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# Phoenix Talent Plan, Digital Economy and Industrial Structure Upgrading: A Difference-in-Differences Estimation

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## Abstract

Based on panel data from cities in Hebei Province from 2009 to 2021, this paper regards the new talent introduction policy in Tangshan, The Phoenix Talent Plan, as a quasi-natural experiment. It establishes an index system for the development efficiency of the digital economy in various cities and constructs a double difference model to empirically examine the impact of The Phoenix Talent plan on industrial structural upgrading in Tangshan and its operating mechanism. The main research conclusions are as follows: (1) The Phoenix Talent plan significantly promotes the upgrading of industrial structure. After a series of robustness tests such as placebo tests, this conclusion still holds. (2) Data envelopment analysis results show that the overall digital economy development efficiency in Hebei Province from 2010 to 2021 is relatively high, with Tangshan's digital economy development efficiency ranking at the forefront within the province. (3) DEA-Malmquist analysis results indicate that the development efficiency of the digital economy in cities plays a significant moderating role between talent policies and the upgrading of industrial structure. Given this, Tangshan should actively attract talents and intellects, enhance technological innovation capabilities, and promote high-quality economic development.

**Keywords:** industrial structure upgrading, Phoenix Talent Plan, digital economy, DID Estimation.

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# 1. Introduction

In recent years, with the deep advancement of the national goal of high-quality development, a series of measures have created favourable external conditions for the sustained and healthy development of resource-based urban economies. Tangshan, as a typical resource-based city mainly focused on heavy industry, has ushered in a valuable period of development opportunities. Looking at the overall economic level of Tangshan, its GDP has long been at the forefront within the province, evidently becoming an important part of the Bohai Rim region. Assessing the current development status of the three major industries in Tangshan, the secondary industry, as the pillar industry, holds a significant proportion in both output value and economic contribution. The tertiary industry shows steady and robust development momentum, but still lags behind developed cities nationwide, while the primary industry has the smallest proportion, developing relatively steadily.

However, against the backdrop of the macro requirement for high-quality economic development, issues such as uncoordinated industrial structure, weak innovation capabilities, and talent shortages have become bottlenecks restricting economic development. This hampers the establishment of a modern industrial system in Tangshan and poses a significant obstacle to its entry into the "trillion-dollar club". Therefore, Tangshan must promptly change its development mindset, strive to reduce dependence, promote innovation with talents, drive industrial structure optimization and upgrading through innovation, and focus on creating a new industrialized city that leads the era.

Research on the factors influencing industrial structure upgrading has been quite rich. Yan (2010) studied the influencing factors of industrial structure upgrading in the Yangtze River Delta region, and the conclusion shows that technological innovation and government scale have a positive effect on industrial structure upgrading. Research by Fu et al. (2013) also found that innovation input positively impacts industrial structure upgrading. Additionally, Gao et al. (2015) used panel data from 28 provinces in China from 1992 to 2012 to construct a spatial econometric model of industrial structure upgrading. Empirical analysis concluded that social demand plays a decisive role in industrial structure upgrading, with consumer demand having the greatest driving effect on the level of industrial structure upgrading. Xu et al. (2023) found that technological innovation and talent settlement have a synergistic effect on the upgrading of industrial structures. In terms of strategies for industrial transformation and upgrading, Li et al. (2016) pointed out the need to adhere to the principle of replacing industries with scientific and rational ones, reducing high-energy-consuming, highly polluting, and low-efficiency enterprises, and selecting advantageous industries that align with future development directions. Mao et al. (2022), from the perspective of government in urban industrial transformation, suggest precise measures based on the different characteristics of industries. For mature industries approaching decline, reasonable planning and moderate regulation are advocated; for industries with high pollution and energy consumption, intervention, production restrictions, or even elimination are suggested; for emerging high-tech industries, proactive protection, support, cultivation, and guidance are recommended to promote industrial structure optimization and upgrading. Zhang et al. (2014) Used the grey relational analysis method, xxx calculated the stock of human capital and studied the coupling and correlation between human capital and the evolution of industrial structure. The conclusion showed that increasing the cultivation of innovative talents and high-skilled talents, promoting the integration of industry, academia, and research, and improving the coupling degree between human capital and the evolution of industrial structure is crucial for promoting the transformation and upgrading of China's industrial structure. From the perspective of human capital and technological progress, Yang et al. (2018) studied the impact relationship between the accumulation speed of human capital and technological progress and the upgrading speed of the manufacturing industry. The results showed that human capital accumulation and technological progress significantly promoted the upgrading of the manufacturing industry, and the upgrading speed of the manufacturing industry lagged behind the accumulation speed of human capital and technological progress and showed regional differences.

In summary, this paper attempts to answer the following questions based on existing research: whether talent introduction policies contribute to the development of regional industrial structure upgrading, and what role digital economy play in the interaction between talent introduction policies and industrial structure upgrading? The marginal contributions of this paper are as follows: (1) providing some supplements to the research on talent policies and industrial structure upgrading; (2) using the difference-in-differences method to compare the effects of the implementation of the Phoenix Talent Plan on industrial structure upgrading before and after implementation, effectively avoiding measurement errors and endogeneity issues; (3) employing entropy method and data envelopment analysis to measure the efficiency of urban digital economy development, providing policy suggestions for the empirical research on talent and industrial upgrading, thus contributing to the development of industrial structure upgrading.

## 2. Theoretical Mechanism and Research Hypotheses

### 2.1 The Impact of the Phoenix Talent Plan on Industrial Structure Upgrading

In recent years, with the increase in labour costs and the transition of the economy to a stage of high-quality development in China, the production model characterized by large-scale, high-energy consumption, and low-technology products has become unsustainable. To effectively address these issues, the support of talent is indispensable (Zhao et al., 2019). Studies have shown that talent is crucial for the high-quality development of industries. Research indicates that the implementation of talent policies significantly promotes the level of regional industrial structure upgrading. Industrial structure upgrading mainly manifests as the transformation of urban dominant industries from labour-intensive industries to capital-intensive and technology-intensive ones. The upgrading of the industrial structure imposes higher requirements on the technical knowledge threshold of the talent pool. High-quality talents can induce technological research and innovation activities in industrial sectors through the "learning by doing" and "knowledge spillover" effects, thereby promoting the development of industrial structure towards a higher level. Simultaneously, the knowledge accumulation brought about by the aggregation of talent resources also creates more conditions for technological innovation and industrial structure upgrading.

The Phoenix Talent Plan is a proactive measure adopted by the Tangshan municipal government to deepen the reform of the talent development system and accelerate the construction of a city with high-quality talent. Its promotion of industrial structure upgrading mainly manifests in two aspects. Firstly, the introduction of the Phoenix Talent Plan will attract a large number of professionals to flow into the city, providing talent guarantee and technical support for improving the regional industrial layout and industrial structure, thereby promoting industrial structure upgrading. Secondly, the improvement of human capital quality helps cities break through the bottleneck of their industrial development and climb to higher ends of the value chain. The enhancement of talent utilization efficiency can effectively promote industrial structure upgrading and economic development. The continuous improvement of regional economic levels will further strengthen the attractiveness of cities to talents, prompting the Phoenix Talent Plan to exert its maximum utility and further promote industrial structure upgrading. Based on this, Hypothesis 1 is proposed.

**Hypothesis 1:** *Talent introduction policies promote the development of urban industrial structure upgrading.*

## 2.2 The Regulatory Effect of the Digital Economy

The development of the digital economy has fundamentally changed the traditional mode of production and operation. The deep integration of the digital economy with the three major industries has become an increasingly important focus of urban development. Firstly, the digital economy promotes the construction of smart agriculture. By using technologies such as big data and cloud computing, farmers can obtain more accurate information on weather and cultivation on time, providing more scientific decision-making for crop planting and cultivation (Qi and He, 2023). Additionally, through Internet platforms, farmers can expand the sales channels of agricultural products, shifting from single on-site sales to a combination of diverse online and on-site sales. Furthermore, internet platforms can also expand the sales scope of agricultural products, transforming regional products into national or even global ones. Secondly, the digital economy promotes the development of smart manufacturing. Enterprises can collect data information generated throughout the entire production process, forming exclusive "data" resources for enterprises.

Digital technology empowers the manufacturing industry, not only improving the production efficiency of manufacturing enterprises but also facilitating the integration and optimization of resources throughout the entire industry chain ecosystem, reducing transaction costs in procurement, processing, and other links, ultimately achieving the digital transformation of manufacturing enterprises. Lastly, the digital economy promotes the upgrade of intelligent service provision. Digital development significantly enhances the service level of enterprises, allowing them to expand value-added services based on intelligent production, broaden their service business, and stimulate new vitality in service businesses through data sharing and reuse. The development of the digital economy and the upgrading of industrial structure rely on the accumulation of high-quality human capital. On the one hand, the overall layout of industrial digitization relies on a strong team of scientific and technological talents. On the other hand, digital industrialization provides more complete technical services, more accurate product services, and more efficient educational services for cultivating new talents. Based on this, Hypothesis 2 is proposed.

**Hypothesis 2:** *The development of the digital economy strengthens the promotion effect of talent introduction policies on industrial structure upgrading.*

# 3. Research Design

## 3.1 Model Construction

### 3.1.1 Baseline Model

This paper regards the Phoenix Talent Plan as a quasi-natural experiment and utilizes the difference-in-differences (DID) method to evaluate the effect of the Phoenix Talent Plan on industrial structure upgrading. Based on the basic principles and steps of the difference-in-differences method, time dummy variables and policy dummy variables are constructed. Specifically, regarding the setting of time dummy variables, considering that the policy started in 2018, years from 2018 onwards are defined as 1, while years before 2018 are defined as 0. As for the policy dummy variables, the sample is divided into experimental and control groups, where the experimental group consists of cities implementing the Phoenix Talent Plan, defined as 1, and the control group consists of cities not implementing the Phoenix Talent Plan, defined as 0. The constructed model is as follows:

$$AIS_{it}=\beta_0+\beta_1 DID_{it}+\beta_2 controls_{it}+\lambda_i+\mu_t+\varepsilon_{it} \tag{1}$$

In the following, $i$ represents cities, $t$ represents years, and *AIS* is the dependent variable; *DID* is the core explanatory variable, i.e., the interaction term of policy dummy variables and time dummy variables, expressed as $DID_{it} = Treat_i \times Time_t$, where *Treat* represents the policy dummy variable, with a value of 1 assigned to cities implementing the Phoenix Talent Plan and 0 assigned to cities not implementing the Phoenix Talent Plan, and *Time* represents the time dummy variable, with a value of 1 assigned to years after the policy implementation in 2018 and 0 assigned to years before 2018; controls represent a series of control variables; $\lambda_i$ denotes city fixed effects, $\mu_t$ denotes time fixed effects; $\varepsilon_{it}$ denotes the random error term.

### 3.1.2 Moderation Effects Model

To demonstrate the transmission mechanism by which the Phoenix Talent Plan promotes the upgrading of industrial structure, we construct the following moderation effects model, referring to the study by Han and Li(2022).

$$AIS_{it}=\beta_0+\beta_1 DID_{it}+\gamma_1 Dig_{it}+\gamma_2(DID_{it}\times Dig_{it})+\beta_2 controls_{it}+\lambda_i+\mu_t+\varepsilon_{it} \qquad (2)$$

In the following, $Dig_{it}$ represents the moderating variable, indicating the efficiency of digital economic development. $DID_{it} \times Dig_{it}$ denotes the interaction term between the core explanatory variable and the moderating variable.

## 3.2 Variable Descriptions

### 3.2.1 Dependent Variable

Industrial Structure Upgrading (*AIS*). Following the approach of Gan et al. (2011), this study measures the level of industrial structure upgrading in cities by the ratio of the output value of the tertiary industry to that of the secondary industry. A higher ratio indicates a growing output value of the tertiary industry relative to the secondary industry, indicating a gradual optimisation and rationalization of the industrial structure.

### 3.2.2 Core Explanatory

Variable Phoenix Talent Plan (*DID*). Based on official government reports, the core explanatory variable extracts information on the implementation time and specific measures of the Phoenix Talent Plan. Accordingly, cities implementing the Phoenix Talent Plan after 2018 are defined as 1, while others are defined as 0.

### 3.2.3 Control Variables

Drawing from existing research, the following variables are selected as control variables for this study: Total Factor Productivity (*TFP*), calculated using the stochastic frontier analysis method, with actual GDP of each city as the output factor; input factors include the number of employees and fixed asset data of each city, measuring the efficiency of human and material capital in various cities in Hebei Province; Foreign Investment Level (*Foreign*), represented by the proportion of actual foreign capital utilization to GDP after logarithmic transformation; Financial Development Level (*Finance*), represented by the proportion of various loans of financial institutions at the end of the year to GDP; Economic Development Level (*GDP*), represented by regional GDP.

### 3.2.4 Moderating Variable

Efficiency of Digital Economic Development (*Dig*).

### 3.3 Data Selection

This study utilizes panel data from 11 cities under the jurisdiction of Hebei Province spanning from 2009 to 2021 to evaluate the industrial structure upgrading effect of the Phoenix Talent Program. The data primarily come from the "China City Statistical Yearbook," "Hebei Statistical Yearbook," as well as statistical yearbooks of various cities within the province. Descriptive statistics of variables are presented in Table 1.

**Table 1: Descriptive statistics of variables**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| **VARIABLES** | **N** | **mean** | **sd** | **min** | **max** |
| *DID* | 143 | 0.0280 | 0.165 | 0 | 1 |
| *AIS* | 143 | 1.007 | 0.419 | 0.241 | 2.115 |
| *Dig* | 143 | 0.0371 | 0.105 | 0.0001 | 0.893 |
| *TFP* | 143 | 1.504 | 0.768 | 0.141 | 2.945 |
| *Foreign* | 143 | 8.785 | 0.910 | 5.401 | 10.40 |
| *Finance* | 143 | 14.92 | 0.653 | 13.25 | 16.63 |
| *GDP* | 143 | 2.039 | 0.0747 | 1.869 | 2.199 |

# 4. Measurement of the efficiency of digital economy development

## 4.1 Indicators of Digital Economic Development Efficiency

Most scholars adopt the entropy method or principal component analysis (PCA) to construct the development level of the digital economy, mainly characterizing dimensions such as the level of digital infrastructure, the digitalization of industries, and digital industrialization. For instance, Han et al. (2019) and Liu et al. (2021) have employed these methods in their respective studies. Following the study by Jin et al. (2022), this study constructs input-output indicators to evaluate the efficiency of digital economic development and employs the entropy method to calculate the digital economic development efficiency scores of various cities. Input indicators mainly consider three aspects: digital infrastructure, digital innovation, and digital governance. For digital infrastructure input indicators, the penetration rates of mobile phones and broadband internet access are represented by the number of end users of mobile phones and the number of broadband internet access users. For digital innovation input indicators, the level of digital innovation input in cities is determined by high-tech talents and high-tech innovation achievements, thus the number of students in regular higher education institutions and the number of patent applications and authorizations are selected to represent the input of various cities in digital innovation. Regarding the selection of digital governance input indicators, the scientific expenditure of municipal governments and the frequency of digital economy-related policy terms are used to measure the level and importance of government departments' digital governance capabilities. The output indicator is directly reflected in terms of revenue, representing the benefits of the transformation of input indicators. The indicator of digital industrialization represented by telecommunications revenue is used as the conversion benefit of cities through indicators such as digital infrastructure construction, innovation, and governance. As shown in Table 2.

**Table 2: Input-output Indicators of Digital Economic Development Efficiency**

| Primary Indicators | Secondary Indicators | Unit | Explanation |
|---|---|---|---|
| Digital Infrastructure | Mobile Phone Penetration Rate | Per Ten Thousand Households | Number of Year-End Mobile Phone Users |
| | Broadband Penetration Rate | Per Household | Number of Internet Broadband Access Users |
| Digital Innovation | Number of Students in Regular Higher Education Institutions | Persons | — |
| | Number of Patent Applications Granted | Units | — |
| Digital Governance | Technology Expenditure | Ten Thousand Yuan | — |
| | Number of Policies Related to the Digital Economy | Items | Number of Digital Economy-related Terminologies in Government Work Reports |
| Digital Industrialization | Telecommunications Service Revenue | Ten Thousand Yuan | — |

## 4.2 The Entropy Method

(1) When establishing an indicator system, determining the weight of each indicator is a crucial step. To avoid the influence of subjective opinions on indicator weights, objective weighting methods can be employed. In this article, the entropy method is chosen as the objective weighting method to determine the evaluation weights of sub-indicators for the efficiency of digital economy development. This method ensures that the determination of indicator weights is not influenced by personal subjective factors.

(2) Based on the given data indicators, the hierarchical structure of evaluation indicators is determined, including primary indicators, secondary indicators, and tertiary indicators. In this article, the primary indicators are digital infrastructure, digital innovation and governance, and digital industrialization.

(3) To achieve comparability across comprehensive indicators, it is necessary to standardize the raw data under different indicators. This is because these indicators have different units and magnitudes, and only through standardization can they be compared horizontally. At the same time, positive indicators and negative indicators have different directional effects when measuring the efficiency of digital economy development. Therefore, different data processing methods need to be used to standardize them. This ensures that high values for positive indicators indicate better performance, while lower values for negative indicators indicate better performance. By selecting appropriate standardization methods, the range and direction of indicators can be unified, enabling accurate comprehensive evaluation and comparison.

The dimensionless processing method for positive indicators (where $i$=1,…,$n$ represents a provincial or municipal administrative region, and $j$=1,…,$m$ represents the evaluation indicators for digital economy development efficiency):

$$a_{ij} = \frac{a_{ij} - min\,\{a_{ij}\}}{max\,\{a_{ij}\} - min\,\{a_{ij}\}} \tag{3}$$

(4) Calculate the proportion of the jth indicator value in the ith provincial or municipal administrative region:

$$w_{ij} = \frac{\dot{x_{\iota J}}}{\sum_{i=1}^{n} \dot{x_{\iota J}}} \tag{4}$$

(5) Calculate the information entropy of the jth indicator:

$$k_j = -\frac{1}{ln(n)} \sum_{i=1}^{n} w_{ij} \times ln w_{ij} \tag{5}$$

(6) Calculate the weight of each indicator:

$$w_j = \frac{1 - k_j}{\sum_{j=1}^{m} (1 - k_j)} \tag{6}$$

(7) Calculate the comprehensive evaluation score for the efficiency of digital economy development in each region:

$$s_i = \sum_{j=1}^{m} w_j \times a_{ij} \tag{7}$$

## 4.3 Measurement of urban digital economy development efficiency based on the DEA-Malmquist index analysis method

This paper employs the Malmquist index model, which is based on Data Envelopment Analysis (DEA), to conduct a static measurement of the changes in the development efficiency of the digital economy in 11 prefecture-level cities in Hebei Province from 2009 to 2021. The traditional DEA-CCR model and DEA-BCC model can only compare the efficiency values of cross-sectional data and cannot perform efficiency analysis on panel data. Fare et al. (1994) first combined the Malmquist index theory with DEA methods to propose the DEA-Malmquist model.

Assuming （$inp^t$，$outp^t$） represents the input and output in the t-th year, and （$inp^{t+1}$，$outp^{t+1}$） represents the input and output in the (*t+1*)-*th* year, where $D^t$（$inp^t$，$outp^t$） and $\Delta D^t$（$inp^t$，$outp^t$） are the output distance functions under constant returns to scale and variable returns to scale in the t-th year, respectively, and $D^{t+1}$（$inp^{t+1}$，$outp^{t+1}$） is the output distance function in the (*t+1*)-*th* year. The Malmquist index can be expressed using the following formula:

$$TFP=Malmquist^{t,\ t+1}=\left[\frac{D^t(inp^{t+1},\ outp^{t+1})}{D^t(inp^t,\ outp^t)} \times \frac{D^{t+1}(inp^{t+1},\ outp^{t+1})}{D^{t+1}(inp^t,\ outp^t)}\right]^{\frac{1}{2}} \tag{8}$$

Under the assumption of constant returns to scale, the Malmquist index can be decomposed into the efficiency change index (*effch*) and technological change index (*tech*), with the following specific formula:

$$TFP=effch\times tech=\frac{D^{t+1}(inp^{t+1},\ outp^{t+1})}{D^t(inp^t,\ outp^t)} \times \left[\frac{D^t(inp^{t+1},\ outp^{t+1})}{D^{t+1}(inp^{t+1},\ outp^{t+1})} \times \frac{D^t(inp^t,\ outp^t)}{D^{t+1}(inp^t,\ outp^t)}\right]^{\frac{1}{2}}$$
$$=\left[\frac{D^t(inp^{t+1},\ outp^{t+1})}{D^t(inp^t,\ outp^t)} \times \frac{D^{t+1}(inp^{t+1},\ outp^{t+1})}{D^{t+1}(inp^t,\ outp^t)}\right]^{\frac{1}{2}} \tag{9}$$

Under the assumption of variable returns to scale, the efficiency change index can be further decomposed into pure efficiency change index (*pech*) and scale efficiency change index (*sech*), with the following specific formula:

$$pech = \frac{\Delta \boldsymbol{D}^{t+1}(\boldsymbol{inp}^{t+1},\ \boldsymbol{outp}^{t+1})}{\Delta \boldsymbol{D}^{t+1}(\boldsymbol{inp}^{t},\ \boldsymbol{outp}^{t})} \tag{10}$$

$$sech = \frac{\Delta D^{t+1}(inp^{t+1}, outp^{t+1})/D^{t+1}(inp^{t+1}, outp^{t+1})}{\Delta D^{t}(inp^{t}, outp^{t})/D^{t}(inp^{t}, outp^{t})} \tag{11}$$

In summary, the calculation formula for the efficiency of digital economy development is:

$$TFP=Effch\times Tech=pech\times sech\times tech \tag{12}$$

Considering the availability and rigour of data, the input-output indicators for calculating the level of digital economy development continue to be those determined by the entropy method described earlier, and the analysis is conducted using the DEAP 2.1 software. The specific variable settings are presented in Table 3.

**Table 3: Input-output Indicators of DEA-Malmquist**

| Type | Variable name | code |
|---|---|---|
| Output | Telecommunications Service Revenue | *outp* |
| Input | Mobile Phone Penetration Rate | *inp1* |
| | Broadband Penetration Rate | *inp2* |
| | Number of Students in Regular Higher Education Institutions | *inp3* |
| | Number of Patent Applications Granted | *inp4* |
| | Technology Expenditure | *inp5* |
| | Number of Policies Related to the Digital Economy | *inp6* |

Table 3 displays the changes in overall digital economic technical efficiency, pure efficiency, and scale efficiency among the 11 prefecture-level cities in Hebei Province from 2010 to 2021. Looking at the overall characteristics of the 11 cities, the average Malmquist productivity index is 0.91, indicating relatively high efficiency in digital economic development. However, in 2016 and 2021, the Malmquist productivity index was less than 0.8, indicating lower levels of development. From the individual characteristics of the 11 prefecture-level cities, except for Chengde, Langfang, Qinhuangdao, and Zhangjiakou, the digital economic development efficiency of the remaining cities exceeds the overall average. According to the Malmquist index, the top three cities in terms of efficiency are Tangshan, Handan, and Shijiazhuang, respectively. The results of the calculations indicate that in the process of digital economic development, most cities have fully utilized the effects of innovation and technological progress, thereby exerting a positive influence on the advancement towards a more advanced industrial structure.

**Table 4: Malmquist index summary of city means**

| City | effch | techch | pech | sech | TFP |
|---|---|---|---|---|---|
| Baoding | 1.000 | 0.914 | 1.000 | 1.000 | 0.914 |
| Cangzhou | 1.000 | 0.911 | 1.000 | 1.000 | 0.911 |
| Chengde | 1.000 | 0.863 | 1.000 | 1.000 | 0.863 |
| Handan | 1.000 | 0.925 | 1.000 | 1.000 | 0.925 |
| Hengshui | 1.000 | 0.913 | 1.000 | 1.000 | 0.913 |
| Langfang | 1.000 | 0.904 | 1.000 | 1.000 | 0.904 |
| Qinhuangdao | 1.000 | 0.904 | 1.000 | 1.000 | 0.904 |
| Shijiazhuang | 0.987 | 0.935 | 1.000 | 0.987 | 0.923 |
| Tangshan | 0.999 | 0.927 | 1.000 | 0.999 | 0.926 |
| Xingtai | 1.000 | 0.915 | 1.000 | 1.000 | 0.915 |
| Zhangjiakou | 1.000 | 0.881 | 1.000 | 1.000 | 0.881 |
| mean | 0.999 | 0.908 | 1.000 | 0.999 | 0.907 |

**Table 5: Malmquist index summary of annual means**

| Year | effch | techch | pech | sech | TFP |
|---|---|---|---|---|---|
| 2010 | 1.001 | 0.900 | 0.999 | 1.002 | 0.901 |
| 2011 | 0.961 | 1.104 | 0.987 | 0.974 | 1.061 |
| 2012 | 1.034 | 0.958 | 1.013 | 1.021 | 0.990 |
| 2013 | 0.994 | 1.024 | 0.993 | 1.001 | 1.018 |
| 2014 | 1.008 | 0.883 | 1.008 | 1.001 | 0.891 |
| 2015 | 1.003 | 0.917 | 1.000 | 1.003 | 0.92 |
| 2016 | 0.886 | 0.874 | 0.975 | 0.909 | 0.774 |
| 2017 | 1.117 | 0.902 | 1.025 | 1.090 | 1.008 |
| 2018 | 0.991 | 0.901 | 0.985 | 1.006 | 0.893 |
| 2019 | 1.002 | 0.906 | 1.013 | 0.988 | 0.908 |
| 2020 | 1.008 | 0.888 | 1.002 | 1.006 | 0.895 |
| 2021 | 0.994 | 0.730 | 1.000 | 0.994 | 0.726 |
| mean | 0.999 | 0.912 | 1.000 | 0.999 | 0.910 |

# 5. Empirical Analysis

## 5.1 Baseline Regression

This study employs a stepwise addition of control variables in regression using the difference-in-differences method while controlling for differences at the city and time levels. The regression results are presented in Table 6. Column (1) shows the results without the inclusion of control variables, while columns (2), (3), (4), and (5) display the results after gradually incorporating a series of control variables including Total Factor Productivity (*TFP*), Foreign Direct Investment (*Foreign*), Financial Development Level (*Finance*), and Gross Domestic Product (*GDP*). Despite the decrease in the regression coefficient from 0.561 in column (1) to 0.522 in column (5) upon the inclusion of other control variables, the policy dummy variable $DID_{it}$ remains significantly positive at the 1% level. This suggests that the Phoenix Talent Program promotes the development of advanced industrial structures in Tangshan City, thus validating Hypothesis 1. In the process of optimizing industrial structure, proactive and effective talent policies not only retain talents but also attract more high-skilled and high-quality talents to Tangshan, providing sustained momentum for the advanced development of the city's industrial structure.

**Table 6: Regression results of the impact of the Phoenix Talent Plan on industrial structure upgrading**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| **VARIABLES** | **AIS** | **AIS** | **AIS** | **AIS** | **AIS** |
| *did* | 0.561*** | 0.539*** | 0.563*** | 0.394*** | 0.522*** |
| | (6.15) | (5.91) | (6.12) | (4.47) | (5.70) |
| *TFP* | | -0.077* | | | |
| | | (-1.74) | | | |
| *Foreign* | | | 0.009 | | |
| | | | (0.27) | | |
| *Finance* | | | | -0.519*** | |
| | | | | (-5.28) | |
| *GDP* | | | | | -3.038** |
| | | | | | (-2.22) |
| *Constant* | -0.743*** | -0.613*** | -0.817*** | 6.564*** | 5.245* |
| | (-17.04) | (-7.09) | (-2.92) | (4.74) | (1.94) |
| | | | | | |
| *Observations* | 143 | 143 | 143 | 143 | 143 |
| *R-squared* | 0.859 | 0.863 | 0.859 | 0.886 | 0.865 |
| *Number of city* | 11 | 11 | 11 | 11 | 11 |
| *city fe* | YES | YES | YES | YES | YES |
| *year fe* | YES | YES | YES | YES | YES |

Note: ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

### 5.2 Parallel Trends Assumption Test

To test whether the premise of using the difference-in-differences model in this study is valid, we draw on the method of Jacobson et al. (1993), He and Wang (2017) to examine whether the experimental and control groups exhibit parallel trends before policy implementation. The model is constructed as follows:

$$AIS_{it}=\beta_0+\sum_{u=1}^{6}\beta_{t-u}DID_{t-u}+\beta_t DID_t+\sum_{v=1}^{3}\beta_{t+v}DID_{t+v}+\beta_2 controls_{it}+\lambda_i+\mu_t+\varepsilon_{it} \quad (13)$$

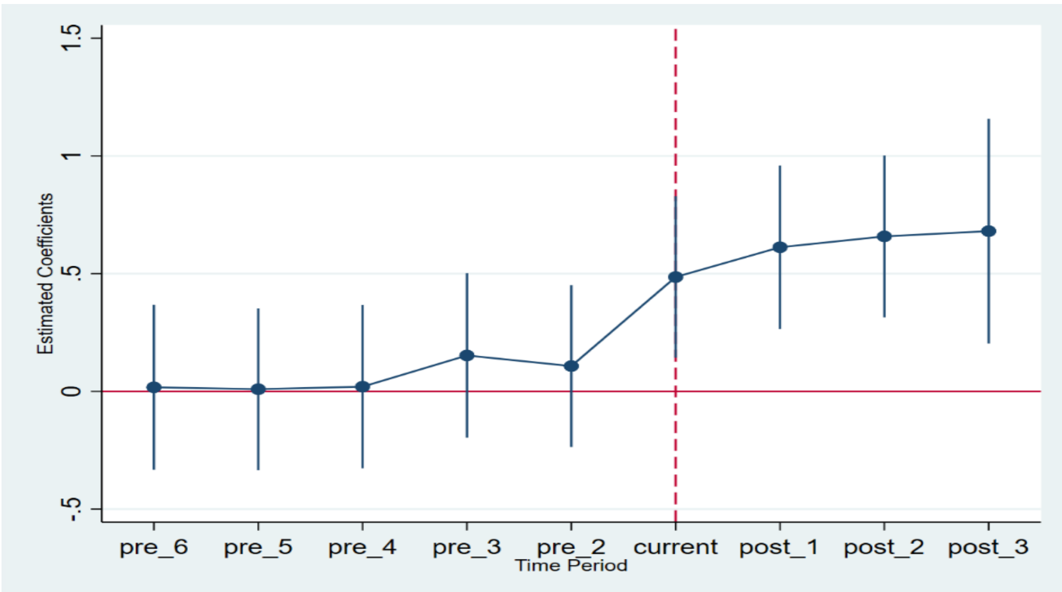


**Figure 1: Parallel Trends Assumption Test**

In the context, where *DID* serves as a dummy variable for policy effects, *t* represents the base year of the experiment, which is the year when the Phoenix Talent Plan was implemented in Tangshan, as per this study. *t-u* represents *u* years before the pilot, and *t+v* represents *v* years after the pilot, where *u*=1, 2..., 6, and *v*=1, 2, 3. The selected time interval for testing is from *t*-6 to *t*+3. To avoid multicollinearity issues, the period immediately before the base year (*pre*_1), i.e., the *t*-1 period, is excluded. The parallel trends test results for various prefecture-level cities in Hebei Province for the 6 years preceding and 3 years following the policy implementation are shown in Figure 1. Before the policy implementation, the confidence intervals fluctuate around zero, indicating no significant difference between the experimental and control groups, thus confirming the parallel trends assumption. However, after the policy implementation year and the subsequent 3 years, parallel trends were not met, suggesting that the effects of the Phoenix Talent Plan on the development towards a more advanced industrial structure began to manifest in the implementation year itself, showing an overall upward trend.

### 5.3 Placebo Test

To mitigate the potential influence of random factors or unobservable variables on the baseline regression results after policy implementation, following the approach of Chetty et al. (2009), placebo tests were conducted through 500 random samples taken from 11 cities. This was achieved by substituting the experimental group, thereby conducting placebo tests. The test results, as shown in Figure 2, indicate that the majority of p-values are above 0.1, suggesting that most sampling results are not significant at the 10% level. Thus, this largely eliminates the interference of random factors on the baseline regression results, and from a counterfactual perspective, verifies the Phoenix Talent Program's role in promoting industrial structural upgrading.

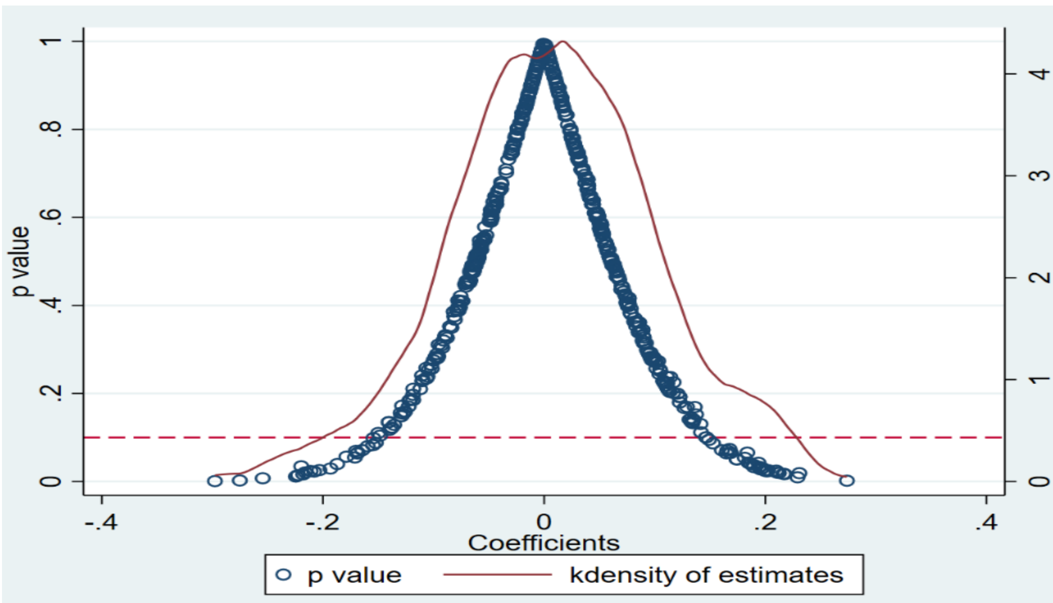


**Figure 2: Placebo Test**

## 6. Analysis of the Moderating Effect of the Digital Economy

Table 7 reports the results of the moderation effect test on the development efficiency of the digital economy. As indicated in column (1), the coefficient of the interaction term between the Phoenix Talent Program and digital economy development efficiency is 0.121, and it is significant at the 1% level. This implies that digital economy development efficiency positively moderates the relationship between the Phoenix Talent Program and the advancement of industrial structural upgrading. This suggests that the higher the digital economy development efficiency, the stronger the impact of the Phoenix Talent Program on promoting industrial structural upgrading in Tangshan City. Hypothesis 2 is thus supported.

**Table 7: Analysis of the Moderating Effect of the Digital Economy**

| | **(1)** |
|---|---|
| **VARIABLES** | **AIS** |
| *did* | 0.392*** |
| | (3.91) |
| *Dig* | 0.211 |
| | (0.94) |
| *did_dig* | 1.121*** |
| | (2.48) |
| *Constant* | 7.304*** |
| | (2.83) |
| *Observations* | 143 |
| *Number of city* | 11 |
| *R-squared* | 0.889 |
| *controls* | YES |
| *city fe* | YES |
| *year fe* | YES |

Note: ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

## 7. Conclusion

Based on panel data from 2009 to 2021 of 11 prefecture-level cities in Hebei Province, this study establishes an indicator system for digital economic development efficiency in each city and empirically examines the impact of the Phoenix Talent Program on the industrial structural upgrading of Tangshan City and its mechanism. The results indicate that the Phoenix Talent Program significantly promotes the advancement of industrial structural upgrading. Even after a series of robustness tests such as placebo tests, this conclusion remains valid. Mechanism analysis results demonstrate that the digital economy development efficiency of cities plays a significant moderating role between the Phoenix Talent Program and industrial structural upgrading.

In light of the research conclusions, this study proposes the following policy recommendations:

(1) Enhance Technological Innovation Capability. Strengthen research and development in cutting-edge technologies and focus on technological frontiers. Emphasize the development of platforms and support policies for technology transfer, improve patent examination and protection systems, and continuously attract innovation resources such as research institutions and high-end intelligent technologies to gather in Tangshan. Actively attract domestic high-tech companies to establish branches in Tangshan, provide assistance to innovative enterprises, offer loans and financial support, and provide certain tax incentives to promote high-quality development in the city by drawing on experiences in attracting investment from domestic major cities.

(2) Actively Attract Talent. Talent is the key to success (Shi and Shen, 2022) .To address development challenges in Tangshan, promoting the construction of talent teams and actively attracting talent and expertise becomes crucial. Tangshan should continue to implement the upgraded version of the "Phoenix Talent" policy 3.0 for the new era and strengthen talent construction in the city. Specific measures include: Expanding the coverage of policy benefits. Provide support and guarantees not only to new types of management talents, overseas high-level personnel, and highly skilled workers, but also directly offer housing and living subsidies to young talents such as undergraduate, master's, and doctoral students, as well as high-level vocational and technical personnel.

Ensuring settlement and placement of talents. Construct special residences for talents in high-tech development zones and innovation and entrepreneurship bases, create service-oriented and beautiful living communities for talents, effectively address the housing needs of talents in the early stages of employment, attract young talents to return to Tangshan for entrepreneurship and employment, and promote talent influx to support Tangshan's development.

Providing a favourable service environment for talent development, simplifying procedures, improving service efficiency, and igniting the enthusiasm of talents for entrepreneurship and practical work.

Adhering to a combination of introducing and cultivating talents both domestically and internationally, slightly tilting fiscal policies towards universities and research institutions, providing adequate financial support to key construction universities in the city, and striving to do a good job in talent incentive work within the city to retain and make good use of talents.

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