efficiency. Their study introduces potential causal relationships through correlation analysis and employs heterogeneous grouping criteria such as fiscal decentralization and digitalization levels, providing insights for logical derivation and heterogeneity analysis. Related research [10] focuses on enterprise green transformation, emphasizing the important fact that China's social governance manifests as interactions between central and local governments—each city is a unique development "space" while being deeply influenced by central will. This suggests that we should refer to central-level policy documents before considering local government attention. Additionally, Cao et al. [11] employed text mining methods to study the impact of government environmental attention on carbon reduction, providing methodological experience for this paper's textual analysis of Government Work Reports (GWR). Although government environmental attention is not directly related to the AI industry, the above studies provide important theoretical and methodological support for measuring government AI attention.

Research on government digital attention mostly examines the digital economy as a whole, deepening our overall understanding of the digital economy. Xu et al. [12] thoroughly explored the mechanisms through which government digital attention affects enterprise digital transformation, particularly focusing on the important role of digital infrastructure and technology investment. Given that enterprise digital transformation is closely related to artificial intelligence industry development, this study provides an important analytical perspective for this paper. Li and Yue [13] specifically studied the

impact of government digital attention on digital economy output efficiency, elucidating the implicit influence of government attention relative to specific policy documents, especially its direct boosting effect on market confidence. This is of great significance for the formulation of the core hypothesis in this paper.Additionally, some studies bridge environment attention and the digital economy, investigating how government adoption of digital economic practices supports carbon reduction initiatives [14].

In conclusion, studies on government attention provide a solid theoretical and empirical foundation for our research, while displaying considerable overlap in the research of digital economy[15], which leaves room for specialized investigations on AI.

The remainder of this paper is structured as follows: Section 2, "Research Background and Marginal Contribution" introduces the practical context of this study, focusing primarily on economic and policy backgrounds, and outlines the significance of this research. Section 3, "Theoretical Analysis and Hypothesis Development," derives the mechanism by which government attention promotes the development of the artificial intelligence industry through theoretical reasoning and accordingly proposes the research hypotheses. Section 4, "Empirical Design," sets out the econometric models, explains the variables, and details the data sources, thereby laying the groundwork for the empirical analysis that follows. Section 5, "Descriptive Statistics and Results Analysis," provides a detailed examination of the data characteristics and research findings, and discusses their relevance to the earlier theoretical framework. The final section, "Conclusion and Policy Implications," summarizes the main findings of the paper and offers recommendations regarding government AI attention.

2. Research Background and Marginal Contribution

2.1. Research Background

Amid China's slowing economic growth and a shift from rapid development to high-quality development, the significance of researching the artificial intelligence industry is self-evident. AI industry policies constitute key normative documents through which the government promotes the development of the sector, reflecting its planning, support, and regulation regarding the industry's growth. In short, the introduction of government policies serves as a clear demonstration of strong government support for the development of the AI industry.

In recent years, the development potential of the AI industry has attracted increasing attention from the Chinese government. As a country characterized by a combination of centralization and decentralization—and sometimes rivalry—China's industrial policies exhibit a pattern of "central leadership followed by local response." Changes in national policy can steer the allocation of local government attention through various channels. For example, Ye[16] illustrates that central government pilot policies can prompt local governments to focus more on specific areas, while other research[17] finds that ingrained policy styles, such as official accountability systems, can enhance policy effectiveness.

Specifically, the development of China's artificial intelligence industry can be roughly divided into four stages, each characterized by distinct features of government attention. Overall, the continuous increase in attention has closely accompanied the robust growth of the AI industry.

The table 1 summarizes the characteristics and corresponding policies of the AI industry in China across different periods. As shown in the table, the period from

1978 to 2006 marked the initiation and planning stage of China's artificial intelligence industry. During this time, China's economy was undergoing rapid recovery and growth. The attention paid by Western countries such as the United States to the AI sector attracted some interest from Chinese policymakers. However, due to technological lag and limited funding, government support for AI development was confined mainly to educational and academic spheres, with very little attention allocated to the industry itself.

Table 1. Development Stages of Artificial Intelligence in China

Development Stage	**Stage Characteristics**	**Representative Policy**
Planning Stage (1978-2006)	The Chinese Association for Artificial Intelligence was officially established	In 2006, the 11th Five-Year Plan mentioned AI development
Exploration Stage (2006-2016)	Internet companies such as Baidu and Tencent emerged; technologies like machine learning were widely adopted	In 2016, the State Council released the "Three-Year Action Plan for Internet+ Artificial Intelligence"
Rapid Development Stage (2017-2022)	Internet giants accelerated AI industry layout; widespread application of technologies such as cloud computing and AI chips	In 2017, the "Next Generation Artificial Intelligence Development Plan" was issued; from 2019 to 2021, national pilot zones for AI innovation and development were established
High-Quality Development Stage (2023–present)	Numerous AI unicorn enterprises emerged; AI commercialization became increasingly mature; growing demand for small-scale and domain-specific large models	In 2023, the "Interim Measures for the Management of Generative Artificial Intelligence Services" was issued; "Artificial Intelligence+" has been included consecutively in the government work reports

From 2006 to 2016, the learning and exploration stage began, as the rise of internet companies catalyzed the meaningful start of AI development in China. In response, the State Council released a special development plan dedicated to AI.

Between 2017 and 2022, the industry entered a phase of rapid development. The Chinese government issued the milestone "New Generation Artificial Intelligence Development Plan," significantly strengthening policy support and reflecting a substantial increase in government attention to AI. Furthermore, from 2019 to 2021, the central government established 18 National New Generation AI Innovation and Development Pilot Zones to explore practical industrial applications of artificial intelligence.

Since 2023, the focus has shifted to high-quality development. Government attention to AI has continued to intensify, and the trend toward industrial commercialization has become increasingly evident.

2.2. Marginal Contribution

Drawing on previous research experiences, this paper offers the following potential marginal contributions in terms of research topic, research subjects, and theoretical analysis.

First, regarding the research topic, based on the extensive research conducted by predecessors on the digital economy as a whole, this paper focuses specifically on the artificial intelligence industry within the digital economy. This provides clearer and more precise insights into the development trajectory of the AI sector.

Second, with respect to research subjects, earlier studies have often evaluated the effects of explicit industrial policies reflected in official documents, overlooking the implicit impact of local government attention on economic development within their jurisdictions. This paper addresses this gap by employing text analysis techniques to quantify these implicit influences.

Third, in terms of theoretical analysis, this study innovatively integrates government intervention theory with attention allocation theory and introduces the concepts of functional and selective policies. We correspondingly propose and empirically test two key mechanisms. Moreover, building on the implicit nature of government attention, this paper elucidates a virtuous cycle of "market expectations-factor allocation" that emerges through enhanced market confidence, offering practical guidance for AI industry development.

In addition, based on the findings of this study, the paper proposes a series of recommendations aimed at promoting the development of regional AI industries.

3. Theoretical Analysis and Hypothesis Development

3.1. Government Attention, Optimal Resource Allocation, and Industrial Development

Shifts in government attention often trigger the movement of production factors, leading to changes in overall factor allocation and, consequently, influencing the development of specific industries. Two typical pathways for such influence are: "functional industrial policy"and "selective industrial policy."

Functional industrial policies refer to general policies aimed at specific functions instead of concrete targets. Examples of such policies include intellectual property protection and infrastructure construction. Existing research[18] has shown that functional policies can enhance the business environment at a deeper level, thus promoting the output of high-quality innovative enterprises. In this paper, the number of technology enterprises incubators is used as a proxy for the outcomes of functional policies.

Selective industrial policies, on the other hand, are policies through which the government uses policy incentives to guide resources toward specific industries. For high-tech industries such as artificial intelligence, industrial development requires substantial upfront investments, but its technology and product designs tend to generate spillover effects, making it difficult to ensure effective incentives for "industry pioneers"—as Coase[19] pointed out, due to the impossibility of perfect property rights delineation, positive externalities inevitably lead to distortions in factor allocation. In this context, greater government AI attention signals stronger commitment to promoting technological advancement and commercialization. Studies on "Individual Champion Cultivation Policy " [20] indicate that selective policies can enhance enterprise innovation by easing financing constraints and optimizing human capital; Italian

experience[21] further demonstrates that targeted support during the startup phase of high-tech firms can have a more pronounced scale-expansion effect than general policies. In this paper, the number of financing events of AI firms is used as a proxy for the outcomes of selective policies.

Moreover, government attention, as an implicit factor, operates both through specific policies and beyond their direct implementation. Signaling theory posits that signalers possess superior information and seek to achieve their objectives through information transmission, while signal recipients require this information to make informed decisions. In this study, the government serves as the signaler and the market as the signal recipient: the government conveys signals of "supporting AI industry development" through Government Work Reports (GWRs), leading to enhanced market confidence in the AI sector. This increased confidence subsequently motivates market actors to actively support technology incubator development and relax financing constraints for AI firms. These supportive behaviors effectively foster the initial prosperity of the AI industry, which in turn further reinforces market confidence. Thus, government AI attention acts as a catalyst, facilitating the formation of a "market expectations-factor allocation" virtuous cycle.

Accordingly, Hypothesis 1 is formulated.

Hypothesis 1: Increased government AI attention has an obvious positive effect on AI industry development.

3.2. Mechanism Analysis of the Role of Government Attention

Hypothesis 1 has established proxy outcome variables corresponding to selective and functional policies, which serve as the mechanism variables in this study. These variables are subject to both direct influence from the two types of government policies and the moderating effect of market confidence. The mechanism is clearly illustrated in Figure 1.

In Mechanism 1, an increase in government attention may lead to measures such as encouraging financial institutions to extend loans to AI enterprises and easing financing constraints for these firms. The funds obtained by enterprises are typically invested in high-end talent recruitment, updates to core technologies, and the purchase of computing equipment. The easing of financing constraints thus promotes the development of the AI industry. In terms of business scale, financing constraints often limit a firm's ability to expand fully[22], while access to financing increases a firm's confidence in hiring talent and developing new markets and businesses. In terms of R&D, Easing financing constraints can therefore significantly boost R&D motivation[23], allowing local AI companies to secure a competitive edge in the industry.

In Mechanism 2, increased government attention leads to improvements in the development environment for local artificial intelligence and its upstream and downstream science and technology industries, which is manifested in the emergence of more technology enterprise incubators. Generally, business incubators provide start-ups with office space, equipment, and mentoring services, as well as financial, legal, and administrative support, collectively referred to as producer service industries. Research has shown that enterprise incubators play a pivotal role in improving the innovation performance of start-ups[24]. In addition, technology enterprise incubators possess special technological service capabilities, such as facilitating talent supply-demand matching and serving as patent intermediaries. The study by Tang et al.[25], which employed field interviews, gave a detailed account of the operation processes

and impact pathways of the new generation of technology enterprise incubators. Such incubation services are of great significance for AI enterprises whose initial investments are substantial but whose future potential is immense.

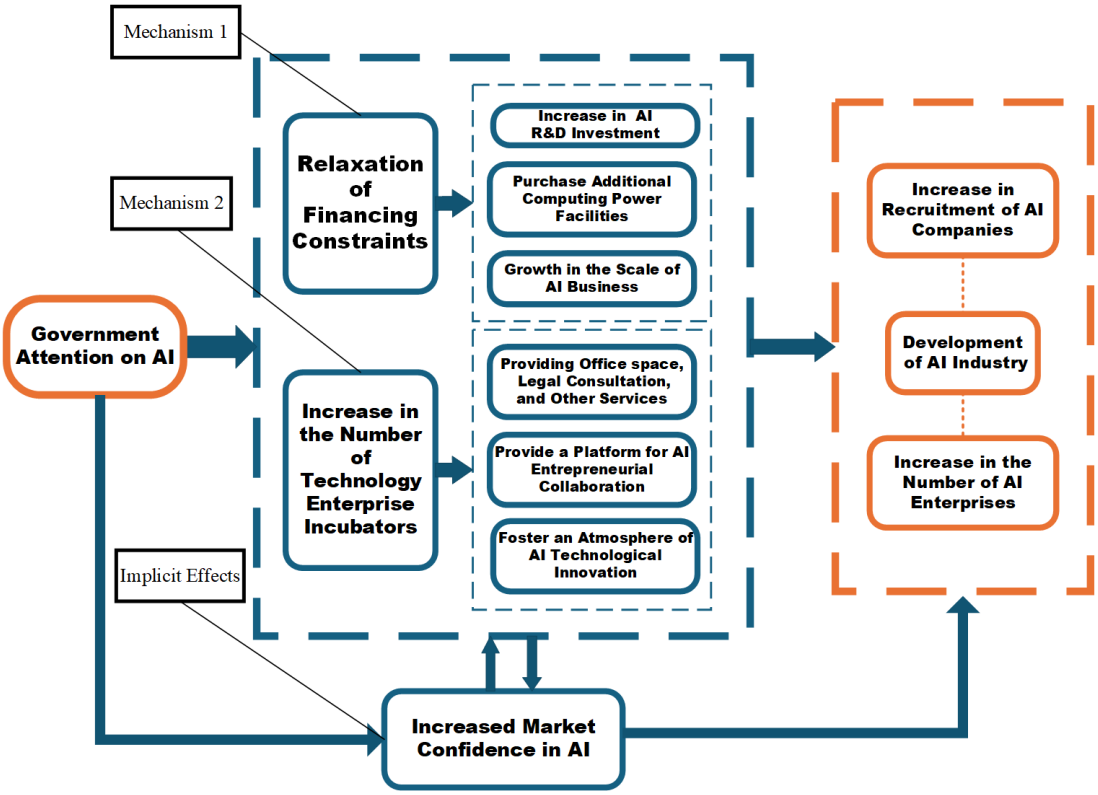


Figure 1. Mechanism Analysis Diagram

As shown in the figure 1, Mechanism 1 and Mechanism 2 demonstrate the process by which government attention creates a development environment for artificial intelligence and its related industries, with specific pathways manifested as easing the financing constraints and increasing the number of technology enterprise incubators. A positive reinforcing cycle emerges between these two mediating variables and market confidence.[1] Their common outcome is the flourishing development of AI industry. Based on this, Hypothesis 2 is proposed.

Hypothesis 2: Government attention promotes the development of the AI industry by easing the financing constraints and increase the number of technology enterprise incubators.

3.3. Heterogeneity Analysis of the Role of Government Attention

Government attention reflects the government's tendency toward resource reallocation, but whether this tendency can actually promote industrial development in different

[1]Within our integrated signaling framework, market confidence functions as a psychological intermediary converting government signals into market behaviors. Given that market confidence is (1) conceptually embedded in the signaling process, (2) empirically captured through financing and incubator mechanisms, and (3) difficult to isolate without endogeneity issues, we employ a reduced-form specification measuring the overall impact of government AI attention.

regions remains uncertain. Empirical evidence suggests that variations in factors such as the degree of marketization, digital infrastructure, business environment, and fiscal pressure on the government may all influence both the magnitude and even the direction of government attention's impact.

The degree of marketization is a comprehensive indicator that measures the fairness of market transactions within a region, the maturity of the market system, the effectiveness of property rights protection, and more. Specifically, given the large number of state-owned enterprises in China, the degree of marketization also takes into account the proportion of the private sector in the local economy. The significance of marketization lies in the fact that regions with higher marketization levels tend to more closely approximate the "perfectly competitive market" assumption in neoclassical economics—namely, the full voluntariness of transactions, complete freedom of entry and exit in industries, total transparency of information, and full judicial impartiality regarding market disputes. Under such circumstances, market factors automatically flow to enterprises with stronger innovation capabilities. Su's study[26] demonstrates the critical role of marketization in sustainable economic development.

Digital infrastructure refers to the construction of a new generation of information infrastructure that embodies the features of the digital economy, including specific facilities such as data centers and cloud computing centers. Existing literature [27] emphasizes the importance of digital infrastructure for regional development, pointing out that digital infrastructure can enhance innovation levels within a region, which benefits the development of high-tech industries such as artificial intelligence. Specifically for the AI industry, if government AI attention increases but the digital infrastructure is relatively underdeveloped, it remains difficult for the region to acquire key elements for AI industry development, such as data and computing power. Therefore, even if government attention plays a promotive role in the development of the AI industry, the effect will be significantly weakened. Conversely, in areas with well-developed digital infrastructure, the strengthening of government attention often quickly brings about the aggregation of key elements such as data and computing power to the AI industry.

Government–business relations generally refer to the economic, political, judicial, and other multifaceted connections between governments and local enterprises. It is generally believed that excellent government–business relations mean that local governments and enterprises cooperate relatively well, enterprises can enjoy more convenient administrative procedures and greater tax incentives, and the government is more honest and fair in handling enterprise-related affairs. A research[28] details how new types of government–business relations promote the development of urban digital economies. Accordingly, the article proposes: In regions with a better business environment, the effect of government attention concentration on the development of the AI industry will be more pronounced. Fiscal pressure similarly affects the effectiveness of government attention through this pathway. Research [29] points out that deficiencies in government fiscal and administrative capacity may render policies ineffective. Based on the above references, this paper conducts heterogeneity analysis on the sample cities from different perspectives.

Hypothesis 3: In regions with a higher degree of marketization, better government–business relations, lighter fiscal pressure, and more advanced digital infrastructure, the promotive effect of government attention on the AI industry is more pronounced.

4. Empirical Design

4.1. Baseline Model

We employ a two-way fixed effects model, using prefecture-level cities across China (including municipalities directly under the central government) as spatial units, to measure the impact of government attention to AI on the development of the artificial intelligence industry. The empirical model is specified as shown in equation:

$$AI_{i,t} = \alpha_0 + \alpha_1 Gov_attention_{i,t} + \alpha_i Controls_{i,t} + \gamma_{i,t} + \nu_t + \varepsilon_{i,t}$$

Where, i represents the city, t represents the year, $AI_{i,t}$ represents the level of AI industry development in region i in year t, $Gov_attention_{i,t}$ is government AI attention, $Controls_{i,t}$ denotes control variables, $\gamma_{i,t}$ represents province fixed effects, ν_t represents year fixed effects, $\varepsilon_{i,t}$ denotes the random disturbance term.

4.2. Variable Description

4.2.1. Dependent Variable

Because the artificial intelligence industry is an emerging sector, statistics related to the scale of the AI industry are not yet mature. Consistent with prior literature [30], this paper uses the number of locally registered AI firms (AI_firm) as a proxy variable for the degree of AI industry development (AI). This setting is reasonable as the number of AI firms directly reflects the market participation in the AI industry and also indicates the development environment of the local AI sector.

4.2.2. Key Explanatory Variable

Following previous studies[31], government attention is measured by compiling a relevant vocabulary list and counting how often these keywords appear in government documents. Taking into account China's local administrative system, this paper uses the most common report—annual government work reports as the data source. Moreover, since government attention exhibits a certain accumulation over consecutive years in the medium to short term, this paper uses the cumulative occurrences of AI-related keywords in the reports as the core explanatory variable (Gov_attention). Based on experience, we determine the specific keywords to include artificial intelligence, deep learning, foundation model, machine learning, agent, neural network, etc.[2] The word frequency statistics are conducted using Python's jieba library. To avoid information interference, the statistics use the precise mode.

4.2.3. Mediating Variables

Based on the hypotheses in the theoretical analysis, this paper uses two mediating variables for mediation effect analysis.

- Government AI attention can bring tax reductions, financial support, and other supporting assistance to AI enterprises, greatly improving market expectations for AI companies and thereby enhancing their financing capacity. Given data

[2]Keyword list: Artificial Intelligence, AI, Foundation Model, Deep Learning, Machine Learning, Neural Network, Agent, Industrial Robot, Image Recognition, Speech Recognition, Computer Vision

availability, this paper mainly studies the equity financing received by AI firms. Empirical evidence from Europe[32] shows that Venture Capital(VC) can significantly promote business expansion and investment, and positively impact technological innovation; empirical studies after the 2008 financial crisis[33] indicate that Private Equity(PE) can contribute to the stabilization of the financial system, which is crucial for financing high-tech enterprises. In summary, the financing capacity of AI firms is measured by the number of PE/VC events received by local AI enterprises in the given year. Data is filtered and downloaded from CVsource.

- Government AI attention can also foster a local entrepreneurial environment conducive to technological innovation, especially stimulating the emergence of technology enterprise incubators. The specific mechanism of this effect has been studied before[34], where it is explained from a co-evolutionary perspective that incubator entities positively influence the innovation activities of emerging enterprises. This promoting effect can be measured by the number of local technology enterprise incubators, and this indicator is obtained through Qichacha, which is a corporate information search tool that covers over 580 million business entities.[3]

4.2.4. Control Variables

Due to significant differences in the economic development levels of different cities, as well as variations in industrial structure, foreign trade levels, government revenue, local market scale, and telecommunications industry foundations, it is necessary to introduce control variables to account for these disparities. The following control variables are set in this paper: economic development level (Eco), measured by per capita GDP; industrial structure optimization (Ind), measured by the ratio of the value added of the tertiary industry to that of the secondary industry; government revenue (Fis), measured by the annual fiscal revenue of the local government; foreign trade (Tra), measured by the total import and export trade volume of the locality in that year; telecommunications industry foundation (Tel), measured by the telecommunications revenue of the locality in that year; science and technology investment (Sci), measured by the local annual investment in science and technology; and local overall purchasing power (Pur), measured by the local total retail sales of consumer goods. Data for the control variables are collected from the China Urban Statistical Yearbook and local statistical yearbooks.

4.3. Data Description

Considering data availability and continuity, this paper uses continuous 11-year panel data at the prefecture-level city scale between 2013 and 2023. Specifically, the data description is as follows:

[3]Screening criteria: established between 2013 and 2023, currently active status, and classified in the industry category of science and technology intermediary services, entrepreneurial space services, other science and technology service industries, or other technical services (meeting any one of these criteria is sufficient).

Table 2. Summary of Data Sources

Data Item	Data Source
Government Work Reports	Official websites of municipal governments
Number of AI enterprises	Qiyan China Big Data Platform for Social-Science (CBDPS)
AI-related PE/VC events	CVsource
Number of technology enterprise incubators	Qichacha
Per capita GDP	China City Statistical Yearbook
Proportion of secondary industry	Local Statistical Yearbooks
Proportion of tertiary industry	Local Statistical Yearbooks
Government fiscal revenue	China City Statistical Yearbook, Local Statistical Yearbooks
Total value of foreign trade	China City Statistical Yearbook, Government Work Report
Telecommunications business revenue	China City Statistical Yearbook, Local Statistical Yearbooks
Science expenditure	China City Statistical Yearbook
Total retail sales of consumer goods	China City Statistical Yearbook, Local Statistical Yearbooks

Note: All data items cover the period 2013–2023.

Based on the reliable data sources mentioned above, we have collected a basically complete set of prefecture-level city data: in terms of coverage, the data encompass 284 prefecture-level cities nationwide, with a few cities (such as Chamdo in Tibet and Danzhou in Hainan) excluded due to missing data. Regarding completeness, most data have no missing values, and for a very small number of missing yearly values, linear interpolation was used for imputation. For some values with substantial fluctuations, 5% winsorization was applied at both ends.

At this point, we have established a solid research foundation: both the level of the artificial intelligence industry and government AI attention have reasonable proxy variables, and other factors affecting the development of the AI industry (such as economic development level, scientific and technological level) have also been controlled.

5. Descriptive Statistics and Results Analysis

5.1. Descriptive Statistics

Descriptive statistics are shown in Table 3. The Obs column indicates that there are 3,124 rows of data for all categories, demonstrating data completeness. The Mean and SD columns show the average distributions and standard deviations, respectively. The Min and Max columns reflect the minimum and maximum values for each variable. In particular, in terms of Gov_attention, the range is quite large: in the most attentive cases, government reports mention the AI industry up to 36 times in total, while in the least attentive cases, there is no relevant content in their reports. This, to some extent, confirms the research gap of this paper—the varying degrees of attention reflect the uneven policy inclinations of local policymakers toward the AI industry, and these inclinations tend to be distributed unevenly across regions.

Table 3. Descriptive statistics

VarName	Obs	Mean	SD	Min	Max
AI_firm	3124	1302.37	4715.04	0.00	74629.00
Gov_attention	3124	1.88	3.61	0.00	36.00
Eco	3124	61745.50	36691.64	8407.00	467749.00
Ind	3124	1.18	0.64	0.01	6.39
Tra	3124	10945.22	37322.71	0.03	420000.00
Tel	3124	501.17	836.16	0.02	13964.01
Pur	3124	12500.09	17835.02	377.56	185155.00
Fis	3124	2841.13	6199.76	130.57	83125.01
Sci	3124	1519.35	4566.60	-1.64	55498.17

Based on this, the average values of the core dependent variable and independent variables across all cities are calculated, and a time series plot is created accordingly:

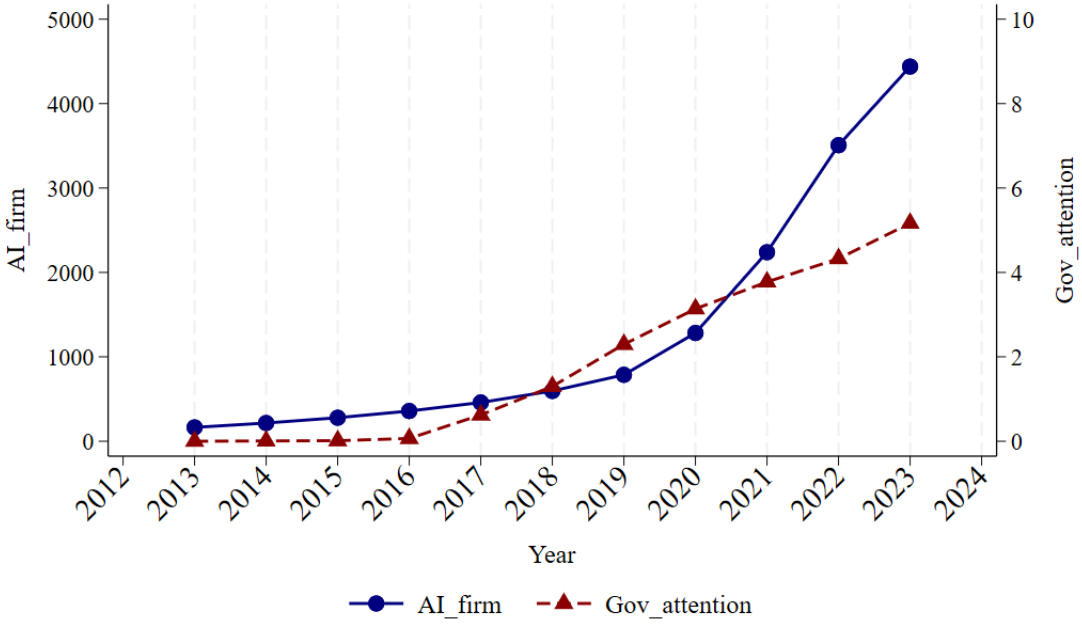


Figure 2. Average Trend Chart of Gov_attention and AI_firm

As shown in Figure 2, the increasing focus on AI by the government is accompanied by a continuous rise in the number of AI enterprises, demonstrating a clear correlation between the two. This prompts further exploration of the casual relationships between them.

5.2. Baseline Regression Results

Based on the regression models discussed above, the baseline regression results are presented in Table 4.

Table 4. Baseline Regression Results

	AI (1)	AI (2)	AI (3)	AI (4)	AI (5)	AI (6)	AI (7)
Gov_attention	1001.87***	780.73***	783.23***	804.04***	624.62***	619.86***	619.87***
	(152.09)	(153.19)	(152.89)	(150.01)	(135.41)	(138.39)	(138.71)
Sci		0.01***	0.01***	0.01***	0.00***	0.00***	0.00***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ind			813.36***	885.08***	748.61***	751.53***	751.43***
			(305.48)	(301.57)	(277.77)	(276.74)	(274.64)
Fis				0.00**	0.00*	0.00*	0.00*
				(0.00)	(0.00)	(0.00)	(0.00)
Eco					−0.01	−0.01	−0.01
					(0.01)	(0.01)	(0.01)
Tra					0.00***	0.00***	0.00***
					(0.00)	(0.00)	(0.00)
Pur						0.00	0.00
						(0.00)	(0.00)
Tel							0.00
							(0.00)
N	3124.00	3124.00	3124.00	3124.00	3124.00	3124.00	3124.00
R^2	0.55	0.61	0.62	0.62	0.72	0.72	0.72

Standard errors in parentheses, clustered at the city level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

As shown in the table, the estimated coefficient of the government attention variable (Gov_attention) is significantly positive at the 1% level, indicating that government attention has a promoting effect on the number of AI enterprises. The coefficient is 619.87, meaning that for each unit increase in Gov_attention, the average number of AI enterprises increases by 619.87 units. This demonstrates that the greater the attention a local government pays to the AI industry, the more vibrant the local AI industry development. From the perspective of control variables, local government expenditure on science and technology (Sci), industrial optimization degree (Ind), and volume of foreign trade (Tra) also play significant positive roles. The insignificant results for retail sales of consumer goods (Pur) and telecommunications revenue (Tel) can be attributed to the fact that the AI industry mainly provides internet-based services and industrial robotics, which are less related to consumer goods retail and traditional telecom services such as telephony and television. In summary, these results support Hypothesis 1, and confirm the important role that the allocation of government AI attention plays in the development of the AI industry.

5.3. Robustness Checks

To ensure the reliability of the experimental results, we employ three approaches for robustness checks: substituting explanatory variables, substituting the explained variable, and adding control variables.

5.3.1. Adding Control Variables

In the baseline regression, the main controls include local economic development level (Eco), foreign trade volume (Tra), scientific and technological development scale (Sci), telecommunications industry foundation (Tel), local market purchasing power (Pur), level of industrial structural optimization (Ind), and government fiscal revenue (Fis). However, merely controlling these variables does not sufficiently address the capital-intensive nature of the AI industry. In reality, the development of the AI industry relies heavily on substantial investment in algorithms, computing power, and data—for example, building computing centers requires significant funding.

To account for the capital environment, we add an additional control variable: the year-end balance of loans by financial institutions. A higher loan balance indicates a higher level of local financial development, meaning that enterprises and individuals in the area have greater access to funds to invest in the AI industry. This data is sourced from the China City Statistical Yearbook.

The regression results are presented in Column 1 of Table 5. The significance remains unchanged. The coefficient indicates that, after controlling for the loan balance variable, each additional mention of AI-related keywords in the government work report is still associated with an average increase of 257.69 AI enterprises in the locality.

5.3.2. Replacing the Explanatory Variable

On one hand, in the baseline regression, we use the frequency of AI-related keywords in government work reports to represent government AI attention. However, government work reports are intended for the general public and the media, emphasizing major achievements, which may not fully or accurately reflect the allocation of government attention. Additionally, these reports are updated only once a year, resulting in a relatively limited sample size (11 reports per city).

To address these shortcomings, we instead use the number of local government regulations related to artificial intelligence as an alternative measure of government AI attention. The data are collected from the "local regulations" section of Peking University Law (PKULaw), which is a comprehensive database for Chinese laws and regulations. The regression results are shown in Column 2, which maintains the same strong significance as the baseline regression.

On the other hand, because the determination of AI industry keywords contains a degree of subjectivity, different choices of keywords may yield different results. Therefore, based on the original government work reports, we modify the scope of AI-related keywords and conduct word frequency statistics again. Specifically, keywords such as "big data," "data transaction," etc.—which indirectly impact the development of artificial intelligence—are added[4]. The regression results are shown in Column 3, and remain significant at the 1% confidence level. Each additional occurrence of the new keywords in the reports is associated with an increase of more than 500 AI enterprises

[4]New keywords list: artificial intelligence, AI, Large Language Model, deep learning, machine learning, neural network, agent, industrial robot, data transaction, image recognition, speech recognition, computer vision, big data, chip, digital economy, IoT, cloud computing,natural language processing

on average, indicating strong robustness.

5.3.3. Replacing the Dependent Variable

Although the number of AI enterprises reflects the local atmosphere of innovation and entrepreneurship in the AI industry to a large extent, using it as the proxy variable for the development of the AI industry omits the impact of firm size and does not consider the possibility of traditional enterprises expanding into AI-related business.

For the third robustness check, we replace the dependent variable with the number of annual AI-related job postings (Recruits) in the local area, observing the demand for AI talent from the perspective of the human capital market. Recruitment information is scraped from multiple job websites[5], and relevant AI keywords are filtered under job requirements[6], then matched to city data by job location.

According to the original hypothesis, higher Gov_attention should be associated with higher recruitment numbers, meaning that government AI attention promotes the development of the local AI industry and increases local demand for AI talent. The regression results are shown in Column 4 of Table 5.

The coefficients show that the results remain significant, indicating that government AI attention not only increases the number of AI enterprises but also increases local demand for AI professionals. This further supports Hypothesis 1.

5.3.4. One-period Lagged Independent and Control Variables

Given the potential reverse causality between government AI attention and AI industry development—that is, rapid industry growth may inversely influence government attention by attracting policymakers' focus to successful sectors or triggering regulatory responses—we adopt a temporal separation strategy to address this endogeneity concern. Specifically, we lag all independent and control variables by one period to mitigate potential endogeneity issues arising from reverse causation and simultaneity bias.

This approach is grounded in the assumption that while current AI industry performance may influence future government attention allocation, it is unlikely to affect past government attention levels that have already been determined and publicly announced in previous Government Work Reports. By using lagged explanatory variables, we establish a clearer temporal sequence where government AI attention precedes industry outcomes, thereby strengthening the causal interpretation of our estimates.

The regression results using one-period lagged variables are presented in Column 5 of Table 5. It must be acknowledged that this method primarily eliminates the most likely endogeneity issues but does not completely rule out endogenous interference. In the next phase, we will proceed to verify using IV. As for the current results, Hypothesis 1 continues to demonstrate robustness.

[5]Data were collected from major online recruitment platforms, including Zhilian Hiring, 51job, 58.com, among others, which collectively represent the majority of China's digital recruitment market.

[6]Keywords list: artificial intelligence, AI, Large Language Model, deep learning, machine learning, neural network, agent, industrial robot, data transaction, image recognition, speech recognition, computer vision, big data, chip, digital economy, IoT, cloud computing,natural language processing

Table 5. Robustness Test Results

	Add Control	**Repl. Exp. a**	**Repl. Exp. b**	**Repl. Dep.**	**Lagged Var.**
Gov_attention	257.693***	—	534.179***[a]	0.028***	683.256***
	(62.943)		(109.568)	(0.006)	(143.470)
Policy	—	312.304***	—	—	—
		(77.726)			
Sci	-0.003***	0.003***	0.003***	0.000***	0.004***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Ind	457.561**	458.887*	782.975***	-0.033	725.407**
	(219.114)	(259.522)	(266.987)	(0.028)	(272.915)
Fis	-0.000	-0.000	-0.000*	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Eco	-0.008*	-0.011	-0.012	0.000	-0.016
	(0.004)	(0.009)	(0.011)	(0.000)	(0.014)
Tra	0.000**	0.000***	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pur	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tel	-0.000	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fin	0.000***	—	—	—	—
	(0.000)				
Constant	-	-	-	-0.071	-
	2154.825***	1190.075**	1737.161***		1864.760**
	(371.858)	(580.022)	(581.711)	(0.063)	(735.204)
Obs.	3,124	3,124	3,124	3,124	2,840
R^2	0.827	0.745	0.714	0.250	0.734

Standard errors in parentheses, clustered at the city level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[a] In (3), Gov_attention uses New_gov_attention.

5.4. Endogeneity Test

5.4.1. Instrumental Variable Approach

The allocation of government attention is not determined solely by the government's perspective on an industry; it can also be influenced by the characteristics of the local industry itself. Due to the potential for bidirectional causality in the baseline model, it is necessary to conduct an endogeneity test to verify the robustness of the conclusions. This paper addresses the endogeneity problem using the instrumental variable (IV) approach.

A suitable IV should significantly affect government attention to artificial intelligence but should not directly impact the development of the local AI industry (its influence should be only indirect, through government attention to AI). In this study, the AI pilot policy satisfies these requirements: on one hand, such policies are likely to draw government attention to the AI industry; on the other hand, whether a city becomes a pilot zone is a quasi-exogenous factor and, within a certain period, would need to act through enhanced government attention to facilitate the development of the local AI industry.

To assess the effect of the pilot policy, we use a difference-in-differences (DID) indicator for National New Generation Artificial Intelligence Innovation and Development Pilot Zone as the instrumental variable. The construction is as follows: for cities designated as AI pilot zones, the DID variable equals 1 beginning in the official implementation year and afterwards, and 0 before implementation; for non-pilot cities, it remains 0 throughout. The regression results are shown in Table 6.

Table 6. 2SLS Regression Results

Variable	(1) First Stage	(2) Second Stage
DID	9.591***	
	(7.04)	
Government attention		1,044.545***
		(5.41)
Controls	Yes	Yes
Province fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Kleibergen–Paap rk LM	11.719***	
Kleibergen–Wald rk F	49.560{16.38}	
Observations	3,124	3,124

Note: { } indicate the 10% critical value for the Stock–Yogo weak identification test.
***p <0.01, **p <0.05, *p <0.1

Columns (1) and (2) of Table 6 report the 2SLS regression results. In the first stage, the coefficient of the DID variable on local government AI attention is significantly positive at the 1% statistical level and passes both the under-identification and weak identification tests for the instrumental variable. In the second stage, the coefficient of local government AI attention on AI industry development is 1044.545, which is also significant at the 1% level. This indicates that, after addressing reverse causality, the baseline research conclusion remains valid.

5.4.2. Propensity Score Matching Approach

While the instrumental variable method effectively addresses issues of bidirectional causality and omitted variables, it struggles to ensure statistical balance in observable characteristics between the treatment and control groups, leaving residual endogeneity concerns. Following previous studies [35], this study further employs the Propensity Score Matching (PSM) method to mitigate sample selection bias. In terms of matching design, this paper constructs the treatment variable based on the 90th percentile of government attention, defining cities in the top 10% as the high-attention group (treatment group) and the rest as the control group. The rationale for choosing the 90th percentile is twofold: first, to accurately identify cities that truly receive "key attention" from the government, reducing within-group heterogeneity in the treatment group; second, to improve matching quality and enhance the policy relevance of the results. For propensity score estimation, a Logit model is used to calculate the conditional probability of a city receiving high government attention, with control variables and year fixed effects set consistently with previous analyses (it should be noted that data for 2013–2016 are omitted due to perfect prediction failure). Regarding the matching strategy, a kernel matching approach is adopted, using a normal kernel function with a bandwidth of 0.06. This method constructs counterfactual outcomes by weighting multiple similar observations in the control group, while restricting matching to the common support region. The figure 3 presents the standardized % bias across covariates.

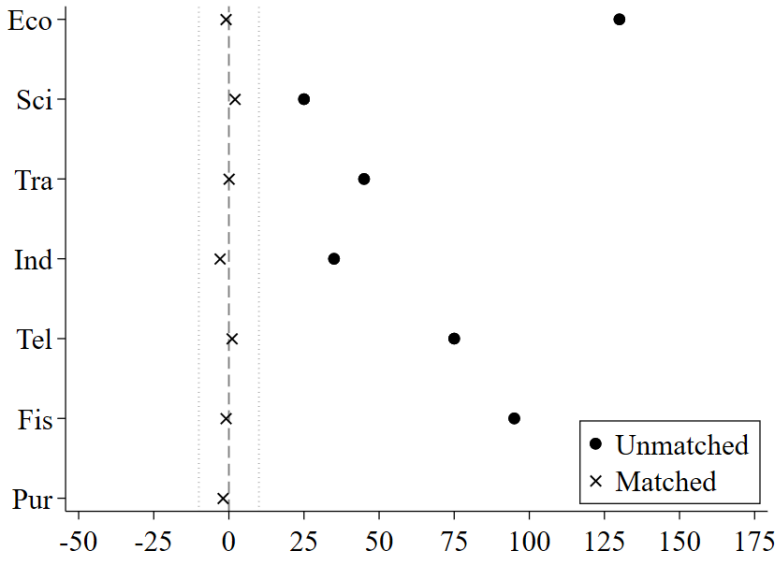


Figure 3. Standardized % Bias Across Covariates Before and After PSM

Results of the matching quality test indicate that the PSM method successfully resolves selection bias in observable characteristics: first, all covariates achieved excellent statistical balance after matching, with p-values from t-tests for the 7 control variables all exceeding 0.05; second, the p-value of the likelihood ratio test is 0.812, far greater than the 0.05 significance level, indicating no significant difference in the joint distribution of covariates between the treatment and control groups post-matching; third, the average bias decreased from 54.5% before matching to 6.8% after matching,

with a significant reduction rate, reflecting substantial improvement in covariate balance. Additionally, the common support test shows that only 18 observations in the treatment group were excluded for falling outside the overlapping region, resulting in a final sample of 263 treated and 1,707 control observations with a high retention rate.

PSM estimates reveal that high government attention exerts a significantly positive impact on the number of artificial intelligence enterprises in cities, with this effect being significant at the 1% level. This result is consistent with the instrumental variable estimates in both direction and significance. The complementary value of the two methods lies in: the instrumental variable method addresses endogeneity arising from unobservable confounding factors, while PSM ensures perfect balance in observable characteristics, together forming a "doubly robust" causal identification framework that significantly enhances the credibility of the results.

Notably, the average treatment effect on the treated (ATT) identified by PSM carries direct policy implications: for cities that actually received high government attention, the number of artificial intelligence enterprises would decrease significantly without such attention. Compared to the local average treatment effect estimated by instrumental variables, ATT is more aligned with the practical needs of policy evaluation, providing more targeted references for policymakers and highlighting the critical role of focused government attention and precision efforts in advancing the development of the artificial intelligence industry.

Table 7. Post-Matching Fixed Effects Regression Results

VARIABLES	**Post-Matching FE**
Gov_attention	1,228.180***
	(471.882)
Controls	YES
Year Fixed Effects	YES
Observations	1,970
R^2	0.443

Standard errors in parentheses, clustered at the city level.

*** p<0.01, ** p<0.05, * p<0.1

5.5. Mediation Effect Analysis

As discussed in the theoretical analysis, government attention to artificial intelligence has a significant influence on the local AI industry. To further explore the underlying mechanism, this section conducts a mediation effect analysis, building upon the previous research. Specifically, the analysis aims to test Hypothesis 2 by examining the mediating pathway. The mediation effect testing method follows the approach of Jiang Ting[36]. The constructed mechanism testing models are as follows:

$$Tec_ser_{i,t} = \xi_0 + \xi_1 Gov_attention_{i,t} + \xi_2 Control_{i,t} + \mu_i + \sigma_t + \varepsilon_{i,t}$$

$$AI_PEVC_{i,t} = \psi_0 + \psi_1 Gov_attention_{i,t} + \psi_2 Control_{i,t} + \mu_i + \sigma_t + \varepsilon_{i,t}$$

By utilizing the above equations, we can observe the significance of the coefficients ξ_1 and ψ_1 to determine the relationship between government attention to artificial intelligence and the two aforementioned mediating variables. Table 8 reports the corresponding results:

Table 8. Mechanism Test Results

	(1) AI	(2) Mechanism_test_1	(3) Mechanism_test_2
Gov_attention	619.8731***	7.9309***	3.0042***
	(138.7117)	(1.3004)	(0.6545)
_cons	-1720.7748***	-1.8838	2.5238
	(604.2886)	(13.1192)	(7.2913)
Controls	YES	YES	YES
N	3124	3124	3124
r2	0.7156	0.5392	0.3773

Standard errors in parentheses, clustered at the city level

*$p < 0.1$, *$p < 0.05$, *p*< 0.01

5.5.1. Analysis of the Easing Effect on Financing Constraints

According to the theory of government attention, increased government focus on the AI industry leads to higher valuations of AI companies in the local capital market, giving rise to more investment activities targeting AI enterprises. As previous studies have shown, policy support can positively influence enterprise IPO performance[37]. Investment activities greatly promote the growth of AI firms, and because many of these investments are ongoing and directly contribute capital to the local AI sector, the effect is cumulative and persistent. Therefore, we can infer a possible mediation effect: Gov_attention improves the level of AI industry development (AI_firm) by increasing the cumulative number of PE/VC investments received by local AI firms. In column (2) of Table 8, the coefficient of government attention to AI is 7.9309 and is significant

at the 1% level, indicating that greater attention from local governments helps to easing financing constraints for AI enterprises.

5.5.2. Analysis of the Effect of Technology Enterprise Incubators

According to innovation environment theory, the development of technology enterprises requires a high-quality environment, such as low-cost startup space and convenient platforms for inter-firm technology exchange. Innovation platforms like technology enterprise incubators not only provide these objective conditions, but are also more conducive to cultivating entrepreneurial spirit[38], thereby exerting a profound impact on the innovation potential of AI enterprises. Technology service companies serve as key market entities that provide such an environment, offering affordable office space, comprehensive staff training, and platforms for technical exchange, which can effectively promote the growth of local AI-related technology firms. In column (3), the coefficient of Gov_attention is 3.0042 and is significant at the 1% level, indicating that government attention to AI can promote the development of the AI industry by optimizing the local scientific and technological innovation environment.

5.6. Heterogeneity Analysis

Based on the above analysis, it is concluded that increased government attention to artificial intelligence significantly enhances the development level of the AI industry. Next, we explore whether the strength of this relationship varies with different regional characteristics. All cities are classified according to four criteria: government-business relations, marketization level, fiscal pressure, and digital infrastructure, with corresponding regression analyses conducted. The results for the first three criteria are reported in Table 9, while the regression results for digital infrastructure—using two classification standards—are presented separately in Table 10. In the following, we analyze each of these four heterogeneity characteristics in turn[7].

Notably, the heterogeneity analyses based on government-business relations, marketization level, Broadband China pilot, and Big Data pilot demonstration zones are all significant at the 1% level. Therefore, Chow tests were conducted to confirm whether structural differences exist within these groupings. The results show that the p-values for all five groupings are less than 0.01, rejecting the null hypothesis of no structural change. This indicates that significant structural differences indeed exist between different groups, confirming the statistical necessity of conducting heterogeneity analysis.

Figure 4 presents the government AI attention coefficients across different subgroups. The dark markers represent regions with better government-business relations, higher marketization levels, lower fiscal pressure, and superior digital infrastructure (including big data and broadband facilities). It can be observed that the coefficients for the dark groups are consistently higher than those for the light groups. Given that structural differences between groups have been confirmed through testing, this indicates that all five grouping dimensions significantly influence the strength of government AI attention effects.

[7]Since the government-business relationship index was first calculated in 2017, and both the Big Data pilot and Broadband China pilot officially began in 2017, all three heterogeneity analyses use data from 2016 onwards.

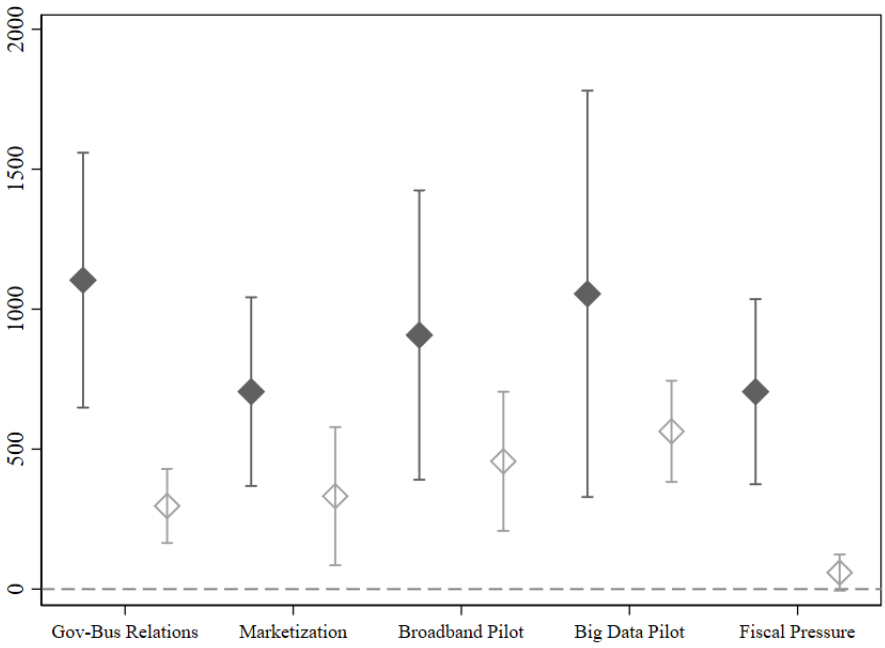


Figure 4. Heterogeneity Analysis: Coefficient Comparison

5.6.1. Heterogeneity of Government–Business Relations

Government–business relations refer to the connection between local governments and enterprises within a region. More intimate and amicable government–business relations may promote enterprise innovation, entrepreneurship, and strategic transformation, thereby boosting regional economic development[39]. This paper hypothesizes that in regions with better government–business relations, the effect of government AI attention on AI industry development is more pronounced. Data on government–business relations are drawn from the Government–Business Relations Index developed by Professor Nie Huihua's team at Renmin University of China[40] (see appendix for index details). According to columns (1) and (2), column (1) represents regions with above-average government–business relations, while column (2) represents those below the average. The results clearly show that regardless of the quality of relations, government AI attention significantly promotes AI industry development. However, the coefficients indicate that this promotive effect is stronger in regions with better government–business relations.

5.6.2. Heterogeneity of Marketization Level

The level of marketization is a broad economic concept, encompassing factors such as economic freedom, financial marketization, and administrative intervention. Research shows that higher levels of marketization facilitate the circulation of production factors and the optimal allocation of resources[41], thereby improving economic development efficiency. This paper hypothesizes that a greater degree of marketization promotes the flow of data, technology, and other resources to more competitive enterprises, thus amplifying the effect of local government policies designed to support AI industry development. The China Urban Marketization Index calculated by Fan Gang's team

is adopted here as the standard for assessing marketization level (see appendix for index details). Regression results are reported in columns (3) and (4): column (3) corresponds to cities with above-average marketization levels, and column (4) to those below average. Both types of cities show significant results at the 1% level, but the coefficient for cities with higher marketization is noticeably greater, confirming our hypothesis.

5.6.3. Heterogeneity of Fiscal Pressure

Fiscal pressure refers to the constraints imposed by a local government's fiscal conditions. Research has shown that excessive fiscal pressure has a significant inhibitory effect on entrepreneurial activity[42]. We posit that this inhibitory effect is especially pronounced in AI, an industry characterized by rapid technological iteration and substantial capital requirements. Thus, higher fiscal pressure makes it more difficult to translate government AI attention into economic outcomes. Fiscal pressure is proxied by the level of fiscal deficit. Columns (5) and (6) in the table represent cities with above- and below-average fiscal pressure, respectively. It is clear that government attention to AI is more significant in areas with lighter fiscal pressure, lending support to the heterogeneity hypothesis regarding fiscal stress.

Table 9. Heterogeneity Test Result 1

	(1) GB_1	(2) GB_2	(3) Marketization_1	(4) Marketization_2	(5) Fiscal_1	(6) Fiscal_2
Gov_attention	1103.6665***	296.8990***	705.4026***	332.0790***	705.2730***	59.0481*
	(230.0374)	(66.9659)	(170.6000)	(124.6358)	(167.2453)	(32.7257)
_cons	-3594.7133	-17.7815	-3046.0292***	-481.1105	-3350.3337***	-60.3681
	(2425.5018)	(570.9483)	(916.2367)	(484.2868)	(1055.5066)	(132.1030)
Controls	YES	YES	YES	YES	YES	YES
N	889	1099	1738	1386	1562	1562
r2	0.7934	0.5772	0.7557	0.4980	0.7499	0.4839

Standard errors in parentheses, clustered at the city level
*$p < 0.1$, *$p < 0.05$, *p*< 0.01

5.6.4. Heterogeneity of Digital Infrastructure

Digital infrastructure forms the foundation for the development of digital economy sectors such as artificial intelligence, encompassing elements like broadband networks, telecom base stations, and data centers. In addition to providing well-known data and computing power support, research shows that the development of digital infrastructure facilitates enterprise digital transformation[43], thereby indirectly creating a favorable environment for the AI industry. This paper hypothesizes that in regions with more comprehensive digital infrastructure, the impact of government attention to AI on AI industry development will be more significant.

To robustly test the heterogeneity effect of digital infrastructure development, the analysis leverages two groups of pilot policies: The first is the Broadband China pilot, a systematic broadband enhancement plan for participating cities. Existing empirical research[44] indicates that this policy marks areas with digital infrastructure advantages from an early stage (2011 and later). The second is the Big Data Pilot Demonstration Zone, which promotes the construction of facilities such as data centers in

designated pilot cities. Literature[45][46] indicates that big data support plays a positive role in optimizing factor allocation in manufacturing and in the transformation of the service sector, and this paper regards it as an important manifestation of digital infrastructure improvement. The two pilot policies have different emphases in digital infrastructure construction: the Broadband China pilot focuses on broadband rollout, supporting the development of advanced industries such as IoT and cloud computing; the Big Data Pilot Demonstration Zone emphasizes the application of big data technologies, providing critical data support for AI training and tuning.

As shown in the table, columns 1 and 2 present regression results for regions that do and do not participate in the Broadband China pilot, respectively, while columns 3 and 4 display the results for regions that do and do not participate in the Big Data Comprehensive Pilot, respectively.

According to the results in Table 10, under both classification standards and at the 1% significance level, regions with more advanced digital infrastructure exhibit larger coefficients. This indicates that the heterogeneity of digital infrastructure supports our hypothesis—better digital infrastructure provides the AI industry with greater access to essential resources such as data and computing power, enabling leapfrog development. Consequently, government attention to the AI industry is more effective in promoting its development in these regions.

Table 10. Heterogeneity Test Result 2

	(1) Broadland_1	(2) Broadland_2	(3) Bigdata_1	(4) Bigdata_2
Gov_attention	907.3503***	456.5571***	1054.7852***	563.5009***
	(260.5475)	(125.9433)	(362.0119)	(91.6733)
_cons	-5359.0102***	-1311.7616	-5040.5834**	-1283.5077
	(1839.6563)	(920.5831)	(2062.6847)	(1055.6704)
Controls	YES	YES	YES	YES
N	749	1239	385	1603
r2	0.7771	0.5672	0.8078	0.6710

Standard errors in parentheses, clustered at the city level
*$p < 0.1$, *$p < 0.05$, *p*< 0.01

6. Conclusion and Policy Implications

In recent years, the rapid development and application of artificial intelligence technology has guided the direction of a new round of scientific and technological revolution. Undoubtedly, AI is an important driving force for this new wave of scientific progress and industrial transformation, and the AI industry is becoming a new engine to promote high-quality economic development[47].

Through theoretical analysis and empirical testing, this paper finds that local government attention to the AI industry significantly improves the development level of the AI industry by alleviating financing constraints for AI enterprises and providing a business-friendly incubation environment. This positive effect is particularly pronounced in regions with more harmonious government–business relations, higher marketization, lower fiscal pressure, and more comprehensive digital infrastructure. Based on these findings, the following recommendations are proposed:

First, governments at all levels should establish differentiated mechanisms for transmitting government AI attention signals. The central government should formulate and publish comprehensive AI development plans, while local governments should fully leverage governmental credibility and influence, using government attention as an anchor to guide local market resources toward AI industry agglomeration. Attention allocation theory and signaling theory jointly demonstrate that government AI attention not only promotes AI industry development through specific policies, but also activates a virtuous cycle of market confidence and factor agglomeration, generating positive externality incentives for AI pioneer enterprises.

Second, the government needs to collaborate with financial institutions to establish a precision-oriented financing support system for AI enterprises. The empirical analysis of Mechanism 1 indicates that the relaxation of financing constraints serves as an important mediator through which government AI attention affects the actual development of AI enterprises. On one hand, governments and state-owned enterprises can directly invest in AI companies; on the other hand, they can also relax financing approval processes for AI enterprises, forming a categorized, full-chain financing constraint alleviation mechanism. Meanwhile, it is also necessary to establish an AI enterprise credit evaluation system to address information asymmetry problems in bank lending and ensure effective capital allocation.

Third, local governments should create high-quality AI-specialized incubation ecosystems. The empirical analysis of Mechanism 2 demonstrates that government attention influences the AI industry by promoting the increase of technology enterprise incubators. This increase in incubators facilitates the formation of agglomeration effects and synergistic effects, enhancing the overall innovation capacity and competitiveness of the AI industry. Considering the distinctive characteristics of AI industry development—being computation-intensive, talent-intensive, and capital-intensive—it becomes increasingly important to transcend traditional incubator models and construct AI-specialized, service-professional entrepreneurial incubation systems.

Finally, local government AI policies should fully account for regional heterogeneity. Heterogeneity analysis reveals that regions with more coordinated government–business relations, higher levels of marketization, more abundant fiscal resources, and better digital infrastructure are better able to leverage government attention to promote AI industry development. On one hand, the government should strive to optimize those conditions that can influence the effectiveness of attention allocation; on the other hand, it should also adapt to local circumstances, increasing government attention allocation in regions that possess better conditions for high-tech industry development.

References

[1] Xueyi Wang, Taiyi He, Shengzhe Wang, and Haoxiang Zhao. The impact of artificial intelligence on economic growth from the perspective of population external system. *Social Science Computer Review*, 43(1):129–147, 2025.

[2] Hongyuan Zhang, Yibing Ding, Jing Niu, and Samuel Jung. How artificial intelligence affects international industrial transfer — evidence from industrial robot application. *Journal of Asian Economics*, 95:101815, 2024.

[3] Pinku Chandra Nath, Awdhesh Kumar Mishra, Ramesh Sharma, Biswanath Bhunia, Bishwambhar Mishra, Ajita Tiwari, Prakash Kumar Nayak, Minaxi Sharma, Tamanna Bhuyan, Sushant Kaushal, Yugal Kishore Mohanta, and Kandi Sridhar. Recent advances

in artificial intelligence towards the sustainable future of agri-food industry. *Food Chemistry*, 447:138945, 2024.

[4] Shuang Lin, Minke Wang, Chongyi Jing, Shengda Zhang, Jiuhao Chen, and Rui Liu. The influence of AI on the economic growth of different regions in china. *Scientific Reports*, 14(1):9169, April 2024.

[5] Bengt Åke Lundvall and Cecilia Rikap. China's catching-up in artificial intelligence seen as a co-evolution of corporate and national innovation systems. *Research Policy*, 51(1): 104395, 2022.

[6] J. Dreyer. China made waves with deepseek, but its real ambition is ai-driven industrial innovation. *Nature*, 638(8051):609–611, 2025.

[7] Sharon Gifford. Allocation of entrepreneurial attention. *Journal of Economic Behavior Organization*, 19(3):265–284, 1992.

[8] Jianpei Li and Shijun Deng. Driving digital innovation: the role of government attention in chinese firms. *TECHNOLOGY ANALYSIS & STRATEGIC MANAGEMENT*, 2025.

[9] Hongxia Wang, Wenyueyang Deng, Zenglian Zhang, and Ming Li. Does government's environmental attention improve urban energy efficiency? *International Review of Financial Analysis*, 91:103046, 2024.

[10] Shucheng Liu and Yilong Li. Does government's attention to green development promote enterprise green transition? evidence from china. *EMERGING MARKETS FINANCE AND TRADE*, 2025 APR 3 2025.

[11] Yuxuan Cao, Li Yue, and Xianqiao Gao. Exploring the carbon emission reduction effect of local government attention: an analysis based on an environmental policy perspective. *Environmental Science and Pollution Research*, 30(49):107634–107649, 10 2023.

[12] Wanli Xu, Zihao Peng, Zhiyun Feng, and Caodie Peng. The impact of government digital attention on enterprise digital transformation: empirical insights from china. *Applied Economics Letters*, 0(0):1–6, 2024.

[13] Xiang Li and Shujing Yue. Does the government digital attention improve china's digital economy output efficiency: Accelerator or inhibitor. *Economic Analysis and Policy*, 85: 607–625, 2025.

[14] Rong Hu and Kaiyi Song. Carbon reduction effects of government digital attention. *Frontiers in Environmental Science*, Volume 13 - 2025, 2025.

[15] Kai Li, Dan J. Kim, Karl R. Lang, Robert J. Kauffman, and Maurizio Naldi. How should we understand the digital economy in asia? critical assessment and research agenda. *Electronic Commerce Research and Applications*, 44:101004, 2020.

[16] Z. Ye et al. Local government capacity and response strategies to central policy piloting goals: a case study of china's new-type urbanization plan. *Humanities and Social Sciences Communications*, 11(1):1648, 2024.

[17] Ciqi Mei. Policy style, consistency and the effectiveness of the policy mix in china's fight against covid-19. *Policy and Society*, 39(3):309–325, 06 2020.

[18] Taoxiong Liu, Wenwen Yan, and Yadi Zhang. Functional or selective policy? - research on the relationship between government intervention and enterprise innovation in china. *International Review of Economics Finance*, 86:82–96, 2023.

[19] Ronald H. Coase. The problem of social cost. *The Journal of Law & Economics*, 3:1–44, 1960.

[20] Jiang Shan and Sun Guangguo. Selective industrial policy, corporate innovation and high-quality development of manufacturing enterprises. *Science Research Management*, 46(01):24–33, 2025. .

[21] Massimo G. Colombo, Silvia Giannangeli, and Luca Grilli. Public subsidies and the employment growth of high-tech start-ups: assessing the impact of selective and automatic support schemes. *INDUSTRIAL AND CORPORATE CHANGE*, 22(5):1273–1314, OCT 2013.

[22] Chunyang Wang, Sujuan Zhao, Haitao Zheng, and Yiyi Bai. Does financial constraint hinder firm growth? *EMERGING MARKETS FINANCE AND TRADE*, 58(15, SI): 4195–4206, DEC 8 2022.

[23] Qinqin Zhuang, Weijie Luo, and Yupeng Li. How does covid-19 affect corporate research and development? evidence from china. *EMERGING MARKETS FINANCE AND TRADE*, 59(9):3011–3023, JUL 15 2023.

[24] Silvia Rita Sedita, Roberta Apa, Thomas Bassetti, and Roberto Grandinetti. Incubation matters: Measuring the effect of business incubators on the innovation performance of start-ups. *R & D MANAGEMENT*, 49(4):439–454, SEP 2019.

[25] Mingfeng Tang, Grace Sheila Walsh, Cuiwen Li, and Angathevar Baskaran. Exploring technology business incubators and their business incubation models: case studies from china. *JOURNAL OF TECHNOLOGY TRANSFER*, 46(1):90–116, FEB 2021.

[26] Tingying Chen, Haitian Lu, Rong Chen, and Lina Wu. The impact of marketization on sustainable economic growth—evidence from west china. *Sustainability*, 13(7), 2021.

[27] YIN Ximing, CHEN Tailun, JIN Jun, and GAO Yuchen. How does digital infrastructure promote regional high-quality development? *China Soft Science*, (12):90–101, 2023.

[28] Yongyu Chen, Zihao Peng, Caodie Peng, and Wanli Xu. Impact of new government–business relations on urban digital economy: Empirical evidence from china. *Finance Research Letters*, 58:104325, 2023. ISSN 1544-6123.

[29] Timothy Besley and Torsten Persson. State capacity, conflict, and development. *Econometrica*, 78(1):1–34, 2010.

[30] Vernon Henderson. Externalities and industrial development. *Journal of Urban Economics*, 42(3):449–470, 1997. ISSN 0094-1190.

[31] TIM LOUGHRAN and BILL MCDONALD. When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of Finance*, 66(1):35–65, 2011.

[32] Smaranda Pantea and Marcel Tkacik. Venture capital and high-tech start-ups in europe: a systematic review of the empirical evidence. *Venture Capital*, 0(0):1–24, 2024.

[33] EMILY JOHNSTON-ROSS, SONG MA, and MANJU PURI. Private equity and financial stability: Evidence from failed-bank resolution in the crisis. *The Journal of Finance*, 80 (1):163–210, 2025.

[34] Dong Jiachang Li Jialin. A study of the impact of local government attention allocation on theinnovation activities of enterprises. *Science esearch Management*, 44(09):47–59, 2023.

[35] Roni Michaely and Michael R. Roberts. Corporate dividend policies: Lessons from private firms. *REVIEW OF FINANCIAL STUDIES*, 25(3):711–746, MAR 2012. ISSN 0893-9454. .

[36] JIANG Ting. Mediating effects and moderating effects in causal inference. *China Industrial Economics*, (05):100–120, 2022.

[37] Xiaohui Hou and Wanli Li. The effects of industrial policy support on ipo performance: Evidence from listed enterprises of the chinese smes board. *JOURNAL OF SMALL BUSINESS MANAGEMENT*, 57(2):616–639, APR 2019.

[38] Satish Nambisan, Donald Siegel, and Martin Kenney. On open innovation, platforms, and entrepreneurship. *STRATEGIC ENTREPRENEURSHIP JOURNAL*, 12(3):354–368, SEP 2018.

[39] Mohamed Ismail Sabry. Informal state–business connections, institutions, and economic growth. *Economia Politica*, 34(2):233–258, 2017.

[40] Huihua Nie, Donglin Han, Liang Ma, and Nandi Zhang. Zhongguo chengshi zhengshang guanxi pingjia baogao 2023 [china urban government-business relations evaluation report 2023]. Research report, Research Center for Enterprises and Organizations, Renmin University of China, Beijing, 2024. In Chinese.

[41] Zhi-Chao Wang, Chang-Qi Tao, and Ye Xu. Can higher marketization improve the level of entrepreneurship? - Evidence from China's negative list for market access. *International Entrepreneurship and Management Journal*, 21(1):40, 2024.

[42] Jiacai Xiong, Ling Huang, Xin Wang, Martin Bai, and Yafeng Qin. Local government fiscal stress and regional entrepreneurship: Evidence from a natural experiment in china. *Economic Analysis and Policy*, 84:177–193, 2024.

[43] GUO Guanyu YIN Junya WANG Hai, YAN Zhuoyu. Digital infrastructure policy and

digital transformation ofenterprises: “empowerment”or “negative energy”? *Journal of Quantitative Technological Economics*, 40(05):5–23, 2023.
[44] Xing Li, Gang Yang, Tihang Shao, Dan Yang, and Zimin Liu. Does digital infrastructure promote individual entrepreneurship? evidence from a quasi-natural experiment on the “broadband china” strategy. *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE*, 206, SEP 2024.
[45] Qiang Gao, Changming Cheng, and Guanglin Sun. Big data application, factor allocation, and green innovation in chinese manufacturing enterprises. *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE*, 192, JUL 2023.
[46] WANG Dong CHEN Weibin LIU Xiaohui LUO Shihua, DAI Yufang. Mechanism of big data application on the service transformationof manufacturing industry. *ECONOMIC GEOGRAPHY*, 43(10):119–127+138, 2023.
[47] S. Lin et al. The influence of ai on the economic growth of different regions in china. *Scientific Reports*, 14(1):9169, 2024.

7. Appendices

Measurement Method for the Marketization Index: The marketization index is measured based on five key aspects: the relationship between government and the market, the development of the non-state-owned economy, the maturity of the product market, the maturity of the factor market, and the development of market intermediary organizations and the legal environment. The entire system consists of 17 fundamental indicators. The specific structure is illustrated in the table 11.

Measurement Method of the Government–Business Relationship Index: The index consists of two components: the Intimacy Index, which measures the degree of collaboration between governments and enterprises, and the Integrity Index, which assesses the government's integrity and fairness in dealings with businesses. Together, these indices reflect the overall quality of government–business relations. According to the China Urban Government–Business Relationship Evaluation Report 2023, the index system includes 5 primary indicators, 11 secondary indicators, and 16 tertiary indicators. All indicators are standardized. Data sources include Party newspaper databases, China Urban Statistical Yearbooks, Baidu Maps, Google, and the 12306 website; missing data are supplemented using provincial averages.The specific structure is illustrated in the table 12.

8. Data Availability Statement

The data are available from the author upon reasonable request. If needed, please contact via email.

Table 11. Composition of the Marketization Index

Index Name (2021 Report)	Index Type
Total Marketization Index	-
1. Government–Market Relationship	Category Index
1a Proportion of Market Allocating Economic Resources	Primary Sub-Index
1b Reduction of Government Intervention in Enterprises	Primary Sub-Index
1c Downsizing of Government Scale	Primary Sub-Index
2. Development of Non-State-Owned Economy	Category Index
2a Share of Non-State-Owned Economy in Industrial Business Revenue	Primary Sub-Index
2b Share of Non-State-Owned Economy in Total Social Fixed Asset Investment	Primary Sub-Index
2c Proportion of Non-State-Owned Employment in Urban Total Employment	Primary Sub-Index
3. Maturity of Product Market	Category Index
3a Extent of Market-Determined Prices	Primary Sub-Index
3b Reduction of Local Protectionism in Goods Market	Primary Sub-Index
3c Conditions for Fair Market Competition	Primary Sub-Index
4. Maturity of Factor Market	Category Index
4a Marketization of Financial Sector	Primary Sub-Index
(4a1) Competition in Financial Sector	Secondary Sub-Index
(4a2) Marketization of Credit Funds Allocation	Secondary Sub-Index
4b Supply Conditions of Human Resources	Primary Sub-Index
(4b1) Supply of Technicians, Managers, and Skilled Workers	Secondary Sub-Index
(4b2) Resident Population / Registered Population	Secondary Sub-Index
4c Marketization of Technological Achievements	Primary Sub-Index
5. Development of Market Intermediaries and Legal Environment	Category Index
5a Development of Market Intermediary Organizations	Primary Sub-Index
5b Legal Environment for Market Protection	Primary Sub-Index
5c Protection of Intellectual Property Rights	Primary Sub-Index

Table 12. Composition of the Government–Business Relationship Index

Index Name	Index Type
Total Government–Business Relationship Index	-
1. Intimacy Index	Category Index
1a Government Concern for Enterprises (10%)	Primary Sub-Index
(1a1) Official Visits (5%)	Secondary Sub-Index
Number of visits by city major/party secretary to enterprises	Tertiary Indicator
(1a2) Forums with Entrepreneurs (5%)	Secondary Sub-Index
Number of forums between city major/party secretary and entrepreneurs	Tertiary Indicator
1b Government Services for Enterprises (40%)	Primary Sub-Index
(1b1) Infrastructure (10%)	Secondary Sub-Index
Road area per urban area	Tertiary Indicator
Number of high-speed and bullet train stops	Tertiary Indicator
(1b2) Financial Services (10%)	Secondary Sub-Index
Year-end balance of deposits and loans per urban GDP	Tertiary Indicator
Number of financial sector employees per urban population	Tertiary Indicator
Number of bank outlets per urban population	Tertiary Indicator
(1b3) Market Intermediaries (10%)	Secondary Sub-Index
Number of law firms per urban population	Tertiary Indicator
Number of accounting firms per urban population	Tertiary Indicator
(1b4) E-Government Efficiency (10%)	Secondary Sub-Index
Comprehensive evaluation of government website	Tertiary Indicator
1c Enterprise Tax Burden (10%)	Primary Sub-Index
(1c1) Enterprise Tax Burden (10%)	Secondary Sub-Index
Main business taxes and surcharges of industrial enterprises above designated size per average annual gross industrial output	Tertiary Indicator
VAT payable of current year per average annual gross industrial output	Tertiary Indicator
2. Integrity Index	Category Index
2a Government Integrity (10%)	Primary Sub-Index
(2a1) Proxy Price for Food Safety License (5%)	Secondary Sub-Index
Proxy price for food safety license per minimum wage	Tertiary Indicator
(2a2) Corruption Search Index (5%)	Secondary Sub-Index
Number of corruption-related news keywords per total city news articles	Tertiary Indicator
2b Government Transparency (30%)	Primary Sub-Index
(2b1) Online Information Disclosure (15%)	Secondary Sub-Index
Status of online information disclosure and publication	Tertiary Indicator
(2b2) Fiscal Transparency (15%)	Secondary Sub-Index
Fiscal transparency	Tertiary Indicator