sustainability

MDPI

Article

Impact of Innovative City Pilot Policy on Industrial Structure Upgrading in China

Wenqi Zhao [1] and Moau Yong Toh [1,2,3,*]

[1] School of Economics and Management, Xiamen University Malaysia, Sepang 43900, Selangor, Malaysia
[2] School of Economics, Xiamen University, Xiamen 361005, China
[3] Shenzhen Research Institute of Xiamen University, Shenzhen 518000, China
* Correspondence: moauyong.toh@xmu.edu.my

Abstract: Urban innovation has been highly regarded as a modern urban model that drives sustainable urban development by synthesizing knowledge innovation and technological innovation in industrial processes. As such, numerous studies have emerged to investigate the impact of the innovative city pilot policy (ICP), yet the impact of the ICP on industrial structure upgrading has not been explicitly studied. To address the research gap, this study utilizes the ICP in China as a quasi-natural experiment and investigates the impact of the ICP on industrial structure upgrading in Chinese cities. We apply a DID model estimation on a panel dataset of 284 Chinese prefecture-level cities from 2007 to 2019. The results indicate that the innovative city pilot policy greatly helps to upgrade the industrial structure in pilot cities, with the upgrading outcome particularly evident in large and non-natural resource-based cities. Mechanism analyses further reveal three channels via which the ICP promotes industrial structure upgrading, specifically by improving innovation capacity, boosting labor clustering, and lowering pollutant emissions. The results of this study carry significant policy implications for China in building a sustainable and modernized economic system and for other emerging nations in seeking economic transformation and industrial structure upgrading.

Keywords: innovative city pilot policy; industrial structure upgrading; innovation; knowledge; urban development

Citation: Zhao, W.; Toh, M.Y. Impact of Innovative City Pilot Policy on Industrial Structure Upgrading in China. *Sustainability* **2023**, *15*, 7377. https://doi.org/10.3390/su15097377

Academic Editor: Stephan Weiler

Received: 20 January 2023
Revised: 2 April 2023
Accepted: 27 April 2023
Published: 28 April 2023

1. Introduction

Urban innovation is an integral part of industrial structure upgrading in a country as cities are generally rich and diverse in innovation resources, such as technology, knowledge, labor, and culture, which can be turned into the primary drivers of economic and social growth [1]. However, investing in the necessary innovation resources often comes with high upfront costs, risk, complexity, and a long cost-recovery period. It is, therefore, unsurprising that governments across the globe have implemented "innovation city" initiatives since the 1990s to catalyze the private sector's involvement in urban innovation and development [2]. For example, the United Kingdom's central and London governments jointly launched the "Tech City" project in London in 2010 [3]. Through financial and policy support, London has successfully established a pioneer innovation ecosystem in Europe, with numerous high net-worth innovative technology companies. Similar initiatives have been implemented in other cities, including Boston [4] and Sydney [5].

Likewise, the central government of China has implemented an innovative city pilot policy (ICP) via phase arrangement since 2008, with Shenzhen being the first innovative pilot city. Since then, six batches of national innovative city pilot initiatives have been introduced in 2010, 2011, 2012, 2013, 2018, and 2022, as shown in Figure 1. By early 2023, 103 innovative pilot cities had been approved by the National Development and Reform Commission and the Ministry of Science and Technology (see Table 1). The ICP aims to conduct urban innovation activities and improve urban innovation capacity in alignment with the country's innovation-driven development vision. According to the ICP's supervision and monitoring frameworks, each city should invest more in innovation, focus on developing innovation resources, and foster an innovation-friendly environment. Unlike other urban plans, such as the National Healthy City Construction Pilot Policy; the Pilot Policy for Creating New Energy Model Cities; and the Low-Carbon City Pilot Policy, the ICP is more innovation-oriented and envisages exerting a more fundamental and long-term impact on the industrial structure upgrading of cities. However, the extent of the ICP and of how it impacts the industrial-structure upgrading of cities is under-explored. It is expected that the ICP plays a significant role in changing the industrial structure of a city because the associated government support, typically in the form of tax incentives for private research and development (R&D), as well as of incentives for high-skilled labor and public grants, could alter the resource allocation and composition of economic activity in the city to achieve innovation-driven development of the country ultimately. This paper aims to delve into the impact and mechanism path between the ICP and the industrial structure upgrading of cities in China.

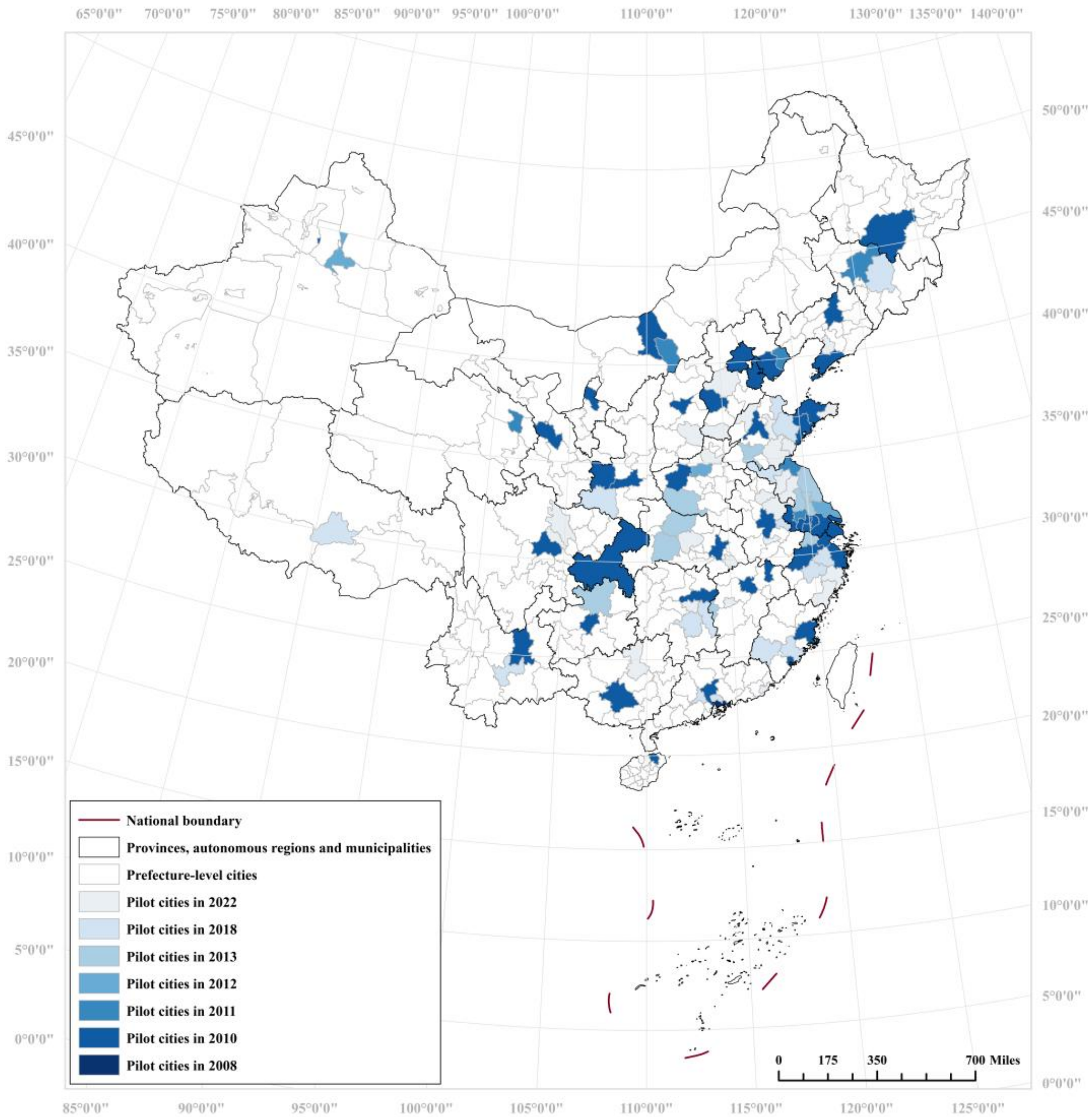

Figure 1. Distribution of seven batches of ICP cities in China.

Table 1. Innovative pilot cities in China.

Year	Eastern China	Central China	Western China
2008	Shenzhen		
2010	Dalian, Qingdao, Xiamen, Shenyang, Guangzhou, Nanjing, Hangzhou, Jinan, Suzhou, Wuxi, Yantai, Beijing, Tianjin, Tangshan, Shanghai, Ningbo, Jiaxing, Shijiazhuang, Changzhou, Fuzhou, Haikou	Hefei, Changsha, Harbin, Luoyang, Wuhan, Taiyuan, Jingdezhen, and Nanchang	Xi'an, Chengdu, Baotou, Chongqing, Lanzhou, Nanning, Guiyang, Kunming, Baoji, Yinchuan, Changji, and Shihezi
2011	Lianyungang, Qinhuangdao, and Zhenjiang	Changchun	Xining, Hohhot
2012	Nantong	Zhengzhou	Urumqi
2013	Yangzhou, Taizhou, Yancheng, Huzhou, Jining	Yichang, Pingxiang, Nanyang, and Xiangyang	Zunyi
2018	Xuzhou, Shaoxing, Jinhua, Quanzhou, Longyan, Weifang, Dongying, Foshan, Dongguan	Jilin, Maanshan, Anhui ,Zhuzhou, and Hengyang	Yuxi, Lhasa, and Hanzhong
2022	Baoding, Handan, Suqian, Huai'an, Wenzhou, Taizhou, Zibo, Weihai, Rizhao, Linyi, Dezhou, Shantou, and Yingkou	Changzhi, Chuzhou, Bengbu, Tongling, Xinyu, Xinxiang, Jingmen, Huangshi, and Xiangtan	Liuzhou, Mianyang, and Deyang

This paper relates to two literature strands. The first literature strand pertains to the economic and social effects of the ICP. Generally, the related literature has documented the positive effects of innovation city policy on sustainable economic and social development [6], technological knowledge diffusion [7], green technology progress [8,9], green innovation [10], and green production and ecology efficiency in cities [11–13]. These positive effects can further serve as mechanisms via which the ICP promotes carbon emission reduction [14] and green total factor energy efficiency improvement in China [15]. However, the prior studies have not directly investigated the effect of the ICP on industrial structure upgrading, which emphasizes the evolution of industry structures from the primary and secondary industries to the tertiary industry in Chinese cities.

The second literature strand pertains to the factors of industrial structure upgrading. Among the wide-ranging policies investigated, the low-carbon city pilot policy has been found to promote industrial structure supererogation in China via technological innovation and reduce the share of high-carbon industries [16]. The carbon emissions trading pilot policy similarly affects the upgrading of industrial structures in China, mainly through green innovation [17,18]. Further, the positive effect of environmental regulation on green technology innovation and industrial structure in Chinese cities is more substantial when the economic development level of cities is higher [19]. The healthy cities pilot policy in China has also been found to facilitate the industrial structure upgrading of cities through technological innovation and green total factor productivity [20].

When reviewing the aforementioned literature, it is evident that the extant literature needs to be expanded in several dimensions. First, there is still a lack of study that directly links the effect of the ICP to industrial structure upgrading in cities. Arguably, various government-supportive initiatives under the ICP, such as tax incentives for private R&D, high-skilled labor, and public grants, could alter economic activity's resource allocation and composition towards high-skill and high-tech orientation, thereby upgrading the industrial structures in pilot cities. This argument is yet to be testified. Second, the mechanisms driving the effect of the ICP on industrial structure upgrading have not been explored. As prior studies have reported that implementing the ICP can affect technological innovation, labor clustering, and pollutant emissions in pilot cities, the present study extends the prior studies by investigating whether these effects are the mechanisms via which the ICP promotes industrial structure upgrading.

This paper carries three significant study contributions. First, our study results contribute to the literature by indicating that the ICP stimulates the industrial structure upgrading in cities. The stimulating effect is more salient in cities of a larger scale and those that are non-natural-resource-reliant. Second, we enrich the literature by documenting evidence that the ICP expands the innovation capacity and labor concentration in cities, thereby providing a conductive innovation environment for the industrial structure upgrading in cities. On the other hand, pollutant emission is a mechanism that hampers the efficacy of the ICP in promoting industrial structure upgrading in cities. Third, our study constructs a more robust industrial structure advancement index (ISAI) for 284 Chinese prefecture-level cities from 2007 to 2019, following the approach introduced by Costa [21]. The ISAI accounts for the level of a city's industry structure advancement from the primary and secondary-industry orientation to the tertiary-industry orientation. This approach deviates from most prior studies that employ the ratio of tertiary industry output value to secondary industry output value to measure industrial structure upgrading and lack due to the consideration of the primary industry and the changing industrial structure over time [22].

The remainder of the paper is organized as follows. Section 2 reviews the related literature and develops the hypotheses of this study. Section 3 explains the research methodology, while Section 4 reports the baseline model results and additional analyses. Section 5 concludes the paper with policy implications.

2. Literature Review

2.1. ICP and Industrial Structure Upgrading

Hall was among the first to define "innovative cities" as cities with innovative quality that exhibit a new urban model driving sustainable economic development [23]. Innovative cities utilize scientific knowledge as the foundation of innovation while taking the synergy between knowledge and technological innovation as an essential component of the urban innovation drive [24,25]. Thus, innovative cities can serve as an integrated innovation network system that clusters and diffuses technological knowledge through the interaction between innovation subjects [7,26].

In China, the ICP has gradually been phased into cities since 2008 under the mandate of the national government to raise investment in innovation, expand the capacity of innovative factors, and create a conductive innovation environment for the private sector. Following the vertical "coercion" mechanism of policy diffusion theory, the ICP creates top-down pressure on local governments to reallocate scarce resources across industries towards achieving urban innovation-driven development. As a result, the institutional reform and resource management model exploration promoted by the ICP effectively stimulates the vitality of the industrial structure in pilot cities, thereby driving the flow of production factors from primary and secondary industries to the tertiary industry and promoting the development of the skilled, service-oriented tertiary industry. Hinging on the rationale, this study develops the first hypothesis as follows:

H1. *ICP promotes the upgrading of the industrial structure of pilot cities.*

2.2. Mechanisms for the Impact of ICP on Industrial Structure Upgrading

This paper also explores three mechanisms via which the ICP influences the industrial structure upgrading in pilot cities: innovation capacity, labor clustering, and pollutant emissions in the cities. The theoretical rationale behind these mechanisms is summarized in Figure 2.

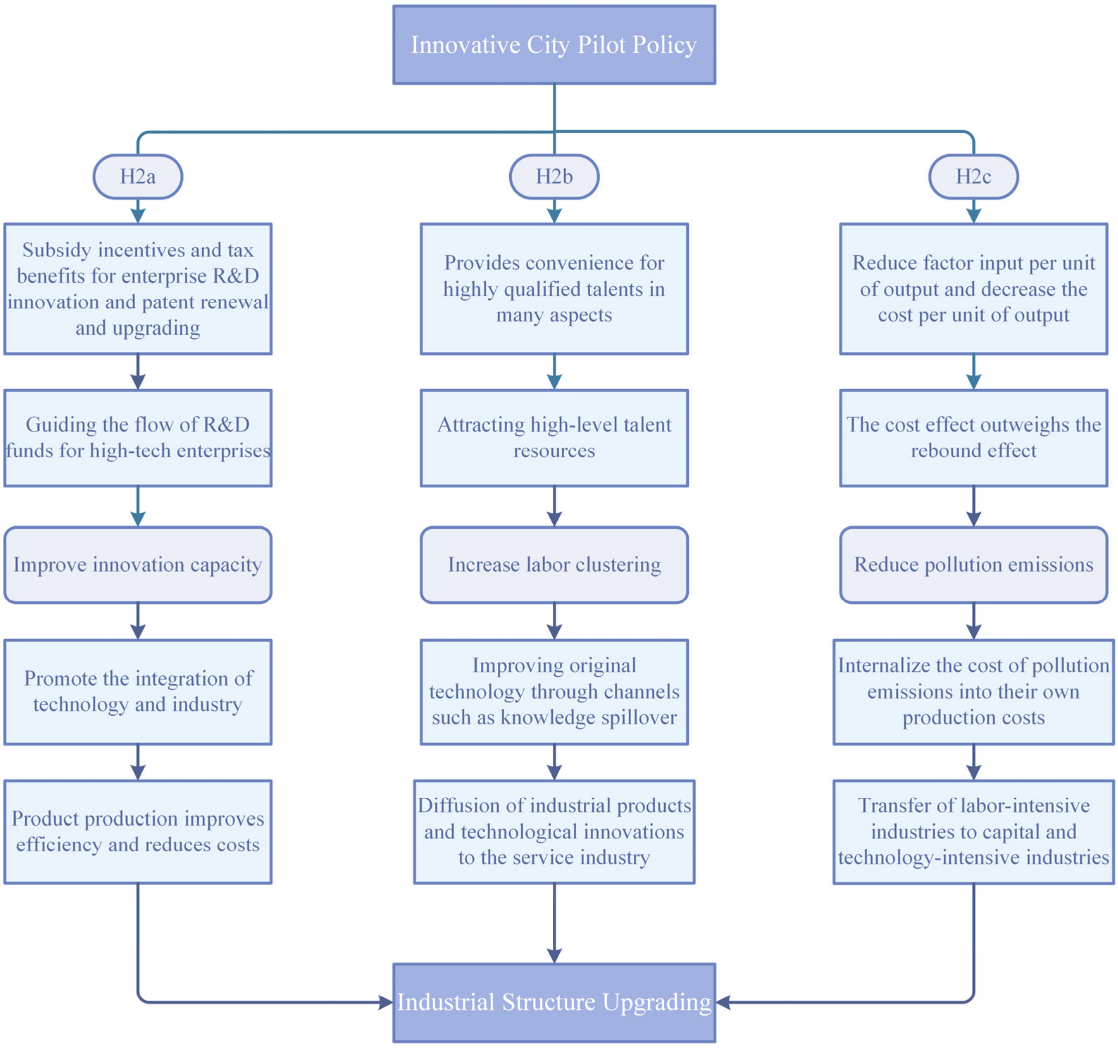

Figure 2. Mechanisms driving the impact of ICP on industrial structure upgrading.

2.2.1. Innovation Capacity

The primary mandate of the ICP is to enhance the innovation capacity of enterprises in pilot cities by effectively promoting enterprise R&D activities and the associated outputs such as patents. To this end, the local governments of pilot cities are directed to inject capital into the R&D of high-tech enterprises by providing subsidies, tax incentives, post-facto awards, and special funds. Subsidies and tax incentives reduce the cost of new products for high-tech enterprises from the tax base and amount, and they motivate the enterprises to innovate their technologies and products, as part of the driving forces for the transformation and upgrading of regional industrial structure [27]. Specifically, technological innovation can promote the flow of quality-production resources from the high-efficiency production sector to the low-efficiency production sector, thereby improving the total labor productivity of the region and upgrading the region's production system towards high-efficiency and low-cost as a whole [28]. Sun et al. also reported that technological innovation could rationalize the production resource's supply and demand structure, optimize the balance between supply and demand, and facilitate technology integration into industries [29]. Chen et al. used data from 30 Chinese provinces from 2005 to 2015. They found that the innovation drive in these provinces promotes the industrial structure upgrading in the region and exerts a positive spillover effect on the industrial structure upgrading in the neighboring regions [30]. This spatial spillover effect decays with the increase in geographical distance.

Collectively, the literature suggests that innovation plays a significant role in changing the industrial structure of a region and even a country by improving resource allocation and production efficiency in industries. In accord with the mandate of the ICP, this study develops the following hypothesis.

H2a. *ICP promotes the upgrading of the industrial structure by increasing innovation capacity.*

2.2.2. Labor Clustering

To support the national ICP, pilot cities have successively introduced "New Talent Policies", including settlements, subsidized housing, and scientific research funding, to support the living and career of high-quality talents in various aspects, attract high-quality talent resources, and lay the foundation of a labor force for industrial structure upgrading. The agglomeration of the labor force strengthens the specialized division of labor in the industry and forms a closer coupling between the regional talent and industrial structures. This coupling effect will significantly reduce labor search costs, help enterprises obtain external resources more efficiently, break through the incumbent resource constraints, improve resource-use efficiency, and promote enterprises' new product development and industrial technology innovation [22].

In addition, the technology dispersion brought about by highly specialized labor can be manifested by the technological spillover from high-tech enterprises to enterprises in other high-end sectors. In the process, the labor force, as a technology carrier, improves the existing technology pool through knowledge spillover, labor flow, imitation learning, and other channels to realize the development and absorption of more advanced technology [31]. Consequently, the new technology penetration into service industries, such as Fintech, could help promote industrial structure upgrading. Similarly, Iftikhar et al. and Hu find that human capital has a significant "knowledge spillover" effect through interaction with innovative skills as high-skilled talents will improve technological R&D in their sectors [32,33].

Tsaurai and Ndou, and Lin and Zhao, argued that as human capital from different knowledge and technical backgrounds clusters, the integration and optimization of various other production factors are enhanced, which further promotes the upgrading of the industrial structure [34,35]. Lim et al. propounded that "knowledge" is the core element of productivity formation, and the benefits produced by knowledge are positively correlated with the pool of knowledge dissemination [36]. The more people there are with professional knowledge, the more likely an industrial development environment will be established. Thus, this study formulates the following hypothesis:

H2b. *ICP promotes the upgrading of the industrial structure by increasing labor clustering.*

2.2.3. Pollutant Emissions

Technological innovation has arguably exerted both a negative cost effect and a positive rebound effect on pollutant emissions [37]. On the one hand, innovation can reduce the factor input per unit of output and improve the cost efficiency of production, which then leads to a decrease in pollutant emissions. On the other hand, while innovation stimulates economic growth, it may increase the demand for energy-related products and services, increasing pollutant emissions. Thus, the net effect of innovation on pollutant emissions depends on the relative magnitude of the two opposing effects.

However, most extant empirical evidence suggests an adverse effect of innovation on pollutant emissions, especially at the macro level. For example, Pan et al., Saud et al., and Yi et al. found that innovation helps to improve energy-use efficiency and reduce greenhouse gas emissions, thus decreasing haze pollution and improving environmental quality [38–40]. At the enterprise level, by transforming and upgrading technology, enterprises eliminate obsolete production capacity, remove the cost of pollutant emissions from their internal production costs, and increase net income, ultimately bringing about the modernization of industrial structures [41]. Since the ICP is implemented at the industrial level, enterprises have adjusted their production actions to transform high energy consumption and low value added, to low energy consumption and high value added. Supported by wide-ranging innovation-related initiatives, industries generally observe a transformation from a labor-intensive model towards a capital- and technology-intensive model [42]. Gao and Yuan also found that constructing innovative cities positively reduces pollution emission intensity, mainly achieved through improving the urban innovation level and industrial R&D personnel concentration [8]. Therefore, based on the prior evidence, the following hypothesis is developed.

H2c. *ICP promotes the upgrading of the industrial structure by reducing pollutant emissions.*

3. Research Methods

3.1. Data

This study started with a balanced panel dataset of 293 prefecture-level cities in China from 2007 to 2019. After removing prefecture-level cities with unavailable and severely missing data, the final number of prefecture-level cities available for analysis was 284. Although the sixth batch of 25 pilot cities was released in 2022, the data of these cities have not been published at the time of this research. Thus, the sample consisted of 78 innovative pilot cities constructed in batches in 2008, 2010, 2011, 2012, 2013, and 2018, which were set as the treatment group in this quasi-natural experiment. The remaining 206 cities were set as the control group. Missing data in some years were replaced using the average interpolation approach, yielding a total of 3692 observations. All of the required data were obtained from the China Statistical Yearbook, the China Environmental Statistical Yearbook, and the China City Statistical Yearbook.

The statistical caliber of the data in this paper was urban areas (municipal districts). This is because, firstly, the core functions of cities are mainly concentrated in urban areas, so when the functions or characteristics of a city are studied, the statistical caliber of "municipal districts" can exclude the interference of non-urban factors well. Secondly, the number of counties (districts) under the jurisdiction of prefecture-level cities changes over time, or some counties are separated from the higher-level prefecture-level cities and elevated to prefecture-level cities. Thus, the classification of "urban area" is relatively stable, which facilitates the comparison of historical data across cities.

3.2. Variable Measurement

3.2.1. Dependent Variable: Industrial Structure Upgrading

Industrial structure upgrading refers to continuous changes in industrial structure according to evolving economic development, reducing the share of primary and secondary industry outputs and increasing the share of tertiary industry outputs in total outputs [43]. Following da Costa's approach, this study measured the industrial structure upgrading of a city in a specified year as follows [21]. Firstly, the GDP of a city was divided into three industries, specifically primary, secondary, and tertiary industries. The proportion of value added by each industry to the city's total GDP was regarded as a component of the spatial vector, thus forming a set of three-dimensional vectors.

$$x_0 = (x_{1,0}, x_{2,0}, x_{3,0}) \tag{1}$$

Then, this study calculated the angle θ_1, θ_2, θ_3 between x_0 and the vector $x_1 = (1,0,0)$, $x_2 = (0,1,0)$, $x_3 = (0,0,1)$ of primary, secondary, and tertiary industries, respectively.

$$\theta_j = \arccos\left(\frac{\sum_{i=1}^{3}(x_{i,j} \cdot x_{i,0})}{\left(\sum_{i=1}^{3}\left(x_{i,j}^2\right)^{1/2} \cdot \sum_{i=1}^{3}\left(x_{i,0}^2\right)^{1/2}\right)}\right), j = 1, 2, 3 \tag{2}$$

where θ_j is the angle between x_0 and the vector x_j. $x_{i,0}$ is the share of value added of *i*th industry in GDP. Finally, the following formula was applied to compute the industrial structure upgrading index (*ISAI*). A higher *ISAI* value indicated a more advanced industrial structure in the city.

$$ISAI = \sum_{k=1}^{3} \sum_{j=1}^{k} \theta_j \tag{3}$$

3.2.2. Explanatory Variables

The core explanatory variable *Treat_time* indicated whether a city is a pilot city for the ICP. It was an interaction term between *Treat* and *time*, where *Treat* was a dummy variable taking the value of 1 if the city was a pilot city for ICP and 0 if the city was not. *time* was a temporal dummy variable taking the value of 0 in the years before the policy implementation and 1 after the year of implementation. This variable measurement was consistent with that of Wang and Zhou and Yang et al. [14,15].

Following prior studies, control variables were also included to estimate the net effect of the ICP on industrial structure upgrading [14,15,18,20]. Upon reviewing related literature, this study identified the following control variables. The financial development level of a city (*FL*) was measured as the ratio of deposit and loan balances to GDP in the city. The sewage discharge level (*DL*) was measured by the amount of sewage discharged in ten thousand tons. Human resource (*HE*) was measured by the population density in people per square kilometer. Infrastructure (*IF*) was measured by the urban road area in square meters per capita. The economic openness level (*OL*) was measured by the amount of foreign direct investment in the city. The education level (*EL*) was measured as the number of college students per 10,000 people. These control variables were log-transformed to eliminate heteroskedasticity.

Additionally, we added a control variable to capture the aggregate innovation condition, investment, performance, and environment in pilot cities. Specifically, we employed the index of regional innovation and entrepreneurship (*IRIE*) published by the Center for Enterprise Research of Peking University to reflect the vitality and performance of innovation and entrepreneurship in various regions of China. The index is constructed based on the three core elements, which are the number of new enterprises, capital investment, and intellectual property registration, by relying on the full set of enterprise information in the national industrial and commercial enterprise registration.

3.2.3. Mediating Variables

To test hypotheses H2a to H2c concerning the mechanisms driving the impact of the ICP on industrial structure upgrading, three mediating variables were included: innovation capacity, labor clustering, and pollutant emissions. Innovation capacity (*IC*) was captured by the number of invention patents granted to enterprises in a city [20]. This output-based measure has strong industrial relevance and can better capture the driving effect of innovation on industrial structure upgrading in pilot cities. Labor clustering (*LC*) was proxied by the number of labors employed in the city. Generally, the rural and urban labor force populations differ in various aspects, including skills and work ethics. The latter tends to contribute more to the promotion effect of labor clustering on the industrial structure upgrading in cities. Pollutant emissions (*PE*) were measured by sulfur dioxide emissions (in tons) as sulfur dioxide is a common by-product in the production process of enterprises and is a commonly used indicator of air pollutants [8,14]. The descriptive statistics of all variables used in this study are provided in Table 2.

Table 2. Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
ISAI	3692	1.07811	0.66195	0.09432	6.53261
FL	3692	1.00340	0.44342	−1.54620	4.14145
DL	3692	8.23521	1.13026	1.94591	11.47731
HE	3692	8.00152	0.73381	5.51343	9.90813
IF	3692	6.92723	0.60840	3.48647	9.30945
OL	3692	11.62686	2.03897	3.00842	16.83473
EL	3692	5.77605	1.02098	−1.49133	8.02656
IRIE	3639	51.91835	28.08909	1.36519	100
IC	3692	0.61154	2.43109	0.00100	52.91700
LC	3692	3.44705	7.03619	0.11000	81.93019
PE	3692	10.20317	1.19125	4.31749	13.43414

3.3. Model Construction

3.3.1. Baseline Model

A quasi-natural experiment is typically used to estimate policy effects with an approximately random selection of treatment and control groups, thereby alleviating endogeneity and selection bias in estimating policy effects. This study considered the ICP a quasi-natural experiment and investigated its effect on industrial structure upgrading by using a multi-period DID model that incorporated the variation of the ICP across pilot cities and years. The conventional DID model was premised on satisfying the common trend assumption that all cities did not differ systematically before policy implementation. The heterogeneity of urban development made it impossible to meet this assumption. Therefore, this paper used a multi-period DID model, which accounted for urban-related differences and addressed the self-selection bias to assess the effects of the ICP on industrial structure upgrading more effectively and accurately [44]. The multi-period DID baseline model is specified as follows:

$$ISAI_{it} = \alpha_1 + \beta_1 Treat\_time_{it} + \sum_{k=1}^{K} c_{1k} X_{kit} + \delta_i + \sigma_t + \varepsilon_{it} \tag{4}$$

where $ISAI_{it}$ is the industrial structure upgrading level of the city i in year t. $Treat\_time_{it}$ is the interaction term between *Treat* and *time*, where *Treat* is the city dummy variable and *time* is the temporal dummy variable. X_{kit} is the kth control variable affecting the *ISAI* of the city i in year t, which includes financial development, sewage discharge, human resources, infrastructure, economic openness, and education levels. δ_i refers to the fixed effect of the city i. σ_t indicates the fixed effect of year t. ε_{it} is the regression error term.

3.3.2. Mechanism Analysis Model

To test the hypotheses H2a-H2c, this study followed Cheng et al. and developed mediating effect models for mechanism testing [45]. Equations (5) to (10) specify the models.

$$IC_{it} = \alpha_2 + \beta_2 Treat\_time_{it} + \sum_{k=1}^{K} c_{2k} X_{kit} + \zeta_i + \psi_t + \xi_{it} \tag{5}$$

$$LC_{it} = \alpha_3 + \beta_3 Treat\_time_{it} + \sum_{k=1}^{K} c_{3k} X_{kit} + \omega_i + \upsilon_t + \tau_{it} \tag{6}$$

$$PE_{it} = \alpha_4 + \beta_4 Treat\_time_{it} + \sum_{k=1}^{K} c_{4k} X_{kit} + \varsigma_i + \sigma_t + \rho_{it} \tag{7}$$

$$ISAI_{it} = \alpha_5 + \beta_5 Treat\_time_{it} + d_1 IC_{it} + \sum_{k=1}^{K} c_{5k} X_{kit} + \vartheta_i + \theta_t + \varpi_{it} \tag{8}$$

$$ISAI_{it} = \alpha_6 + \beta_6 Treat\_time_{it} + d_2 LC_{it} + \sum_{k=1}^{K} c_{6k} X_{kit} + \pi_i + o_t + \nu_{it} \quad (9)$$

$$ISAI_{it} = \alpha_7 + \beta_7 Treat\_time_{it} + d_3 PE_{it} + \sum_{k=1}^{K} c_{7k} X_{kit} + \mu_i + \lambda_t + \kappa_{it} \quad (10)$$

where *IC*, *LC*, and *PE* are mediating variables representing innovation capacity, labor clustering, and pollutant emissions, respectively. $\zeta, \omega, \varsigma, \vartheta, \pi$ and μ are a set of individual city-fixed-effects. $\psi, \upsilon, \sigma, \theta, o$ and λ are a set of year-fixed effects. $\xi, \tau, \rho, \varpi, \nu$ and κ are a set of error terms. The definitions of other variables are the same as in Equation (4).

The estimation procedures can be summarized as follows. First, Equation (4) was estimated. The estimation result should show a significant impact of *Treat_time* on *ISAI* to establish preliminary evidence that the ICP impacts the industrial structure upgrading in pilot cities. Second, Equations (5) to (7) were estimated to explore the impacts of *Treat_time* on the mediating variables *IC*, *LC*, and *PE*. Next, in Equations (8)–(10), the main explanatory variable *Treat_time* and the mediating variables *IC*, *LC*, and *PE* were included and estimated. If *Treat_time* remained statistically significant, it was concluded that the ICP significantly impacts *ISAI* through innovation capacity, labor clustering, and pollutant emissions.

4. Results

4.1. Baseline Regression Analysis

Using a stepwise regression approach, the baseline model Equation (4) estimation results are reported in Table 3. The rationale of applying a stepwise regression approach is to gradually add new variables while evaluating whether to keep the chosen variables after each addition until no further variables are added. This ensures that the best-specified model keeps only variables with significant effects and excludes insignificant variables.

Table 3 column (1) shows that the estimated coefficient of *Treat_time* is 0.0420 without adding any control variables and is significantly positive at the 10% level. The result suggests that the ICP plays a significant role in upgrading the industrial structure of pilot cities. When control variables, such as the financial development level of pilot cities, were gradually added, the magnitude and significance of the estimated coefficient of *Treat_time* increased, affirming that the launch of innovative city policy promotes industrial structure upgrading. In terms of economic significance, the estimation results in column (7) show that the *ISAI* of innovative pilot cities increased by 7.28% compared to non-pilot cities, ceteris paribus. Considering that China's sub-provincial cities have provincial economic management authority and are unsuitable for parallel studies with ordinary prefecture-level cities, this paper excludes sub-provincial cities from the sample. Regression estimation was performed based on the new sample with the results in column (8). After the removal of sub-provincial cities, the ICP still significantly impacted the industrial structure upgrading of the pilot cities. The overall results for *Treat_time* show that the ICP promotes industrial structure upgrading in pilot cities, with or without considering the control variables. Thus, H1 is supported.

Table 3. Baseline regression results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat_time	0.0420 *	0.0714 ***	0.0760 ***	0.0769 ***	0.0785 ***	0.0754 ***	0.0728 ***	0.0552 **	0.0579 **
	(1.75)	(3.04)	(3.25)	(3.29)	(3.35)	(3.23)	(3.11)	(2.12)	(2.43)
FL		0.3552 ***	0.3558 ***	0.3556 ***	0.3504 ***	0.3425 ***	0.3494 ***	0.3577 ***	0.3462 ***
		(14.10)	(14.16)	(14.16)	(13.85)	(13.51)	(13.58)	(13.52)	(13.42)
DL			−0.0488 ***	−0.0488 ***	−0.0492 ***	−0.0482 ***	−0.0483 ***	−0.0489 ***	−0.0509 ***
			(−4.44)	(−4.45)	(−4.49)	(−4.40)	(−4.41)	(−4.25)	(−4.65)
HE				0.0309 **	0.0298 **	0.0313 **	0.0327 **	0.0319 **	0.0324 **
				(2.35)	(2.27)	(2.38)	(2.48)	(2.34)	(2.47)
IF					0.0346	0.0386 *	0.0482 **	0.0443 *	0.0537 **
					(1.63)	(1.82)	(2.18)	(1.95)	(2.43)
OL						−0.0230 ***	−0.0225 ***	−0.0240 ***	−0.0214 ***
						(−3.86)	(−3.77)	(−3.91)	(−3.57)
EL							−0.0271	−0.0277	−0.0222
							(−1.53)	(−1.53)	(−1.25)
IRIE									0.0369 **
									(2.51)
Constant	0.9343 ***	0.6528 ***	1.0649 ***	0.8192 ***	0.6074 ***	0.8231 ***	0.8886 ***	0.9331 ***	0.9713 ***
	(54.55)	(25.11)	(11.06)	(5.77)	(3.15)	(4.11)	(4.34)	(4.43)	(4.69)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	3692	3692	3692	3692	3692	3692	3692	3497	3639
R-squared	0.3607	0.3960	0.3995	0.4005	0.4010	0.4036	0.4040	0.3971	0.4016

Notes: This table presents the estimation results of Equation (4) by using a stepwise regression approach. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Estimated t-values are in parentheses.

Pertaining to the results for control variables in column (9), it was noted that the estimated coefficient of *FL* is significantly positive across the columns, suggesting that the increased depth of the financial system contributes to the advancement of the industrial structure, typically by making the capital allocation and circulation in private sectors more cost and time efficient. The estimated coefficient of *DL* is negative and statistically significant, implying that sewage discharge is lower in cities that rely more on the tertiary industry than primary and secondary industries for development. Further, the *HE* coefficient is significantly positive, suggesting that human capital is vital to industrial structure upgrading in cities. Similarly, well-developed infrastructure, transportation, and public facilities are essential to industrial structure upgrading, as evidenced by the positive coefficient of *IF*. The estimated coefficient of *OL* is significantly negative. This result can be explained by the inflows of foreign direct investments by labor-intensive and low-tech enterprises that take advantage of China's relatively lower labor and production costs, which subsequently hamper industrial structure upgrading. In addition, the education level (*EL*) of people is insignificant in terms of affecting the industrial structure of cities generally. The *IRIE* is significantly positive, indicating that implementing the ICP in the pilot cities can effectively optimize innovation conditions, inputs, performance, and environment.

4.2. Mechanism Analysis

This study further investigates whether the ICP influences the industrial structure in pilot cities via three mechanism paths following the preceding hypotheses H2a to H2c, specifically by improving innovation capacity, rising labor aggregation, and reducing pollutant emissions of the cities. Table 4 reports the estimation results of Equations (5) to (10).

Table 4. Mechanism-analysis results.

	(1)	(2)	(3)	(4)	(5)	(6)
	IC	**ISAI**	**LC**	**ISAI**	**PE**	**ISAI**
Treat_time	1.5255 ***	0.0403 *	2.3609 ***	0.0562 **	−0.0812 **	0.0713 ***
	(14.30)	(1.68)	(16.69)	(2.30)	(−2.07)	(3.04)
IC		0.0213 ***				
		(5.66)				
LC				0.0007 **		
				(2.48)		
PE						−0.0189 *
						(−1.85)
Constant	2.4378 ***	0.8367 ***	10.1156 ***	0.8173 ***	6.4606 ***	1.0110 ***
	(2.62)	(4.10)	(8.19)	(3.96)	(18.86)	(4.70)
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Control	Y	Y	Y	Y	Y	Y
Obs.	3692	3692	3692	3692	3692	3692
R-squared	0.1617	0.4096	0.2214	0.4051	0.6677	0.4046

Notes: This table presents the estimation results of Equations (5)–(10) pertaining to the "innovation capability", "labor clustering", and "pollutant emissions" mechanisms. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Estimated t-values are in parentheses.

Regarding the "innovation capacity" mechanism, the results in column (1) indicate that the coefficient of *Treat_time* is significant at the 1% level with a coefficient value of 1.5255, suggesting that the ICP's implementation can significantly increase the innovation capacity of pilot cities. Next, the column (2) results indicate that *Treat_time* is significantly positive at the 10% level and that the coefficient of *IC* is significantly positive at the 1% level. Comparing this result with that in Table 3, the coefficient of *Treat_time* becomes weaker in magnitude and statistical significance, which points to the mediating effect of IC on the nexus between *Treat_time* and *ISAI*. Thus, the combined results in columns (1) and (2) in Table 4 reveal that the ICP promotes industrial structure upgrading by expanding pilot cities' innovation capacity. These results support H2a.

Columns (3) and (4) show the mechanism-analysis results for labor clustering. It is observed in column (3) that the core explanatory variable *Treat_time* is significantly positive at the 1% level with a coefficient value of 2.3609, suggesting that implementing the ICP fostered labor clustering. Further, the coefficient of *Treat_time* in column (4) is significantly positive at the 5% level, while its magnitude has dropped compared to that in Table 3. The overall results affirm that labor clustering is one of the mechanisms via which the ICP influenced industrial structure upgrading in pilot cities. These results thus support H2b.

Regarding the "pollution emissions" mechanism, the results in column (5) show a negative and statistically significant coefficient of *Treat_time*, which suggests that the launch of the ICP significantly cuts the pollutant emissions in pilot cities. Additionally, the coefficient of *Treat_time* in column (6) is significantly positive at the 1% level, and the coefficient of *PE* is significantly negative at the 10% level. These results, therefore, support H2c by showing that the ICP affected the industrial structure upgrading in pilot cities by reducing pollutant emissions.

4.3. Heterogeneity Analysis

4.3.1. Heterogeneity of City Scale

Agglomeration effects in large cities can improve the production factor structure and lower the marginal cost of public investment in the private sector, allowing for the production factors to be better used for the economic development vision of the cities [46]. However, when a city becomes overpopulated, it may create a problem called "urban illness", characterized by resource scarcity, excessive energy use, and environmental degradation. It is plausible that the pace of economic development and the extent of production-factor utilization differ across cities of different scales, thereby altering the promotion effect of the ICP on industrial structure upgrading. This heterogeneity effect requires further investigation. To this end, this study divided the sample into four sub-samples of small cities (below 0.5 million people), medium-sized cities (0.5–1 million people), large cities (1–3 million people), and mega cities (more than 3 million people) by following the State Council's 2014 Notice on Adjustment of City Size Classification Standard. The newly estimated regression results based on Equation (4) for each city sub-sample are presented in Table 5.

Table 5. Results of the city-scale heterogeneity test.

	(1)	**(2)**	**(3)**	**(4)**
	Small Cities	**Medium Cities**	**Large Cities**	**Mega Cities**
Treat_time	−0.0204	0.0270	0.1058 ***	−0.0938
	(−0.09)	(0.36)	(4.48)	(−1.24)
Constant	1.5536 **	1.8161 ***	1.2625 ***	−0.7952
	(2.47)	(4.39)	(4.15)	(−0.83)
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Control	Y	Y	Y	Y
Obs.	608	1299	1473	312
R-squared	0.3991	0.4014	0.4988	0.6011

Notes: This table presents the estimation results of Equation (4) for subsamples of small cities (below 0.5 million people), medium cities (0.5–1 million people), large cities (1–3 million people), and mega cities (more than 3 million people). ***, and ** indicate statistical significance at the 1%, and 5% levels, respectively. Estimated t-values are in parentheses.

This study observed that the coefficient of *Treat_time* is positive and statistically significant only in column (3), which implies that the ICP significantly improved the industrial structure in large cities. In contrast, smaller cities and mega cities do not show evident changes in their industrial structure. This result appears to support the "agglomeration effect" theory that large cities possess more significant comparative advantages in attracting, retaining, and utilizing production factors towards the achievement of the economic development vision of the cities and thus can better attain innovation-driven development and industrial structure upgrading in alignment with the ICP [47].

4.3.2. Heterogeneity of City Resources

Resource-based cities are cities where the primary industries involve natural resource extraction and processing. They do not have the same industrial structure as cities without natural resource endowments. Thus, there may be differences in the impact of the ICP on industrial structure upgrading across cities with different resource endowments. A heterogeneity analysis of city resource endowments is necessary. Using the National Sustainable Development Plan for Resource-Based Cities (2013–2020) as a guide, the sample was divided into resource-based and non-resource-based cities to explore the heterogeneity of resource endowments.

Table 6 reports the effects of the ICP on upgrading the industrial structure in non-resource-based cities versus resource-based cities. The coefficient of *Treat_time* is insignificant for resource-based cities, while the coefficient of *Treat_time* is positive and significant at the 1% level for non-resource-based cities. The result suggests that the promoting role of the ICP in the industrial structure is more salient in non-resource-based cities. This is reasonable because the cities have been poised towards the needs of tertiary industries that rely more on skills and technologies and less on natural resources.

Table 6. Results of city-resource-heterogeneity test.

	(1)	(2)
	Non-Resource-Based Cities	**Resource-Based Cities**
Treat_time	0.1071 ***	−0.0022
	(3.78)	(−0.05)
Constant	0.6901 **	1.4355 ***
	(2.41)	(4.91)
City FE	Y	Y
Year FE	Y	Y
Control	Y	Y
Obs.	2197	1495
R-squared	0.3738	0.4743

Notes: This table presents the estimation results of Equation (4) for subsamples of non-resource-based cities and resource-based cities. ***, and ** indicate statistical significance at the 1%, and 5% levels, respectively. Estimated t-values are in parentheses.

4.4. Robustness Tests

4.4.1. Parallel Trend Test

A prerequisite for applying the asymptotic DID estimation is that the parallel trend assumption must be satisfied, i.e., the difference between the treatment group and control group is constant over time before the policy implementation. In this paper, we drew on the study of Roth and used an event-study approach to test whether the study sample demonstrated a parallel trend [48]. The specified model is as follows:

$$\begin{aligned} ISAI_{it} = \; & \beta_0 + \beta_1 Treat\_time_{it}^{-4} + \beta_2 Treat\_time_{it}^{-3} \\ & + \ldots + \beta_6 Treat\_time_{it}^{1} + \sum_{k=1}^{K} \beta_k X_{kit} + l_i + \eta_t + \gamma_{it} \end{aligned} \tag{11}$$

The timeline was divided into four time periods before the ICP policy implementation and one period following the policy implementation. Then, this study assessed whether the treatment effects complied with parallel trends by averaging the treatment effects over the pre- and post-policy implementation periods, using the policy implementation period, t = 0, as the threshold. The test results are reported in Figure 3, which show that the regression coefficients of “before1” to “before4” oscillate near zero in the pre-policy implementation period and are insignificant for the ISAI of pilot cities. The “after1” coefficient exhibits an upward trend after the policy is in effect and has a confidence interval above 0, which is significantly positive. Here, this study asserts that the study’s DID estimation successfully passed the parallel trend test.

4.4.2. Placebo Test

To examine whether any other arbitrary elements contribute to the positive impact of the ICP on industrial structure upgrading, we followed the work of Zhang et al. to construct a placebo test [49]. Specifically, to examine whether the kernel density plot of the randomized *Treat_time* coefficients is centered around 0 and whether it significantly deviated from the observed values, sample cities in the treatment group were randomly sampled and regressed 1000 times. Based on 1000 randomized samples, Figure 4 demonstrates that the *Treat_time* coefficient had a normal distribution centered around 0, indicating that the data passed the placebo test, and the results are valid.

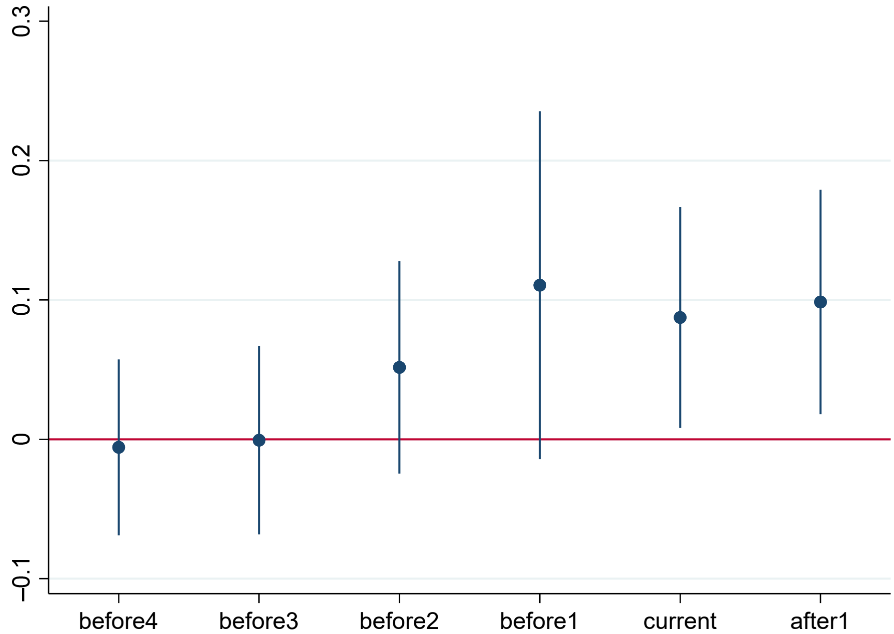

Figure 3. Parallel trend test.

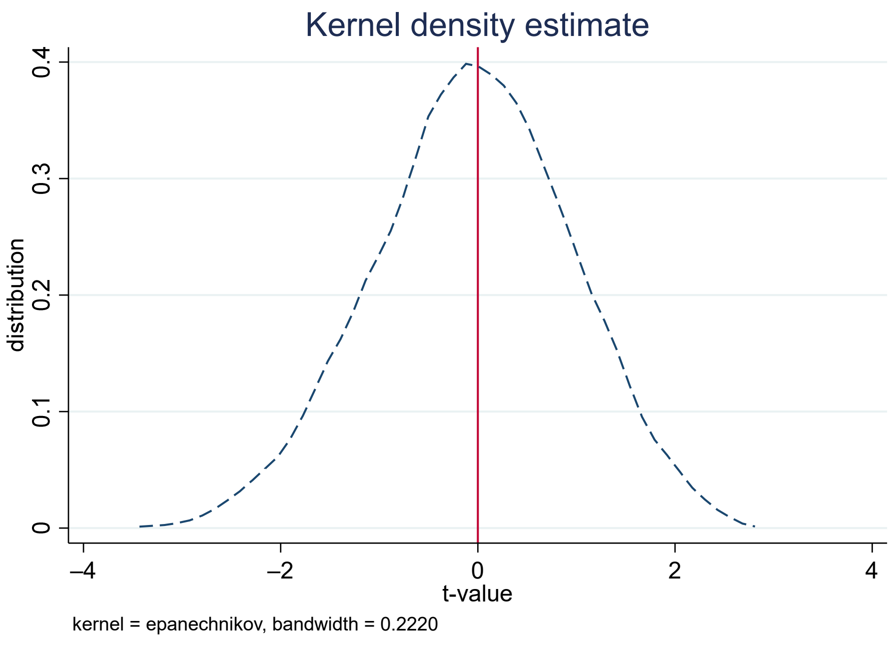

Figure 4. Placebo test.

4.4.3. Excluding the Possible Interference of Other Policies

As the study sample period 2007 to 2019 also covered the launch of "Healthy City", "New-Energy City", and "Low-Carbon City" programs in China, we controlled the influence of these policies independently by adding a dummy variable for the specified policy in Equation (4) and then regressing the model to rule out any possible interference from these programs with the results of this study. Table 7's columns (1), (2), and (3) show the results after controlling for the "Healthy City," "New-Energy City," and "Low-Carbon City" programs, respectively. Even after these policies were incorporated into the model estimations, the coefficient of *Treat_time* did not significantly change and stayed positive at the 1% level, affirming the robustness of the study results.

Table 7. Robustness test results.

	(1)	(2)	(3)	(4)	(5)
	Healthy City	**New-Energy City**	**Low-Carbon City**	**Winsorization**	**PSM-DID**
Treat_time	0.0765 ***	0.0691 ***	0.0728 ***	0.0760 ***	0.0686 ***
	(3.23)	(2.93)	(3.08)	(3.24)	(2.81)
Healthy	−0.0359				
	(−1.11)				
New_Energy		0.0326			
		(1.45)			
Low_Carbon			0.0002		
			(0.01)		
Constant	0.8808 ***	0.8970 ***	0.8885 ***	0.9263 ***	0.7322 ***
	(4.30)	(4.38)	(4.33)	(4.23)	(3.37)
City FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Control	Y	Y	Y	Y	Y
Obs.	3692	3692	3692	3692	3300
R-squared	0.4042	0.4044	0.4040	0.4033	0.4031

Notes: This table presents the robustness test results after accounting for the influences of "Healthy City" program; "New-Energy City" program; and "Low-Carbon City" program, data outliers, and sample-selection bias. The respective results are presented in columns (1) to (5). *** indicates statistical significance at the 1% level. Estimated t-values are in parentheses.

4.4.4. Excluding the Possible Interference of Outliers

To alleviate the possible influence of outliers, this study Winsorized the dataset at the top and bottom 2 percent and re-estimate Equation (4). The newly estimated results reported in column (4) of Table 7 show that the *Treat_time* coefficient remains significantly positive at the 1% level with a coefficient value of 0.0760. This shows that the study's findings are robust and that the impact of the innovation city pilot policy on industrial structure upgrading was significant.

4.4.5. PSM-DID Method

While DID can isolate the overall impact of the ICP on industrial structure upgrading, sample-selection bias is inevitable and may trigger an endogeneity concern. In this robustness test, we applied a propensity-score matching (PSM) technique to alleviate the effect of randomness on model estimations. We adopted a logit regression for Equation (12), where the control variables in Equation (4) were used as co-variates (X) explaining the binary variable of whether the city is an ICP city. The kernel density matches the weight produced by the kernel-density function. The city with the best propensity-score matching is selected as the control group to match with the treatment group. An equilibrium test affirmed no noticeable systematic difference of covariates between the control and treatment groups after matching. Then, the DID model specified by Equation (4) was re-estimated following the propensity-score matching. The estimation results are presented in Column (5) of Table 7. It was observed that the *Treat_time* coefficient is significant and close to that of the multi-period DID model, suggesting that the study results are robust.

$$P(Whether\ it\ is\ ICP\ city) = f(X_{it}) \tag{12}$$

4.4.6. Endogeneity Issue

Endogeneity arises from two sources: specifically omitted variables and reverse causality. Although the models included city fixed-effects, year fixed-effects, and a series of city-specific variables, there may still have been some unobserved and omitted factors. Additionally, while the result of the parallel trend test indicated that the trends of *ISAI* exhibited by the treatment and control groups before the ICP implementation were generally consistent, the study sample may still suffer from the self-selection bias. This is because cities with higher *ISAI* usually have more advanced industrial structures and innovation levels and may be more likely to be selected as pilot cities. To alleviate these possible endogeneity concerns, this study adopted an instrumental variable approach as an alternative for estimating our model.

GDP per capita (*pgdp*) was identified as the instrumental variable for the assumedly endogenous *Treat_time* for two reasons. First, the economic development of cities is closely related to the level of innovation in cities as it pushes the demand and supply of innovation. Fan et al. empirically found that the higher the GDP per capita of a region, the higher the regional innovation level; thus, the GDP per capita of a city can determine whether a city is selected as an innovative pilot city, which satisfies the relevance assumption of instrumental variables [50]. Second, unlike other economic development indicators, GDP per capita does not directly affect a city's industrial structure, which meets the exogeneity requirement of instrumental variables.

The estimation results of the instrumental variable approach are reported in Table 8. The first-stage estimation results show that GDP per capita (*pgdp*) highly correlates with whether a city is selected as an ICP city. The second-stage estimation results show that when the possible endogeneity associated with *Treat_time* is considered, the estimated coefficient of the instrumented *Treat_time* is significantly positive, affirming that the positive effect of the ICP on industrial structure upgrading remains intact.

Table 8. Instrumental variable estimation.

	(1) First-Stage	(2) Second-Stage
	Treat_Time	***ISAI***
pgdp	0.1412 ***	
	(11.04)	
Treat_time		0.9542 ***
		(5.42)
City FE	Y	Y
Year FE	Y	Y
Control	Y	Y
Obs.	3692	3692
R-squared	0.5856	0.2797

Notes: This table presents the two-stage estimation results of Equation (4) by using an instrument variable approach. In the first-stage estimation, GDP per capita (*pgdp*) is used as an instrument for *Treat_time*. In the second-stage estimation, the instrumented *Treat_time* from the first-stage estimation is used as an exogeneous explanatory variable in Equation (4). *** indicates statistical significance at the 1% level. Estimated t-values are in parentheses.

5. Discussion

The results in Table 3 show that the ICP has helped to upgrade the industrial structure of pilot cities in China, supporting the study's hypothesis H1. Under the mandate of the ICP, public and private organizations have worked collaboratively and proactively to transform their operation from a low-skill and low-tech base towards a high-skill and high-tech base. By focusing on the development needs of leading industries in the city, organizations have implemented industrial innovation projects, increased investment in innovation-capacity development, developed high-tech industries and modern service industries, and accelerated the process of high-tech transformation of traditional industries. During the development process, technological knowledge diffusion through the clustering and interaction of innovation factors, such as labor, is also facilitated [7,26]. All of these processes effectively stimulate industrial structure upgrading consequently.

More specifically, the mechanism-analysis results in Table 4 suggest that the positive effect of the ICP on industrial structure upgrading in pilot cities can be attributed to three main reasons: enhanced innovation capacity, higher labor clustering, and lowered pollutant emissions. Supporting Li et al.'s study results, the ICP enhances enterprises' innovation capacity in pilot cities through subsidized incentives for R&D innovation, patent renewal, and upgrading, effectively promoting enterprises' innovative outputs [10]. As a result, the scope of technology application and the efficiency of resource allocation within enterprises are enhanced, which makes enterprises the direct catalysts for the transformation and upgrading of regional industrial structures.

From the perspective of labor clustering, the ICP has attracted high-level talent resources into the pilot city through various incentive packages and facilities for highly qualified talents, strengthening the foundation of labor capacity for industrial structure upgrading. The agglomeration of the labor force will improve labor specialization in industries and form a closer coupling between regional talent and industrial structures. This coupling effect will significantly reduce labor search costs, help enterprises obtain external resources more efficiently, break through the incumbent resource constraints, improve resource-use efficiency, and promote enterprises' new product development and industrial technology innovation [22]. Furthermore, the labor force acts a carrier of knowledge that disseminates technological knowhow through knowledge spillover, labor force flow, and imitation learning, enabling the diffusion of technological innovation in industries and promoting industrial structure upgrading [31,34,35].

Further, the ICP has improved energy utilization efficiency and reduced pollutant emissions in cities, consistent with those of Gao and Yuan, Wang and Zhou, and Yang et al. [8,14,15]. However, this study demonstrated that the pollutant emission reduction is one of the most significant mechanisms driving the effect of the ICP on industrial structure upgrading. The results can be explained at two levels. At the firm level, by removing obsolete production capacity through technological transformation and advancement, firms eliminate the cost of pollutant emissions from their production costs. As a result, the improved production cost and profit efficiency encourage operational system upgrading in firms towards a high-tech and high-skill base. At the industry level, the shift towards a greener production method by firms facilitates the transformation of the industrial structure from industries with high energy consumption and low value added, to industries with low energy consumption and high value added, and from labor-intensive industries to more efficient ones.

The heterogeneity analysis results in Table 5 show that the positive effect of the ICP on industry-structure upgrading is salient only in large cities but not in smaller cities and mega cities. This result appears to complement the argument made by Wang and Zhou that larger cities with larger population bases make implementing the ICP more effective in attaining specific economic, social, and environmental targets [8,10,14]. Larger cities generally have more complete industrial conditions, a more conducive environment for innovation and entrepreneurship, and smoother policy-support channels. These make implementing the ICP more effective, magnifying the industrial agglomeration effect in large cities and subsequently upgrading the industrial structure in large cities. In contrast, the lower technology level, insufficient infrastructure, and lack of agglomeration effect in small and medium-sized cities have caused the investment in industrial structure upgrading to be less cost-efficient in such cities. Moreover, the positive effect of the ICP is not evident in megacities with a resident population of more than 3 million, possibly because environmental pollution and other "urban illnesses" brought on by population agglomeration can make the governance of urban government less effective [18]. Meanwhile, the systems for cross-regional governance and cooperation between megacities and their adjacent cities are still developing. This restricts interregional technology diffusion and resource exchange across regions and precludes the ICP from promoting industrial structure upgrading.

The results in Table 6 suggest that the positive effect of the ICP on industry-structure upgrading is significant only in non-resource-based cities. A plausible explanation is that the "resource curse" phenomenon is more prevalent in resource-based cities than in non-resource-based cities. The resource-dependent economic development model makes it more challenging for resource-based cities to upgrade their leading industries to tertiary industries. A transition in industrial structure could face strong objections from laborers and residents as it could cause employment loss, jeopardize social welfare, and halt economic development. Like Zhao et al., who show the poor efficacy of the carbon emission trading pilot policy in upgrading the industrial structure in resource-based cities [18], this study asserts that the ICP lacks effectiveness in meeting the expected goal of promoting industrial structure upgrading in resource-based cities.

6. Conclusions

Since 2008, China has rolled out a series of the ICP under a phase-in arrangement in various cities to improve urban innovation activities and innovation capacity in alignment with the country's innovation-driven development vision. Under the mandate of the ICP, each city should invest more in innovation; focus on the development of innovative resources; and foster an innovation-friendly environment, which is believed to have a more fundamental and long-term impact on the industrial structure upgrading of cities. Against this background, the present paper empirically examined the effect of the ICP on industrial structure upgrading by employing a panel dataset of 284 Chinese prefecture-level cities from 2007 to 2019.

The findings are summarized as follows: (1) the ICP greatly helps upgrade the industrial structure in pilot cities from primary industries towards secondary and tertiary industries that rely more heavily on advanced skills and technologies; (2) the positive effect of the ICP on industrial structure upgrading is more salient in large cities and non-natural resource-based cities. Large cities provide a more conducive industrial environment for implementing the ICP. In contrast, non-natural resource-based cities offer greater flexibility in resource reallocation towards labor skills and technology innovations to support the ICP's vision; (3) three mechanisms exist via which the ICP promotes industrial structure upgrading, specifically, innovation-capacity improvement, labor clustering, and pollutant emission reduction. Since the extant literature has not explicitly linked the effect of the ICP to industrial structure upgrading, the present findings contribute by shedding light on the causal influence of innovation on industrial structure upgrading and the possible heterogeneities and mechanisms of the influence.

The study results offer policy implications to regulators. As it was found that the positive effect of innovative city construction on industrial structure upgrading is insignificant in small and medium-sized cities, megacities, and resource-based cities, it is suggested that the government pays attention to the experience summarization, sharing, and promotion of pilot work and introduces the successful experience of large non-resource-based towns and cities to cities where the policy effect has not been fully realized, to enhance the industrial structure upgrading effect of innovative city construction. Learning from successful pilot cities is vital for an innovative city's continuous and in-depth development. Since the impact of innovative city policy on industrial structure upgrading is heterogeneous across cities, it is necessary to adhere to the principles of localization, city-by-city, and site-by-site; give full play to the leadership and administrative roles of local governments; strengthen the inclusiveness of policy implementation; and not adopt a one-size-fits-all approach in the process of innovative city construction.

Through mechanism analyses, the present paper finds that the ICP promotes industrial structure upgrading in Chinese cities by improving innovation capacity, boosting labor clustering, and lowering pollutant emissions. This highlights the importance of exploring multi-dimensional ways for innovative city construction to promote upgrading regional industrial structure. Specifically, the government should vigorously promote the development of urban innovation capacity and human capital, accelerate the agglomeration degree of urban innovation and economic factors, and improve the innovative city construction-assessment system. Moreover, strengthening environmental supervision can effectively stimulate the industrial structure upgrading effect of the ICP. At the national level, full coverage of environmental regulations should be implemented, enforced, and effectively supervised. At the social level, all firms, institutions, and social groups should closely manage their conduct in compliance with environmental laws and regulations.

Author Contributions: Conceptualization, W.Z. and M.Y.T.; methodology, W.Z.; software, W.Z.; validation, W.Z. and M.Y.T.; formal analysis, W.Z. and M.Y.T.; investigation, W.Z.; resources, W.Z.; data curation, W.Z.; writing—original draft preparation, W.Z.; writing—review and editing, M.Y.T.; visualization, W.Z.; supervision, M.Y.T.; project administration, W.Z. and M.Y.T.; and funding acquisition, M.Y.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Ministry of Higher Education Malaysia through the Fundamental Research Grant Scheme (FRGS) (Ref. No.: FRGS/1/2022/SS01/XMU/02/2), the Guangdong Basic and Applied Basic Research Foundation (Grant No.: 2022A1515110280), and the Xiamen University Malaysia Research Fund (Grant No.: XMUMRF/2021-C8/ISEM/0033).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The processed data and materials required to reproduce these findings cannot be shared as the data and materials form part of an ongoing study.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Freire-Gibb, L.C. Vallejo, California: A case for promoting a city region innovation system? *Int. J. Innov. Reg. Dev.* **2012**, *4*, 180–195.
2. Nemet, G.F. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. *Res. Policy* **2009**, *38*, 700–709. [CrossRef]
3. Ferm, J.; Jones, E. Beyond the post-industrial city: Valuing and planning for industry in London. *Urban Stud.* **2017**, *54*, 3380–3398. [CrossRef]
4. Van der Voort, H.; De Jong, M. The boston bio-bang: The emergence of a "Regional system of innovation". *Knowl. Technol. Policy* **2004**, *16*, 46–60. [CrossRef]
5. Esmaeilpoorarabi, N.; Yigitcanlar, T.; Kamruzzaman, M.; Guaralda, M. How can an enhanced community engagement with innovation districts be established? Evidence from Sydney, Melbourne and Brisbane. *Cities* **2020**, *96*, 102430. [CrossRef]
6. Mora, L.; Deakin, M.; Zhang, X.; Batty, M.; de Jong, M.; Santi, P.; Appio, F.P. Assembling sustainable smart city transitions: An interdisciplinary theoretical perspective. *J. Urban Technol.* **2021**, *28*, 1–27. [CrossRef]
7. Dahesh, M.B.; Tabarsa, G.; Zandieh, M.; Hamidizadeh, M. Reviewing the intellectual structure and evolution of the innovation systems approach: A social network analysis. *Technol. Soc.* **2020**, *63*, 101399. [CrossRef]
8. Gao, K.; Yuan, Y. The effect of innovation-driven development on pollution reduction: Empirical evidence from a quasi-natural experiment in China. *Technol. Forecast. Soc. Chang.* **2021**, *172*, 121047. [CrossRef]
9. Zhang, M.; Hong, Y.; Zhu, B. Does national innovative city pilot policy promote green technology progress? Evidence from China. *J. Clean. Prod.* **2022**, *363*, 132461. [CrossRef]
10. Li, L.; Li, M.; Ma, S.; Zheng, Y.; Pan, C. Does the construction of innovative cities promote urban green innovation? *J. Environ. Manag.* **2022**, *318*, 115605. [CrossRef]
11. Li, Y.; Zhang, J.; Yang, X.; Wang, W.; Wu, H.; Ran, Q.; Luo, R. The impact of innovative city construction on ecological efficiency: A quasi-natural experiment from China. *Sustain. Prod. Consum.* **2021**, *28*, 1724–1735. [CrossRef]
12. Zhang, X.; Zhang, R.; Zhao, M.; Wang, Y.; Chen, X. Policy Orientation, Technological Innovation and Energy-Carbon Performance: An Empirical Study Based on China's New Energy Demonstration Cities. *Front. Environ. Sci.* **2022**, *10*, 846742. [CrossRef]
13. Zhu, H.; Chen, Z.; Zhang, S.; Zhao, W. The role of government innovation support in the process of urban green sustainable development: A spatial difference-in-difference analysis based on China's innovative city pilot policy. *Int. J. Environ. Res. Public Health* **2022**, *19*, 7860. [CrossRef]
14. Wang, Z.; Zhou, X. Can Innovation-Driven Policy Reduce China's Carbon Emission Intensity?—A Quasi-Natural Experiment Based on the National Innovative City Pilot Policy. *Sustainability* **2023**, *15*, 4383. [CrossRef]
15. Yang, S.; Ding, D.; Sun, C. Does Innovative City Policy Improve Green Total Factor Energy Efficiency? Evidence from China. *Sustainability* **2022**, *14*, 12723. [CrossRef]
16. Zheng, J.; Shao, X.; Liu, W.; Kong, J.; Zuo, G. The impact of the pilot program on industrial structure upgrading in low-carbon cities. *J. Clean. Prod.* **2021**, *290*, 125868. [CrossRef]
17. Li, C.; Xu, J.; Zhang, L. Can emissions trading system aid industrial structure upgrading?—A quasi-natural experiment based on 249 prefecture-level cities in China. *Sustainability* **2022**, *14*, 10471. [CrossRef]
18. Zhao, Z.; Zhou, S.; Wang, S.; Ye, C.; Wu, T. The impact of carbon emissions trading pilot policy on industrial structure upgrading. *Sustainability* **2022**, *14*, 10818. [CrossRef]
19. Du, K.; Cheng, Y.; Yao, X. Environmental regulation, green technology innovation, and industrial structure upgrading: The road to the green transformation of Chinese cities. *Energy Econ.* **2021**, *98*, 105247. [CrossRef]
20. Zheng, J.-Y.; Lv, W.-G.; Shen, J.; Sun, M. Study on the Impact of the Healthy Cities Pilot Policy on Industrial Structure Upgrading: Quasi-Experimental Evidence from China. *Sustainability* **2022**, *14*, 13588. [CrossRef]

21. Costa, K.V.d. Measuring structural upgrading: Applying principal component analysis in a global value chain framework. *Nova Econ.* **2022**, *32*, 329–357. [CrossRef]
22. Zhu, B.; Zhang, M.; Zhou, Y.; Wang, P.; Sheng, J.; He, K.; Wei, Y.-M.; Xie, R. Exploring the effect of industrial structure adjustment on interprovincial green development efficiency in China: A novel integrated approach. *Energy Policy* **2019**, *134*, 110946. [CrossRef]
23. Hall, P.G. *Cities in Civilization*; Weidenfeld & Nicolson: London, UK, 1998.
24. Santos, E.G.; Garcia, R.; Araujo, V.; Mascarini, S.; Costa, A. Spatial and non-spatial proximity in university–industry collaboration: Mutual reinforcement and decreasing effects. *Reg. Sci. Policy Pract.* **2021**, *13*, 1249–1261. [CrossRef]
25. Li, Z.; Yang, S. Has the innovative city pilot policy improved the level of urban innovation? *China Political Econ.* **2021**, *4*, 56–85. [CrossRef]
26. Zhang, S.; Wang, X. Does innovative city construction improve the industry–university–research knowledge flow in urban China? *Technol. Forecast. Soc. Change* **2022**, *174*, 121200. [CrossRef]
27. Ernazarov, N. The Importance of Introducing Tax Incentives for Industrial Enterprises. *Web Sci. Int. Sci. Res. J.* **2022**, *3*, 79–84.
28. Zhao, J.; Tang, J. Industrial structure change and economic growth: A China-Russia comparison. *China Econ. Rev.* **2018**, *47*, 219–233. [CrossRef]
29. Sun, H.; Edziah, B.K.; Kporsu, A.K.; Sarkodie, S.A.; Taghizadeh-Hesary, F. Energy efficiency: The role of technological innovation and knowledge spillover. *Technol. Forecast. Soc. Chang.* **2021**, *167*, 120659. [CrossRef]
30. Chen, L.; Li, W.; Yuan, K.; Zhang, X. Can informal environmental regulation promote industrial structure upgrading? Evidence from China. *Appl. Econ.* **2022**, *54*, 2161–2180. [CrossRef]
31. Ehnts, D.H.; Höfgen, M. The job guarantee: Full employment, price stability and social progress. *Soc. Regist.* **2019**, *3*, 49–65. [CrossRef]
32. Iftikhar, M.N.; Ahmad, M.; Audretsch, D.B. The knowledge spillover theory of entrepreneurship: The developing country context. *Int. Entrep. Manag. J.* **2020**, *16*, 1327–1346. [CrossRef]
33. Hu, G.-G. Is knowledge spillover from human capital investment a catalyst for technological innovation? The curious case of fourth industrial revolution in BRICS economies. *Technol. Forecast. Soc. Chang.* **2021**, *162*, 120327. [CrossRef]
34. Tsaurai, K.; Ndou, A. Infrastructure, human capital development and economic growth in transitional countries. *Comp. Econ. Res.* **2019**, *22*, 33–52. [CrossRef]
35. Lin, K.; Zhao, H. The Impact of Green Finance on the Ecologicalization of Urban Industrial Structure—Based on GMM of Dynamic Panel System. *J. Artif. Intell. Technol.* **2022**, *2*, 123–129. [CrossRef]
36. Lim, S.S.; Updike, R.L.; Kaldjian, A.S.; Barber, R.M.; Cowling, K.; York, H.; Friedman, J.; Xu, R.; Whisnant, J.L.; Taylor, H.J. Measuring human capital: A systematic analysis of 195 countries and territories, 1990–2016. *Lancet* **2018**, *392*, 1217–1234. [CrossRef]
37. Alam, M.M.; Murad, M.W. The impacts of economic growth, trade openness and technological progress on renewable energy use in organization for economic co-operation and development countries. *Renew. Energy* **2020**, *145*, 382–390. [CrossRef]
38. Pan, X.; Ai, B.; Li, C.; Pan, X.; Yan, Y. Dynamic relationship among environmental regulation, technological innovation and energy efficiency based on large scale provincial panel data in China. *Technol. Forecast. Soc. Chang.* **2019**, *144*, 428–435. [CrossRef]
39. Saud, S.; Chen, S.; Haseeb, A. Impact of financial development and economic growth on environmental quality: An empirical analysis from Belt and Road Initiative (BRI) countries. *Environ. Sci. Pollut. Res.* **2019**, *26*, 2253–2269. [CrossRef]
40. Yi, M.; Wang, Y.; Sheng, M.; Sharp, B.; Zhang, Y. Effects of heterogeneous technological progress on haze pollution: Evidence from China. *Ecol. Econ.* **2020**, *169*, 106533. [CrossRef]
41. Bessonova, E.; Gonchar, K. How the innovation-competition link is shaped by technology distance in a high-barrier catch-up economy. *Technovation* **2019**, *86*, 15–32. [CrossRef]
42. Miao, Z.; Baležentis, T.; Tian, Z.; Shao, S.; Geng, Y.; Wu, R. Environmental performance and regulation effect of China's atmospheric pollutant emissions: Evidence from "three regions and ten urban agglomerations". *Environ. Resour. Econ.* **2019**, *74*, 211–242. [CrossRef]
43. Fan, W.; Hao, Y. An empirical research on the relationship amongst renewable energy consumption, economic growth and foreign direct investment in China. *Renew. Energy* **2020**, *146*, 598–609. [CrossRef]
44. Strezhnev, A. Semiparametric weighting estimators for multi-period differencein-differences designs. In Proceedings of the Annual Conference of the American Political Science Association, Boston, MA, USA, 30 August–2 September 2018.
45. Cheng, J.; Yi, J.; Dai, S.; Xiong, Y. Can low-carbon city construction facilitate green growth? Evidence from China's pilot low-carbon city initiative. *J. Clean. Prod.* **2019**, *231*, 1158–1170. [CrossRef]
46. Rosenthal, S.S.; Strange, W.C. How close is close? The spatial reach of agglomeration economies. *J. Econ. Perspect.* **2020**, *34*, 27–49. [CrossRef]
47. Yang, N.; Liu, Q.; Chen, Y. Does industrial agglomeration promote regional innovation convergence in China? Evidence from high-tech industries. *IEEE Trans. Eng. Manag.* **2021**, *70*, 1416–1429. [CrossRef]
48. Roth, J. Pretest with caution: Event-study estimates after testing for parallel trends. *Am. Econ. Rev. Insights* **2022**, *4*, 305–322. [CrossRef]

49. Zhang, Z.; Duan, H.; Shan, S.; Liu, Q.; Geng, W. The impact of green credit on the green innovation level of heavy-polluting enterprises—Evidence from China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 650. [CrossRef]
50. Fan, F.; Lian, H.; Wang, S. Can regional collaborative innovation improve innovation efficiency? An empirical study of Chinese cities. *Growth Chang.* **2020**, *51*, 440–463. [CrossRef]