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*Research article*

# The positive effects of the higher education expansion policy on urban innovation in China

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**Abstract:** Higher education not only enhances people's well-being, but also plays an important role in the in-depth implementation of the innovation-driven development strategy. In this paper, we use Chinese urban data for 1995–2020, utilizing the higher education expansion policy implemented in China in 1999 as an external shock. Using Double/Debiased Machine Learning (DML), we examine the impact of the aforementioned policy on urban innovation and its mechanisms. The results show that: (1) The higher education expansion policy significantly promotes urban innovation; (2) the policy promotes human capital expansion and strengthens government financial support, thereby significantly fostering urban innovation; (3) the impact of the policy varies across cities with different geographic locations, population densities and levels of marketization. Therefore, the findings of this paper provide empirical evidence that higher education expansion policy stimulates urban innovation. It also offers useful insights for China's transition from "Made in China" to "Created in China" during its high-quality development phase.

**Keywords:** higher education expansion; urban innovation; Double/Debiased Machine Learning models
**Mathematics Subject Classification:** 62P20, 68T07

# 1. Introduction

## 1.1. Background

Innovation plays a pivotal role in propelling the transformation of China's economic development [1,2]. Therefore, the Chinese government is actively refining its top-level innovation framework, while guiding the transition of its economic model from one driven by factors to an innovation-driven one. With cities acting as innovative hubs, their progress in innovation has become a crucial cornerstone for the advancement of a national innovation framework. However, the "2023 Global City Innovation Ranking" reveals that only two Chinese cities, Beijing and Shanghai, are among the top 50 innovative cities. Fostering the vitality of urban innovation, exploring its potential and elevating the level of urban innovation across cities represent real challenges in the development of China's innovation system.

It is worth noting that innovation not only results from market choice, but also from government promotion. In this context, education reform policy is an important instrument through which government supports innovation. In particular, the higher education expansion policy, implemented in China in 1999, has fundamentally changed the scale and proportion of high-level talents in China, profoundly impacting innovation. In this paper, we aim to explore the following pivotal yet unanswered questions: Does the higher education expansion policy help promote urban innovation? What mechanisms underlie its effects on urban innovation? Does its impact on innovation vary across cities with different geographic locations, population densities and degrees of marketization?

The research in this paper faces two major challenges in identifying the causal relationship between higher education expansion policies and urban innovation. The first challenge lies in the endogeneity problem, a common issue addressed in the existing literature [3–5]. This problem relates to the existence of unobservable factors that affect both higher education expansion policies and levels of urban innovation. In addition, the non-random selection of cities affected by higher education expansion policies, paired with variations in natural resources, geographic locations and levels of economic development among cities, may produce estimation biases in the relationship between higher education expansion policies and urban innovation when using ordinary least squares regression. To solve this problem, we employ the higher education expansion policy implemented in 1999 as a quasi-natural experiment. We apply the Double/Debiased Machine Learning (DML) model to study the impact of higher education expansion policy on urban innovation, thus mitigating the negative impact of unobserved variables on empirical findings. The second challenge involves analyzing the impact mechanism, specifically examining how the higher education expansion policy influences the level of urban innovation. There are few existing studies on the impact mechanism of higher education expansion policies on urban innovation. Basing itself on the challenges of "lack of people" and "lack of money" that may be encountered in urban innovation, we explain the "human capital expansion mechanism" and "financial support mechanism" of the higher education expansion policy on urban innovation through two paths: Human capital and financial support. We use the mediating variable method for empirical verification.

Upon addressing the two aforementioned challenges, we found that the higher education expansion policy has indeed promoted urban innovation in China. After a series of robustness tests, the promotion effect of higher education expansion policy on urban innovation in China remains significant. Further analysis shows that the higher education expansion policy promotes human capital expansion and strengthens government financial support, consequently significantly enhancing urban innovation. These results provide empirical evidence that the higher education expansion policy stimulates urban innovation, and furthermore, provides useful insight into China's transition from "Made in China" to "Created in China" in urban development.

### *1.2. Related literature*

There are two major strands of literature related to the subject of this paper. The first focuses on the influencing factors of urban innovation. Scholars primarily examine these factors in terms of innovation, infrastructure and policy formulation. Concerning innovation factors, human capital and financial resources serve as important guarantees for improving urban innovation capacity. Human capital, providing specialized skills for innovation, serves as the basis for gaining competitive advantages and enhancing the level of urban innovation [6–8]. Additionally, the development of digital finance can offer substantial capital support for innovation, representing a financial innovation mode that also bolsters urban innovation [9]. From an infrastructure perspective, perfect public facilities, including transportation, health, communication services, play an important role in driving urban innovation development. Research has demonstrated the pivotal role of transportation infrastructure such as high-speed rail [10,11], healthcare infrastructure [12] and Internet infrastructure, particularly broadband, in promoting urban innovation [13–15]. Finally, in terms of policy formulation, relevant policies formulated by the government can guide urban innovation as well as provide financial support for it. Domestic and international scholars have explored the impact of government-developed policies on the advancement of urban innovation, considering aspects such as the development of smart cities [16,17], innovative urban construction [18], the establishment of national innovation demonstration zones [19] and pilot initiatives for low-carbon cities [20–22]. Overall, although research perspectives on enhancing urban innovation have diversified, there is still a dearth in literature on the mechanisms and impacts of higher education policy reforms, an important contributing factor.

The second strand of literature centers on assessing the policy implications of expanding higher education. The higher education expansion policy is a common and vital tool used by governments to foster economic and social progress while improving residents' well-being. For example, Che and Zhang [23] used a generalized difference-in-differences model to assess the impact of the higher education expansion policy in China on firms' productivity. Their findings suggest a significant increase in total factor productivity among firms in human capital-intensive industries following the implementation of the policy. Similarly, using a difference-in-differences approach, Wang et al. [24] explored the impact of the policy on regional crime rates, finding a significant reduction in crime rates attributed to the higher education expansion policy. These studies confirm the positive impact of the higher education expansion policy on China's economic development and residents' quality of life.

Furthermore, scholars have explored the impact of higher education expansion policies on various areas, including returns to education [25,26], educational opportunities [27,28], entrepreneurial performance [29] and household savings [30]. It is worth noting that although some of the literature has confirmed the impact of higher education expansion policies on firm innovation [31,32], two shortcomings persist. On the one hand, existing research predominantly assesses the impact of higher education expansion policies on innovation using double-difference models. However, the application of this model is constrained by limitations, including the demanding requirements of the parallel trend test on sample data, and the synthetic control method's dependence on constructing a virtual control group that conforms to the parallel trend, with the condition that the treated group does not exhibit any "extreme value" characteristics. On the other hand, the existing literature lacks a comprehensive depiction of the mechanism through which higher education expansion policy impacts innovation, specifically regional innovation.

Compared to the existing literature, our research innovation manifests in three dimensions. First, the research perspective, centered on the unique lens of higher education expansion, delves into the endogenous dynamics of enhancing the level of urban innovation. Diverging from existing literature that centers on innovation factors, infrastructure and policy-making, we first explore the exogenous occurrence of the higher education expansion policy, thereby enriching the study of influencing factors in urban innovation. Moreover, our focus on the city level better reflects the implementation effects of government policies. Our findings can help prompt the formulation of targeted and scientific policies to promote urban innovation.

Second, in terms of the research methodology, a DML model was developed, which alleviates the issue of endogeneity. Previous assessments on the impacts of higher education expansion policy have primarily adopted the double difference model, yet due to data limitations and the need for a reasonable model setting, they commonly encountered endogeneity problems. Thus, the DML model adopted in this paper effectively mitigates the bias in estimation results caused by endogeneity issues, thereby offering fresh empirical insights and data perspectives for further related research.

Third, the research content reveals the influencing mechanism and impact of higher education expansion policy on urban innovation. Existing research on the policy effect of higher education expansion policy mostly focuses on the enterprise level, lacking comprehensive investigation at the city level. Through theoretical analysis, this paper delineates the role and impact mechanism of higher education expansion policy on urban innovation, emphasizing the roles of human capital and financial support. Furthermore, it uses microdata and a mediation effect model for validation purposes.

Of course, there are some research flaws and limitations in this paper. On the one hand, the DML model has high data requirements, and we are limited by data availability and excludes the samples with serious missing data, which may have an impact on the model regression [33–35]. On the other hand, the mechanism of the impact of higher education expansion policy on urban innovation includes but is not limited to human capital and financial support, which can be further supplemented and improved in the future.

The next section of the paper is structured as follows: Section 2 introduces the background of the development and implementation of the higher education expansion policy and outlines the research hypotheses of this paper; Section 3 explains the DML model, the data sources and the variables; Section 4 presents the outcomes of the baseline regressions, the robustness test, the examination of the transmission mechanism and the test of heterogeneity; and finally, Section 5 summarizes our conclusions and proposes targeted policy recommendations.

## 2. Pilot policy and research hypotheses

### *2.1. Pilot policy*

The causal relationship between higher education expansion policies and urban innovation necessitates a nuanced understanding of the institutional context surrounding the implementation of these policies. Since the Chinese government reinstated the college entrance examination system in

1977, colleges and universities have consistently trained numerous cohorts of scientific researchers and technicians, thereby laying the foundation for China's rapid economic development during the period of reform and opening up. However, in the years following the restoration of the college entrance examination system, the enrollment of colleges and universities increased slowly, with some years even witnessing a decline. Statistics show that by 1998, the country hosted 1022 institutions of higher education, enrolling a total of 6,429,900 students, corresponding to a gross enrollment rate of 9.8%. This rate was far lower than the average level observed in developed countries and fell short of the 15% gross enrollment rate recommended for the widespread accessibility of higher education. The limited scale of higher education enrollment emerged as a constraint hindering China's economic development.

Furthermore, during the late 1990s, the Asian financial crisis and the restructuring of state-owned enterprises placed significant pressure on China's economy, leading to a reduction in domestic demand and a slowdown in foreign exports. The challenges underscored the urgent need for the state to introduce appropriate policies aimed at stimulating consumption and stabilizing economic growth. In December 1998, the Ministry of Education put forward the "Revitalization of Education for the 21st Century Action Plan", which was approved for implementation in January 1999 by the State Council. This marked the initiation of the expansion of colleges and universities. The objective behind the expansion of enrollment in institutions of higher learning was intended to ease employment pressures and boost short-term consumption growth. In the long term, the goal was to strategically foster the country's development through science and education, ultimately enhancing the country's capacity for innovation.

The Action Plan for Revitalizing Education for the 21st Century covered many facets of education, including the "Cross-Century Quality Education Project" aimed at improving the nation's educational standards, the "Project for High-level Creative Talents" strengthening scientific research in universities, the "211 Project" aimed at enhancing the knowledge and innovation capacity of universities and the "Project for High-tech Industrialization of Universities" to promote the development of national high-tech industries. Specifically, the "211 Project" focused on improving the knowledge and innovation capabilities of universities and colleges, and the "High-tech Industrialization Project of Universities and Colleges" was designed to promote the development of national high-tech industry. The latter was specifically related to the expansion policy of higher education.

Of significance to the higher education expansion policy, the plan sought to reach an 11% enrollment rate in higher education by 2000 and a 15% rate by 2012. This paper charts the enrollment trend in China's general higher education institutions from 1985 to 2020, proving an initial observation of the policy's impact. As shown in Figure 1, before the implementation of the higher education expansion policy, the average enrollment in China's higher education institutions from 1985 to 1998 was merely 774,800, with an average growth rate of only 4.8%. Moreover, the enrollment quotas were reduced in years such as 1986, 1989 and 1994. The enrollment trend in 1999 approached 11%, accompanied by an average enrollment growth rate of only 4.8%. In 1999, when the higher education expansion policy was implemented, higher education enrollment surged to 1,596,800, marking a substantial expansion rate of 47% compared to the previous year. Subsequently, enrollment continued to maintain a solid growth rate before stabilizing at a lower growth rate. For example, the average enrollment growth rate for general higher education institutions increased to 19.5% between 1999 and 2008, before declining to 4% between 2009 and 2020.

At the municipal level, the higher education expansion policy was supposed to stimulate urban innovation by fostering the expansion of human capital and increasing financial support. Concerning the expansion of human capital, the higher education expansion policy increased the talent pool within society as well as the number of undergraduate graduates in the cities where the universities were located. The proportion of undergraduate graduates in local cities also rose, which ensured a steady supply of talent for urban innovation. Regarding financial support, the higher education expansion policy was designed to provide increased investment in education. This commitment was reflected in the higher growth of education expenditure compared to the growth in fiscal revenue. It also resulted in an increase in per capita funding for students and teachers, as well as other public funds.

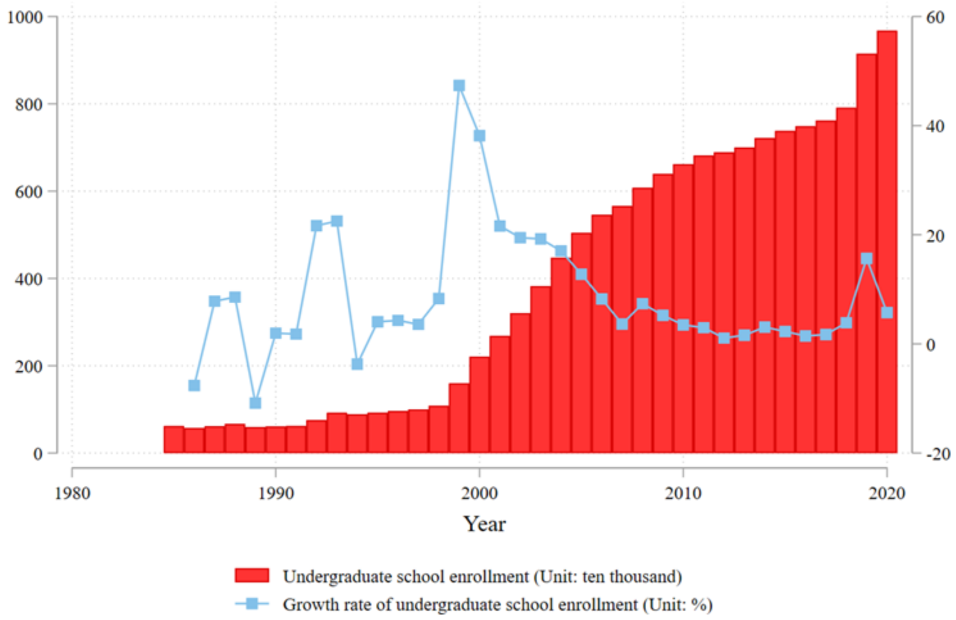


**Figure 1.** Trend of enrollment in China's general institutions of higher education.

### *2.2. Research hypotheses*

The higher education expansion policy, a comprehensive initiative implemented by China to drive educational reform and development, improving the nation's overall quality and innovation capacity, is posited to have fostered urban innovation through the factor agglomeration effect.

On the one hand, since the implementation of the policy, an influx of talented people came into the city and formed new social networks. The human capital agglomeration effect formed by the policy has likely accelerated the flow of information between enterprises and universities within the city and promoted innovative activities. In addition, it may have also contributed to the formation of innovation ecosystems, facilitating inter-industry collaboration in innovation [36–38]. On the other hand, the implementation of the policy will have likely promoted the concentration of financial capital, thus alleviating financial constraints faced by innovative entities. The presence of information asymmetry between investors and these entities may have led to financing limitations, making it difficult to carry out innovative activities [39–41]. The implementation of the policy was expected to reduce the degree of information asymmetry, expanding the channels through which innovators obtained funds, reducing the cost associated with obtaining funds and helping the development of innovative activities. Accordingly, this paper puts forward the following hypothesis:

**Hypothesis 1: Tertiary education expansion policies stimulate urban innovation activities.**

Higher education expansion policies can facilitate the expansion of human capital, in turn promoting urban innovation. Human capital is the catalyst for technological innovation, with a high level of human capital being pivotal to enhancing overall innovation capacity [42–44]. Theoretically, the higher education expansion policy bolsters the quantity and quality of human capital, reducing the costs associated with human capital matching and thus elevating the level of urban innovation.

First, the higher education expansion policy has increased the pool of urban human capital in China. Research shows that university graduates tend to settle in the city where their university is located after graduation [45]. Following the implementation of the higher education expansion policy, there has been an upsurge in the number of university graduates choosing to remain in the university's city, thus alleviating the shortage of high-end talent in the market. Moreover, increases in the volume of human capital are usually likely to foster a competitive effect, leading to improved innovation efficiency and contributing to the development of urban innovation.

Second, the higher education expansion policy has improved the caliber of urban human capital. On the one hand, this policy has contributed to the training of a great number of high-level professionals with specialized knowledge and skills, knowledge integration skills and innovative abilities. On the other hand, the cities affected by the policy experienced a pronounced demand for high-end human capital, effectively transforming into hubs for the concentration of higher education talents. The improvement in the quality of human capital attracted additional resource elements, leading to the optimization of resource allocation for innovation, and consequently having a positive impact on urban innovation.

Finally, the higher education expansion policy has reduced the costs associated with human capital matching. This agglomeration of human capital driven by this policy prompted the rapid dissemination of knowledge across industries and cities, thus significantly reducing the search and matching costs for both skilled professionals and enterprises. Facilitating the alignment between human capital and businesses enables the better introduction, assimilation and application of cutting-edge technologies [46], ultimately improving urban innovation performance. In conclusion, higher education expansion policies can promote urban innovation through human capital expansion. Accordingly, this paper proposes the following hypothesis:

**Hypothesis 2: Tertiary education expansion policies promote urban innovation through the expansion of human capital.**

Higher education expansion policies can increase financial support and thus promote urban innovation. Financial support is an important governmental measure to support urban innovation, which was reflected in the provision of funds to alleviate the persistent challenge of insufficient funds faced by innovators [47,48]. Theoretically, the higher education expansion policy led to an increase in funding for education, science and technology, which has improved individuals' willingness and ability to innovate, thus spurring advancements in the level of urban innovation.

On the one hand, the higher education expansion policy invigorated the drive to innovate because of the enhanced financial support. Innovation, characterized by substantial investments, lengthy cycles and high risk, often encounters hesitancy among most universities and enterprises to engage in creative pursuits [49]. After the implementation of the higher education expansion policy, the government extended financial assistance, leading to a gradual increase in per capita educational expenses and teachers' salaries. The establishment of a special fund addressed the problems related to teacher housing, which greatly stimulated students' and teachers' motivation to innovate. Furthermore, the policy has since supported the development of school-run enterprises, accompanied by the implementation of tax incentives. It has reduced the risk and financing constraints of associated with the innovative pursuits of school-run enterprises, strengthening the incentives for these entities to engage in innovation.

On the other hand, the higher education expansion policy improved the innovation capacity of innovators through increased financial support. Its implementation facilitated increased capital expenditures for the renovation of university teaching infrastructure, providing good teaching and research conditions and ultimately amplifying the innovation capabilities of universities. Moreover, the policy encouraged universities to transfer technology to enterprises, promoting a closer integration between universities and enterprises in technological innovation. This collaborative approach broadened the pathways for enterprises to obtain technology while reducing costs, thus enhancing the innovation capacity of these enterprises. In addition, the implementation of the policy attracted social capital to invest in innovation, providing direct financial support for the innovative pursuits of enterprises and educational institutions. This influx of capital subsequently improved the technological level and innovation capacity of the whole market. In essence, the higher education expansion policy enhanced the innovation willingness and capabilities of enterprises and universities through increased financial support, which in turn promoted urban innovation. Accordingly, we put forward the following hypothesis:

**Hypothesis 3: Higher education expansion policies promote urban innovation through greater financial support.**

## 3. Methodology

### *3.1. Double/Debiased Machine Learning (DML) model*

Drawing on the study by Chernozhukov et al. [50], we employ the linear DML model, as outlined in formulas (1) to (8), where $i$ represents city, $t$ denotes the year, $Y_{it}$ signifies the explanatory variable, which corresponds to urban innovation, and $Event_{it}$ represents the disposition variable, denoting the higher education policy variable. Notably, the cities that experienced the greater impact after the implementation of the policy are assigned a value of 1, while the others are denoted as 0. $X_{it}$ is the set of control variables, while $U_{it}$ is the error term, characterized by a conditional expectation as shown in formulas (1) and (2).

$$Y_{it+1} = \theta_0 Event_{it} + g(X_{it}) + U_{it}. \tag{1}$$

$$E(U_{it} | Event_{it}, X_{it}) = 0. \tag{2}$$

Formula (3) calculates the estimated value $\hat{\theta}_0$ of the coefficient $\theta_0$, which represents the causal policy effect, given a sample size of $n$. Formula (4) computes the estimation bias, where

$$a = (\frac{1}{n} \sum\nolimits_{i \in I, t \in T} {Event_{it}}^2)^{-1} \frac{1}{\sqrt{n}} \sum\nolimits_{i \in I, t \in T} Event_{it} U_{it}$$

follows a normal distribution with a mean of 0, and

$$b = (\tfrac{1}{n} \textstyle\sum_{i \in I, t \in T} {Event_{it}}^2)^{-1} \tfrac{1}{\sqrt{n}} \textstyle\sum_{i \in I, t \in T} Event_{it} [g(X_{it}) - \hat{g}(X_{it})].$$

DML uses machine learning and regularization algorithms to estimate $\hat{g}(X_{it})$, yet this approach unavoidably introduces what is known as 'regular bias.' Although it can constrain the variance of the estimator, it also leads to unbiasedness, as evidenced by a slower convergence speed from $\hat{g}(X_{it})$ to $g(X_{it})$ when $n^{-\varphi_g} > n^{-1/2}$. Therefore, as $n$ approaches infinity, $b$ also does so, and $\hat{\theta}_0$ becomes difficult converging to $\theta_0$.

$$\hat{\theta}_0 = (\frac{1}{n}\sum_{i\in I,t\in T} Event_{it}{}^2)^{-1}\frac{1}{n}\sum_{i\in I,t\in T} Event_{it}[Y_{it+1} - \hat{g}(X_{it})]. \tag{3}$$

$$\sqrt{n}(\hat{\theta}_0 - \theta_0) = \left(\frac{1}{n}\sum_{i\in I,t\in T} Event_{it}{}^2\right)^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I,t\in T} Event_{it}U_{it}$$

$$+(\frac{1}{n}\sum_{i\in I,t\in T} Event_{it}{}^2)^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I,t\in T} Event_{it}[g(X_{it}) - \hat{g}(X_{it})]. \tag{4}$$

To accelerate the convergence of $\hat{\theta}_0$ to $\theta_0$, formulas (5) and (6) establish an auxiliary regression, whereby the treatment coefficient estimator $\hat{\theta}_0$ remains unbiased in small samples. Here, $m(X_{it})$ represents the regression function of the treatment with respect to controlling variables, and $\hat{m}(X_{it})$ is its estimator calculated through machine learning. $V_{it}$ is the error term, with a conditional expectation of 0, as shown in formula (6).

$$Event_{it} = m(X_{it}) + V_{it}. \tag{5}$$

$$E(V_{it}|X_{it}) = 0. \tag{6}$$

The specific procedure of DML is as follows: First, a machine learning algorithm is utilized to estimate auxiliary regression $\hat{m}(X_{it})$. Second, the error term estimator must be obtained:

$$\hat{V}_{it} = Event_{it} - \hat{m}(X_{it}).$$

Third, a machine learning algorithm is employed to estimate $\hat{g}(X_{it})$, and the main regression form must be changed to

$$Y_{it+1} - \hat{g}(X_{it}) = \theta_0 Event_{it} + U_{it}.$$

Finally, $\hat{V}_{it}$ should be considered as the instrumental variable of $Event_{it}$ to calculate the regression and get the unbiased estimator $\check{\theta}_0$, as shown in formulas (7) and (8), where $(E(V_{it}^2))^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I,t\in T} V_{it}U_{it}$ follows a normal distribution with a mean of 0.

$$\check{\theta}_0 = (\frac{1}{n}\sum_{i\in I,t\in T} \hat{V}_{it}Event_{it})^{-1}\frac{1}{n}\sum_{i\in I,t\in T} \hat{V}_{it}[Y_{it+1} - \hat{g}(X_{it})]. \tag{7}$$

$$\sqrt{n}(\check{\theta}_0 - \theta_0) = \left(E(V_{it}^2)\right)^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I,t\in T} V_{it}U_{it}$$

$$+(E(V_{it}^2))^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I,t\in T}[m(X_{it}) - \hat{m}(X_{it})][g(X_{it}) - \hat{g}(X_{it})]. \tag{8}$$

Since machine learning estimates are used twice, the convergence calculating speed of $(E(V_{it}^2))^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I,t\in T}[m(X_{it}) - \hat{m}(X_{it})][g(X_{it}) - \hat{g}(X_{it})]$ depends on the convergences of $\hat{m}(X_{it})$

to $m(X_{it})$ and $\hat{g}(X_{it})$ to $g(X_{it})$, equaling $n^{-(\varphi_g+\varphi_m)}$. Compared with formula (4), $\sqrt{n}(\check{\theta}_0-\theta_0)$ converges to 0 faster. Thus, DML can quickly obtain an unbiased estimator for the coefficient.

In this paper, dual/biased machine learning (DML) was chosen for two advantages: On the one hand, it allows the use of nonparametric models, which allows greater use of complex data; on the other hand, it helps to mitigate endogeneity-induced bias and improve the accuracy of estimation results.

### *3.2. Variable selection and definitions*

#### 3.2.1. Explained variable: urban innovation (Patent)

The explanatory variable in this paper is the level of urban innovation, measured in terms of patents. Drawing on Liao et al. [51], the logarithm of the number of patents granted in prefecture-level cities serves as a reliable proxy for urban innovation. Although most existing studies use an innovation index to measure urban innovation [52,53], this index does not capture the intricacies of innovation quality. In contrast, the use of patents offers several advantages. First, patents enable the visualization of the invention of tangible and intangible assets, effectively reflecting the level of innovation output. Second, the process of patent authorization entails application, acceptance, preliminary examination and publication, thus offering a better reflection of the quality of urban innovation. Finally, patent data contains comprehensive information and is readily accessible.

#### 3.2.2. Explanatory variable: higher education expansion policy (Policy)

In this paper, we examine the effects of higher education expansion policies, primarily for cities with undergraduate institutions in China. The temporal marker chosen for this analysis is 1999, and the possession of undergraduate colleges and universities serves as the primary criterion. If a city had one or more undergraduate colleges and universities before the implementation of the policy in 1999, “Policy” is set to 1; conversely, it is set to 0. The selection of undergraduate colleges and universities as the defining criterion is driven by key considerations. First, these institutions represent the microscopic subject influenced by the policy of expansion of higher education, given that it affected their enrollment. Second, the presence or absence of undergraduate colleges reflects the comprehensiveness of a city’s higher education system, with cities possessing such institutions being more profoundly affected by the higher education expansion policy.

#### 3.2.3. Control variables

Building upon the work of Tian et al. [54], we further control for key variables that may affect urban innovation. These include the natural population growth rate (Growth) and population density (Density) at the social level, and the average wage (Wage), foreign direct investment (FDI), the share of secondary output in gross domestic product (GDP) and per capita GDP (PGDP) at the economic level. The specific definitions for all variables are shown in Table 1.

**Table 1.** Definition of all variables.

| Category | Variables | Abbreviation | Definition |
|---|---|---|---|
| Explained variable | Urban innovation | *Patent* | Ln (total patents granted+1) |
| Explanatory variable | Higher Education Expansion Policy | *Policy* | see above |
| Control variables | population growth rate | *Growth* | Natural population growth rate |
| | population density | *Density* | Ln (number of people per unit area+1) |
| | average wage | *Wage* | Ln (average wage of employees+1) |
| | overseas foreign direct investment (OFDI) | *FDI* | Ln (actual foreign investment+1) |
| | Share of secondary output in total output | *GDP2* | Tertiary output/GDP |
| | GDP per capita | *PGDP* | Ln (GDP per capita+1) |

### 3.2.4. Data processing and descriptive statistics

Considering data availability and completeness, we exclude city samples with significant missing data. An empirical study was conducted using a balanced panel dataset comprising 183 cities in China: 78 cities represent the experimental group, with 105 cities forming the control group. Data for the control variables were sourced from the city statistical yearbooks from past years, while the city innovation data were obtained from the State Intellectual Property Office. Recognizing the proposal of the national development strategy through science and education in 1995 and the potential impact of the global pandemic in 2020 on urban innovation, the study's sample period spans from 1995 to 2020.

Table 2 presents the descriptive statistics for the primary variables, including the mean, standard deviation, as well as the minimum and maximum values of the variables. The results demonstrate that during 1995–2020, the average urban innovation value stands at 5.768, with the minimum and maximum values recorded at 0.288 and 11.997, respectively. This variation indicates that there is considerable disparity in the emphasis placed on innovation and innovation output across different cities. The mean value for the policy variable is 0.361, signifying that the higher education expansion policy affected 36% of the cities. Additional descriptive statistics for the control variables are shown in Table 2. Furthermore, the correlations between the main variables are shown in Figure 2, which reveals that the main variables are significantly correlated at the 1% level.

**Table 2.** Descriptive statistics.

| Variables | N | Mean | SD | Min | Max. |
|---|---|---|---|---|---|
| *Patent* | 4,758 | 5.768 | 2.090 | 0.288 | 11.997 |
| *Policy* | 4,758 | 0.361 | 0.480 | 0.000 | 1.000 |
| *Growth* | 4,758 | 5.582 | 6.712 | -46.840 | 79.821 |
| *Density* | 4,758 | 5.774 | 0.899 | 1.548 | 9.040 |
| *Wage* | 4,758 | 9.930 | 0.947 | 6.918 | 12.128 |
| *FDI* | 4,758 | 8.831 | 2.576 | 1.099 | 32.134 |
| *GDP2* | 4,758 | 0.456 | 0.130 | 0.113 | 1.290 |
| *PGDP* | 4,758 | 9.738 | 1.050 | 3.875 | 12.101 |

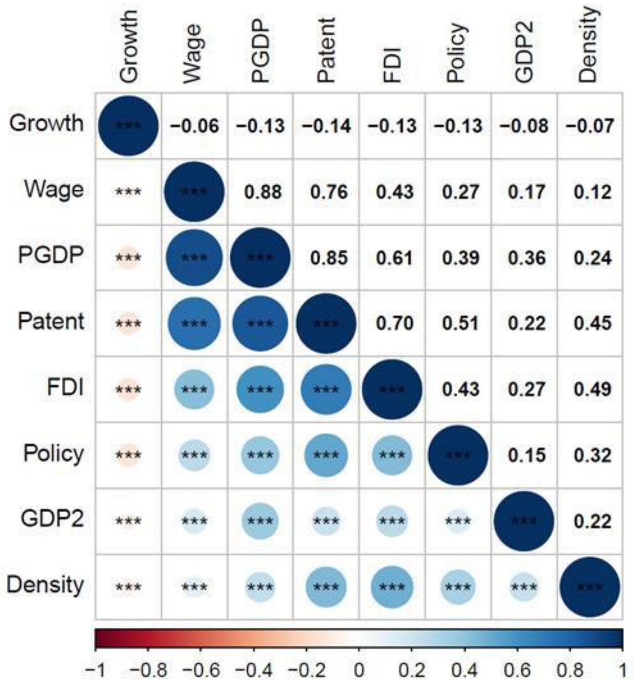


**Figure 2.** Correlation analysis diagram.

## 4. Empirical analysis

### *4.1. Casual effect estimation*

In this paper, the DML model assesses the policy effect of higher education expansion policy on urban innovation. The test set and training set samples are split at a ratio of 1:4. The random forest algorithm is adopted to predict and address both the main and auxiliary regression. The results of the benchmark regression are shown in Table 3.

As observed in column (1) of Table 3, the regression coefficient of the higher education expansion policy on urban innovation is positive and significant at the 1% level, suggesting the effective promotion of urban innovation by the policy. The findings of this paper are similar to those of Kong et al. [31], Yue [32] and others, which confirm that higher education expansion policies promote innovation, with the difference that this paper demonstrates the innovation incentive effect of higher education expansion policies at the city level. Columns (2)–(4) of Table 3 indicate the regression results using the number of invention patents granted (Patent 1), the number of utility model patents granted (Patent 2) and the number of design patents granted (Patent 3) as the proxy variables for urban innovation, respectively. The findings demonstrate consistent promotion of urban innovation by the higher education expansion policy at the 1% significance level. Notably, the policy exhibits the most significant promotion of urban innovation when considering the number of invention patents granted as a proxy variable, indicating that the higher education expansion policy not only improved the quantity of urban innovation, but also elevated the quality of urban innovation.

The possible reason for this finding is that compared with utility model and utility patents, invention patents are more technically complex and require sustained financial investment as well as substantial human capital. The implementation of the higher education expansion policy effectively catered to the requirements for R&D investments and human capital necessary for securing invention patents. In addition, since the policy was initiated, the government has paid more attention to the invention patents that can bring competitive advantages to cities, prompting universities and enterprises and other innovators, to prioritize the research and development activities focused on invention patents in alignment with government objectives.

**Table 3.** Baseline regression results.

| | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| | *Patent* | *Patent 1* | *Patent 2* | *Patent 3* |
| ***Policy*** | 0.593*** | 0.689*** | 0.591*** | 0.452*** |
| | (10.22) | (9.19) | (10.64) | (5.72) |
| **Constant** | -0.003 | 0.004 | -0.005 | 0.006 |
| | (-0.44) | (0.48) | (-0.64) | (0.53) |
| **Observations** | 4,758 | 4,758 | 4,758 | 4,758 |
| **Controls** | YES | YES | YES | YES |
| **City FE** | YES | YES | YES | YES |
| **Year FE** | YES | YES | YES | YES |

Note: The robust z-statistics are put into parentheses. ***, ** and * represent the significance level of coefficients at 1%, 5% and 10%, respectively.

### *4.2. Robustness and endogeneity tests*

To test the accuracy of the results on the impact of higher education expansion policies on urban innovation, we conducted a series of robustness and endogeneity tests, including the parallel trend test, removal of outlier effects, change to the sample time horizon, change to the sample selection interval, placebo test and recalibration of the DML model.

#### 4.2.1. Sample adjustment

An important premise is the presence of a common trend of urban innovations in both the treatment and control groups prior to the policy's implementation. To test this hypothesis, various pre- and post- terms of policy shocks were established, evaluating their impact on the time series. The findings, depicted in Figure 3, show no significant "ex ante difference" between the treatment and the control groups that are not exposed to exogenous policy shocks, before the implementation of the higher education expansion policy. The common trend hypothesis holds. After the implementation of the higher education expansion policy, the coefficients of post_1 to post_3 in the parallel trend are not significant, but the coefficients after post_4 are significant and gradually show a positive effect, indicating an eventual elevation in the innovation levels of the cities in the treatment group post-policy implementation, albeit with a delayed effect.

These findings may be attributed to the standard educational duration of four years in higher education institutions. The initial year of the higher education expansion policy implementation primarily induces changes in enrollment, with the full policy effect not immediately realized. Four years after the implementation of the policy, the number of graduates from tertiary education surged, expanding the human capital in the market, thus fully realizing the policy effect.

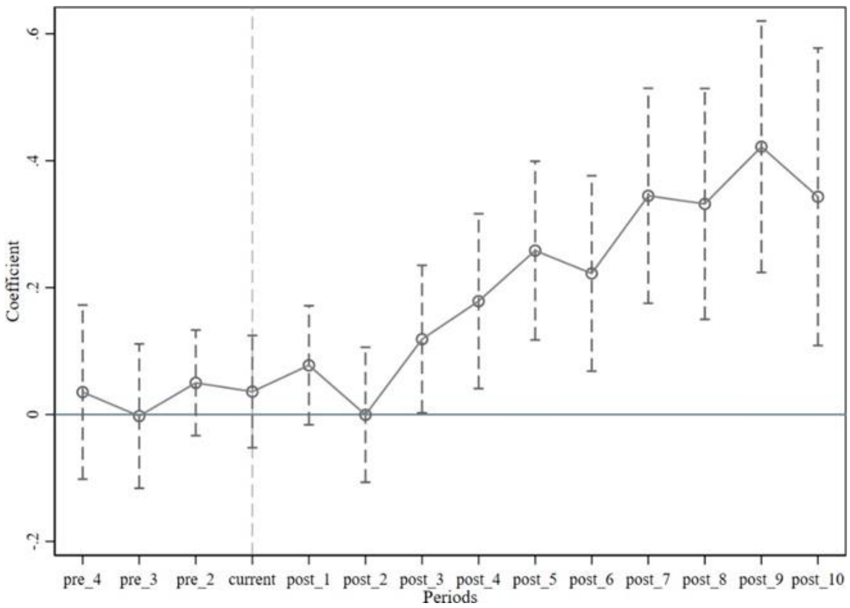


**Figure 3.** Parallel trend graph.

#### 4.2.2. *Removal of outlier effects*

Since outliers in the regression sample could potentially result in biased estimates, we employed a method to address this issue. Specifically, all continuous type variables were subjected to shrinkage at the 1% and 99% quantile points, as well as the 5% and 95% quantile points. Values above the highest and below the lowest quantile were replaced accordingly for the regression analysis. Columns (1) and (2) of Table 4 represent the regressions with 1% and 5% shrink-tail treatment, respectively. The results demonstrate that even after removing outliers, the higher education expansion policy still promotes urban innovation at the 1% significance level, with no substantial deviation from the findings of the baseline regression.

#### 4.2.3. Changing the sample time frame

To examine the potential impacts of the sample time frame on the policy effect of higher education expansion, we explored the sensitivity of the policy to time changes by altering the regression time interval. The original data range, 1995–2020, was adjusted by shortening both ends of the sample by 1 or 2 years, yielding subsamples of 1996–2019 and 1997–2018, for which separate regression analyses were conducted. If the direction and significance of the regression coefficients remained unchanged, this would indicate that the estimation results in this paper are robust. Columns (3) and (4) of Table 4 denote the regressions performed using the 1996–2019 and 1997–2018 subsamples, respectively. It results indicate that even with a shortened sample, the higher education expansion policy stimulates urban innovation at the 1% significance level, confirming the consistency of baseline regression results and the robustness of the findings.

#### 4.2.4. Changing the sample selection interval

Considering that major external events may lead to biased estimation results [55–57], we change the sample selection interval to re-run the regression. Specifically, considering the impact of two major external events on urban innovation, namely the stock market crash in China in 2015 and the 2020 global Covid-19 pandemic, this paper excludes the sample of cities during 2015 and 2020 and re-runs the test. As shown in column (5) of Table 4, the higher education expansion policy promotes urban innovation at the 1% significance level, and the findings are robust.

#### 4.2.5. *Placebo testing*

The placebo tests aim to ensure the robustness of the findings and eliminate the potential influence of unobservable city characteristics on the estimation results. Following the approach by Liu et al. [58], we randomly selected 78 cities as the pseudo-experimental group affected by the higher education expansion policy (FakePolicy), while keeping the remaining cities as the control group. The policy interaction term was then recalculated in the placebo test, the regression was rerun accordingly. Since the pseudo-experimental group was randomly selected, the new policy interaction term does not have a significant effect on the explanatory variables. Column (6) of Table 4 confirms this, with the coefficient of the effect between the new policy interaction term and urban innovation amounting to only 0.016. This discrepancy is significantly divergent from the baseline regression results, yet is not significant in terms of both economic and statistical importance. Hence, the results suggest that the observed impact of the higher education expansion policy on urban innovation can be assessed using a DML model, which yields robust findings.

**Table 4.** Robustness test.

| | (1)<br>Winsor 1% | (2)<br>Winsor 5% | (3)<br>1996–2019 | (4)<br>1997–2018 | (5)<br>Delete 2015&2020 | (6)<br>FakePolicy |
|---|---|---|---|---|---|---|
| *Policy* | 0.588*** | 0.580*** | 0.567*** | 0.447*** | 0.568*** | 0.016 |
| | (10.08) | (10.25) | (9.85) | (7.91) | (10.55) | (0.34) |
| Constant | -0.005 | -0.001 | -0.000 | -0.002 | -0.003 | -0.005 |
| | (-0.65) | (-0.18) | (-0.00) | (-0.28) | (-0.32) | (-0.59) |
| Observations | 4,758 | 4,758 | 4,392 | 4,026 | 4,392 | 4,758 |
| Controls | YES | YES | YES | YES | YES | YES |
| City FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |

Note: The robust z-statistics are put into parentheses. ***, ** and * represent the significance level of coefficients at 1%, 5% and 10%, respectively.

#### 4.2.6. Reset DML model

To ensure the integrity of the conclusions and minimize potential biases from the DML model, this paper verified the robustness of its findings through the following measures: First, changing the sample partition ratio of the DML model from the previous 1:4 to 1:2 and 1:7, thus exploring the possible impact of this partition ratio on the paper's conclusions; second, replacing the previously used Random Forest algorithm with the Gradient Boosting model (Gradient Boosting) and LASSO algorithm (LassoCV) to explore their possible impacts on the study's conclusions; and third, the benchmark regression based on the DML employed a linear model for the analysis, introducing a certain degree of subjectivity. Subsequently, a more general interactive model was constructed using the DML, thereby assessing the impact of the model setup on the conclusions of this paper. The alterations made to the main and auxiliary regression for this analysis are as follows:

$$Y_{it+1} = g(Event_{it}, X_{it}) + U_{it}. \tag{9}$$

$$Event_{it} = m(X_{it}) + V_{it}. \tag{10}$$

The estimated coefficients for the disposition effect were obtained for the interactive model:

$$\check{\theta}_0 = E[g(Event_{it} = 1, X_{it}) - g(Event_{it} = 0, X_{it})]. \tag{11}$$

Finally, while we do attempt to consider various factors affecting urban innovation, there inevitably exists omitted variables, and the regression analysis addresses the problem of endogeneity. To effectively do so, the instrumental variables approach was employed. Therefore, drawing on Chernozhukov et al. [50], this paper formulated a partially linear instrumental variable model for DML, which is structured as follows:

$$Y_{it+1} = \theta_0 Event_{it} + g(X_{it}) + U_{it}. \tag{12}$$

$$Instrument_{it} = m(X_{it}) + V_{it}. \tag{13}$$

In this formula, $Instrument_{it}$ stands as the instrumental variable for $Event_{it}$ the instrumental variables of where $Instrument_{it}$ is the instrumental variable for $Event_{it}$ the instrumental variables. Here, this paper refers to the work by Nunn and Qian [59], which incorporates the interaction term between urban topographic relief and the time trend term. This choice aligns with the exogeneity and correlation assumptions of the instrumental variable. On the one hand, urban terrain undulation correlates with higher education expansion policies. Topographic relief directly influences the construction cost of higher education institutions, leading to more establishments in areas with less topographic relief, thereby facilitating the implementation of higher education expansion policies. On the other hand, topographic relief is an exogenous variable external to the economic system and reflecting the distinctive characteristics of each city. It does not affect urban innovation, fulfilling the exogeneity condition.

The regression results obtained from the DML model adjustments are presented in Table 5. Evidently, neither the sample split proportion in the DML model, the machine learning algorithm used for prediction, the estimation models form, nor the endogeneity issue impacts the conclusion that the expansion policy promotes innovation in the city. They only alter the magnitude of the policy effect to a certain degree, which is sufficient to show that the original conclusions are robust.

**Table 5.** Robustness tests of reset DML model.

| | (1)<br>1:2 | (2)<br>1:7 | (3)<br>GradBoost | (4)<br>LassoCV | (5)<br>Interactive | (6)<br>IV |
|---|---|---|---|---|---|---|
| *Policy* | 0.592*** | 0.585*** | 0.448*** | 0.376*** | 0.689*** | 4.422** |
| | (10.67) | (9.83) | (14.89) | (7.30) | (33.42) | (2.48) |
| Constant | -0.009 | -0.000 | -0.002 | 0.000 | | 0.004 |
| | (-1.07) | (-0.05) | (-0.19) | (0.00) | | (0.36) |
| Observations | 4,758 | 4,758 | 4,758 | 4,758 | 4,758 | 4,758 |
| Controls | YES | YES | YES | YES | YES | YES |
| City FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |

Note: The robust z-statistics are put into parentheses. ***, ** and * represent the significance level of coefficients at 1%, 5% and 10%, respectively.

### 4.3. Transmission mechanism test

The previous paper has verified that the higher education expansion policy significantly promoted urban innovation in China, but its underlying mechanism remains unclear. This section elucidates the impact of the higher education expansion policy on urban innovation from two viewpoints: Human capital and financial support. It addresses issues related to insufficient labor and funding that may arise in urban innovation. Specifically, the “human capital expansion mechanism” of the higher education expansion policy is proposed to address the human resources issues, while the “financial support enhancement mechanism” of the policy is proposed for the issue with financial constraints. For the problem of “lack of money”, the “financial support enhancement mechanism” is proposed for the higher education expansion policy. The specific regression results are shown in Tables 6 and 7.

**Table 6.** Human capital mechanisms.

| | (1)<br>Student_collegial | (2)<br>Staff_rd | (3)<br>Student_career |
|---|---|---|---|
| *Policy* | 0.921*** | 0.035*** | 0.357*** |
| | (15.99) | (2.70) | (5.36) |
| Constant | -0.010 | -0.002 | -0.007 |
| | (-0.67) | (-0.26) | (-0.34) |
| Observations | 4,758 | 4,758 | 4,758 |
| Controls | YES | YES | YES |
| City FE | YES | YES | YES |
| Year FE | YES | YES | YES |

Note: The robust z-statistics are put into parentheses. *** p<0.01, ** p<0.05, * p<0.1.

**Table 7.** Financial support mechanisms.

| | (1)<br>Fiscal_edu | (2)<br>Fiscal_science |
|---|---|---|
| *Policy* | 0.243*** | 0.009** |
| | (11.39) | (2.08) |
| Constant | 0.000 | -0.002 |
| | (0.04) | (-0.86) |
| Observations | 4,758 | 4,758 |
| Controls | YES | YES |
| City FE | YES | YES |
| Year FE | YES | YES |

Note: The robust z-statistics are put into parentheses. *** p<0.01, ** p<0.05, * p<0.1.

#### 4.3.1. Human capital mechanisms

After the implementation of the higher education expansion policy, the quantity and quality of human capital improved, while the matching cost of human capital was reduced, contributing to the improvement of urban innovation levels. To verify the human capital expansion mechanism resulting from the policy, we drew on the practice of Liu et al. [60], using the ratio of students in undergraduate institutions to population (Student_collegial) as a proxy variable for human capital. This analysis was designed to test Hypothesis 2. Additionally, this paper conducted a robustness test using the ratio of R&D personnel to the population (Staff_rd) and the ratio of students in vocational education schools to the population (Student_career). The regression results are shown in Table 6.

In Columns 1 through 3, the coefficients signifying the impact of higher education expansion policy on the level of human capital are determined to be 0.921, 0.035 and 0.357, respectively. Notably, all coefficients are statistically significant at the 1% level, which suggests that the policy promoted the expansion of human capital, thus the findings of the study are robust. Existing studies show that the level of human capital can significantly impact the innovation spirit of enterprises or cities [61,62]. Therefore, the study confirms research Hypothesis 2, demonstrating that higher education expansion policy can promote urban innovation through the expansion of human capital.

#### 4.3.2. Financial support mechanisms

The higher education expansion policy led to an increase in funding for education, science and technology, thereby improving the willingness and ability of innovators, and ultimately elevating the level of urban innovation. To validate the financial support enhancement mechanism of the higher education enrollment expansion policy, we drew on the study by Wei et al. [63], employing education expenditure and science and technology expenditure as measures of financial support. Specifically, the logarithm of education expenditure (Fiscal_edu) and the logarithm of science and technology expenditure (Fiscal_science) served as the proxy variables for financial support to provide empirical evidence for Hypothesis 3. The regression results are shown in Table 7.

As noted in Columns 1 and 2, the coefficients reflecting the influence of the higher education expansion policy on financial support are 0.243 and 0.009, respectively, both of which are significant at the 5% level. This indicates that the policy has resulted in an increase in the government's financial support, and the research findings remain robust. Moreover, existing studies show that financial support, such as education expenditure, has a positive impact on the level of innovation [64]. Therefore, this study confirms the validity of Hypothesis 2, which suggests that higher education expansion policy promotes urban innovation through increased financial support.

### *4.4. Heterogeneity analysis*

#### 4.4.1. Geographic location

In the context of the real world, regional economic development across various regions of China differs due to geographic location and other factors. Consequently, the influence of the higher education expansion policy on innovation in cities with different geographies may also vary. To examine its impact, we drew upon the study by Tu et al. [65], who divided the sample cities into eastern, central and western cities based on their geographic locations and conducted a group regression. The specific regression results are shown in Table 8.

The results in columns (1) to (3) of Table 8 show the regression outcomes of the higher education expansion policy on urban innovation in the eastern, central and western regions of China, respectively. The findings reveal significant positive effects at the levels of 1%, 1% and 10% respectively, indicating that the policy of higher education expansion is conducive to the enhancement of urban innovation in the three general areas. Notably, the promotion effect of the policy on urban innovation levels appears better in the eastern regions compared to the central regions, with the weakest effect observed in western regions. This trend can be attributed to the strong economic foundation, advanced technological landscape, rich financial resources and excellent infrastructure in the eastern region, which may have provided conducive conditions for the higher education expansion policy to stimulate urban innovation. Conversely, the policy might have exerted less influence on urban innovation in central and western regions due to factors such as poor geographical location, limited financial development and relatively weak infrastructure. In addition, the eastern region has historically demonstrated a higher efficiency in innovation and a preference for more effective innovation paths, thus better facilitating urban innovation.

**Table 8.** Geographic location heterogeneity.

| | (1)<br>Eastern | (2)<br>Central | (3)<br>Western |
|---|---|---|---|
| *Policy* | 0.564*** | 0.546*** | 0.172* |
| | (5.15) | (6.31) | (1.80) |
| Constant | -0.012 | 0.002 | -0.011 |
| | (-0.98) | (0.17) | (-0.86) |
| Observations | 1,586 | 1,716 | 1,456 |
| Controls | YES | YES | YES |
| City FE | YES | YES | YES |
| Year FE | YES | YES | YES |

Note: The robust z-statistics are put into parentheses. *** p<0.01, ** p<0.05, * p<0.1.

### 4.4.2. Population density

Population mobility leads to consistent fluctuations in urban population density, which can affect the impact of higher education expansion policies on innovation. To examine how the policy influences innovation in cities with varying population densities, this study categorized cities with population densities below 0.1, 0.1–0.9 and above 0.9 as sparsely populated, moderately populated and congested, respectively. Group regression analysis was conducted, and the results are shown in Table 9.

Columns (1) to (3) in Table 9 present the regression results of the higher education expansion policy on urban innovation in sparsely populated cities, moderately populated cities and crowded cities, respectively. They show that the impact in sparsely populated cities is not significant, whereas the impact in moderately populated cities and crowded cities is significant at the 1% level. This outcome may be attributed to the lower information asymmetry moderately populated cities and crowded cities, leading to a talent agglomeration effect and enhanced resource sharing, which promotes urban innovation. In addition, increases in urban population density accelerate the construction of social relationship networks, aiding the dissemination and diffusion of knowledge [66,67] and boosting innovation efficiency and urban innovation. Conversely, sparsely populated cities are generally limited by their population size, and their response to the higher education expansion policy was relatively slow, resulting in insignificant policy effects.

**Table 9.** Population density heterogeneity.

| | (1)<br>Sparse population | (2)<br>Moderate population | (3)<br>Crowded population |
|---|---|---|---|
| *Policy* | 0.196 | 0.479*** | 0.528*** |
| | (0.79) | (8.09) | (4.22) |
| Constant | 0.003 | -0.007 | 0.000 |
| | (0.13) | (-0.85) | (0.01) |
| Observations | 476 | 3,806 | 476 |
| Controls | YES | YES | YES |
| City FE | YES | YES | YES |
| Year FE | YES | YES | YES |

Note: The robust z-statistics are put into parentheses. *** p<0.01, ** p<0.05, * p<0.1.

### 4.4.3. Degree of marketization

The extent of marketization varied across cities due to differing levels of economic development. Thus, the impact of higher education expansion policies on innovation within these cities also fluctuated. To examine how the policy influenced innovation in cities with differing degrees of marketization, we first categorized cities into three groups: Those with a marketization degree below 0.1 are classified as low-marketization cities, those between 0.1 and 0.9 as moderately-marketized and those above 0.9 as high-marketization cities. A group regression was then carried out, and the specific regression results are shown in Table 10.

Columns (1) to (3) in Table 10 introduce the regression results of the impact of the higher education expansion policy on urban innovation across the three categories: Low-marketized cities, moderately marketized cities and high-marketized cities. Notably, the study reveals that the influence of the policy on urban innovation in low-marketized cities is not statistically significant. Conversely, for moderately and highly marketized cities, the impact is significant at the 1% level. This may be because, in moderately and highly marketized cities, factor resources are abundant, information is easier to obtain and the degree of information asymmetry faced by innovators is relatively low, thereby fostering the development of innovation activities. Furthermore, the more refined legal systems and competitive market mechanisms in these cities may have diminished the risk of product imitation, driving enterprises and other innovation stakeholders to engage in innovative activities.

**Table 10.** Heterogeneity in degree of marketization.

| | (1)<br>Low marketization | (2)<br>Moderate marketization | (3)<br>High marketization |
|---|---|---|---|
| *Policy* | 0.103 | 0.589*** | 0.440*** |
| | (0.87) | (9.75) | (3.25) |
| Constant | -0.002 | -0.009 | -0.030 |
| | (-0.08) | (-0.98) | (-1.20) |
| Observations | 476 | 3,806 | 476 |
| Controls | YES | YES | YES |
| City FE | YES | YES | YES |
| Year FE | YES | YES | YES |

Note: The robust z-statistics are put into parentheses. *** p<0.01, ** p<0.05, * p<0.1.

## 5. Conclusions and policy implications

### *5.1. Conclusions*

Here, we explore the impact of higher education expansion policies on urban innovation, using the DML model to investigate its effects in 183 Chinese cities between 1995 and 2020. The research findings show that the policy had a significant positive influence on urban innovation in China, a conclusion that remains true even after conducting a series of robustness tests. The paper further elucidates the potential mechanisms at work, demonstrating that the higher education expansion policy's impact on urban innovation was facilitated through the expansion of human capital expansion and increased financial support.

Moreover, our analysis of heterogeneity reveals that the effects of the higher education expansion policy varied based on different geographic locations, population densities and marketization levels within different cities. The above results provide empirical evidence of the incentive effects of higher education expansion policies on urban innovation and confirm the importance of human capital and financial support in promoting urban innovation. Furthermore, they provide useful insights for China's high-quality development transition from "Made in China" to "Created in China".

### *5.2. Policy implications*

The findings of this paper suggest three key policy implications. First, there is a need to increase policy support for higher education. The study underscores that higher education expansion policies are effective in elevating the level of urban innovation. Policy makers can thus continue to use higher education to stimulate high-quality urban development. Second, there is a call for the optimization of the urban innovation environment. The research shows how the higher education expansion policy promoted urban innovation through two paths: The bolstering of human capital and additional financial support. Therefore, governments can optimize the business environment to attract top-tier talents and financial resources, thereby promoting urban innovation. Third, it is advised to explore the rational allocation of educational resources. The results show that the impact of the higher education expansion policy on cities in western regions of China, low-marketized cities and sparsely populated cities was low or nonsignificant. Therefore, local governments should implement policies to address local issues and time, increasing policies that will help less developed areas to achieve a balanced and inclusive regional development agenda.

## Use of AI tools declaration

The authors declare that they have not used Artificial Intelligence (AI) tools in the creation of this article.

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## Conflict of interest

The authors declare no competing interests.

## References

1. L. Morales, D. Rajmil, Investing in virtue and frowning at vice? Lessons from the global economic and financial crisis, *Quant. Financ. Econ.*, **7** (2023), 1–18. https://doi.org/10.3934/QFE.2023001
2. Y. Wen, Y. Xu, Statistical monitoring of economic growth momentum transformation: empirical study of Chinese provinces, *AIMS Math.*, **8** (2023), 24825–224847. https://doi.org/10.3934/math.20231266
3. P. Jin, S. K. Mangla, M. Song, The power of innovation diffusion: How patent transfer affects urban innovation quality, *J. Bus. Res.*, **145** (2022), 414–425. https://doi.org/10.1016/j.jbusres.2022.03.025
4. X. Li, J. Tang, J. Huang, Place-based policy upgrading, business environment, and urban innovation: Evidence from high-tech zones in China, *Int. Rev. Financ. Anal.*, **86** (2023), 102545. https://doi.org/10.1016/j.irfa.2023.102545
5. T. Yang, M. Han, Y. Zhong, J. Zhong, Q. Zhang, Relationship between financial development and intelligent transformation of manufacturing: evidence from 69 countries, *Econ. Change Restruct.*, **56** (2023), 1–38. https://doi.org/10.1007/s10644-023-09544-2
6. J. M. Le Page, Structural rate of unemployment, hysteresis, human capital, and macroeconomic data, *Natl. Account. Rev.*, **4** (2022), 135–146. https://doi.org/10.3934/NAR.2022008

7. Li Z, Huang Z, Su Y. New media environment, environmental regulation and corporate green technology innovation: evidence from China, *Energy Econo.*, **119** (2023), 106545. https://doi.org/10.1016/j.eneco.2023.106545
8. R. Wang, W. Cai, H. Ren, X. Ma, Heterogeneous effects of the talent competition on urban innovation in China: evidence from prefecture-level cities, *Land*, **12** (2023), 719. https://doi.org/10.3390/land12030719
9. Z. Li, H. Chen, B. Mo, Can digital finance promote urban innovation? Evidence from China, *Borsa Istanb. Rev.*, **23** (2023), 285–296. https://doi.org/10.1016/j.bir.2022.10.006
10. J. Wang, S. Cai, The construction of high-speed railway and urban innovation capacity: based on the perspective of knowledge Spillover, *China Econ. Rev.*, **63** (2020), 101539. https://doi.org/10.1016/j.chieco.2020.101539
11. C. Tang, M. Guan, J. Dou, Understanding the impact of High Speed Railway on urban innovation performance from the perspective of agglomeration externalities and network externalities, *Technol. Soc.*, **67** (2021), 101760. https://doi.org/10.1016/j.techsoc.2021.101760
12. W. Feng, H. Yuan, The impact of medical infrastructure on regional innovation: An empirical analysis of China's prefecture-level cities, *Technol. Forecast. Soc. Change*, **186** (2023), 122125. https://doi.org/10.1016/j.techfore.2022.122125
13. M. Nagenborg, Urban robotics and responsible urban innovation, *Ethics Inf. Technol.*, **22** (2020), 345–355. https://doi.org/10.1007/s10676-018-9446-8
14. E. Ezzahid, B. Ferrahi, O. El Hamdani, Determinants of urban concentration in African countries, *Natl. Account. Rev.*, **4** (2022), 191–203. https://doi.org/10.3934/NAR.2022011
15. Y. Liu, Y. Fan, Y. Wang, J. Huang, H. Xun, City innovation ability and internet infrastructure development: Evidence from the "Broadband China" policy, *Bull. Econ. Res.*, 2023. https://doi.org/10.1111/boer.12421
16. J. Wang, K. Deng, Impact and mechanism analysis of smart city policy on urban innovation: Evidence from China, *Econ. Anal. Policy*, **73** (2022), 574–587. https://doi.org/10.1016/j.eap.2021.12.006
17. C. Li, G. Long, S. Li, Research on measurement and disequilibrium of manufacturing digital transformation: Based on the text mining data of A-share listed companies, *Data Sci. Financ. Econ.*, **3** (2023), 30–54. https://doi.org/10.3934/DSFE.2023003
18. L. Li, M. Li, S. Ma, Y. Zhang, C. Pan, Does the construction of innovative cities promote urban green innovation, *J. Environ. Manage.*, **318** (2022), 115605. https://doi.org/10.1016/j.jenvman.2022.115605
19. G. Aisaiti, J. Xie, T. Zhang, National Innovation Demonstration Zone policy and city innovation capability—a quasi-natural experimental analysis, *Ind. Manage. Data Syst.*, **122** (2022), 1246–1267. https://doi.org/10.1108/IMDS-12-2021-0772
20. Z. Huang, H. Dong, S. Jia, Equilibrium pricing for carbon emission in response to the target of carbon emission peaking, *Energy Econ.*, **112** (2022), 106160. https://doi.org/10.1016/j.eneco.2022.106160
21. T. Li, X. Li, G. Liao, Business cycles and energy intensity. evidence from emerging economies, *Borsa Istanb. Rev.*, **22** (2022), 560–570. https://doi.org/10.1016/j.bir.2021.07.005
22. C. Zou, Y. Huang, S. Wu, S. Hu, Does "low-carbon city" accelerate urban innovation? Evidence from China, *Sustain. Cities Soc.*, **83** (2022), 103954. https://doi.org/10.1016/j.scs.2022.103954
23. Y. Che, L. Zhang, Human capital, technology adoption and firm performance: Impacts of China's higher education expansion in the late 1990s, *Econ. J.*, **128** (2018), 2282–2320. https://doi.org/10.1111/ecoj.12524

24. C. Wang, X. Liu, Z. Yan, Y. Zhao, Higher education expansion and crime: New evidence from China, *China Econ. Rev.*, **74** (2022), 101812. https://doi.org/10.1016/j.chieco.2022.101812
25. H. Li, Y. Ma, L. Meng, X. Qiao, Skill complementarities and returns to higher education: evidence from college enrollment expansion in China, *China Econ. Rev.*, **46** (2017), 10–26. https://doi.org/10.1016/j.chieco.2017.08.004
26. F. Dai, F. Cai, Y. Zhu, Returns to higher education in China—evidence from the 1999 higher education expansion using a fuzzy regression discontinuity, *Appl. Econ. Lett.*, **29** (2022), 489–494. https://doi.org/10.1080/13504851.2020.1871465
27. Y. Wang, Who benefits more from the college expansion policy? Evidence from China, *Res. Soc. Strat. Mobil.*, **71** (2021), 100566. https://doi.org/10.1016/j.rssm.2020.100566
28. Y. Dong, N. Yu, T. Hong, J. Yue, City administrative level and tertiary educational opportunities: evidence from China's higher education expansion policy, *SAGE Open*, **12** (2022), 21582440221089931. https://doi.org/10.1177/21582440221089931
29. Y. Feng, X. Tan, R. Wang, The value of higher education to entrepreneurial performance: Evidence from higher education expansion in China, *China Econ. Rev.*, **73** (2022), 101789. https://doi.org/10.1016/j.chieco.2022.101789
30. C. Bollinger, X. Ding, S. Lugauer, The expansion of higher education and household saving in China, *China Econ. Rev.*, **71** (2022), 101736. https://doi.org/10.1016/j.chieco.2021.101736
31. D. Kong, B. Zhang, J. Zhang, Higher education and corporate innovation, *J. Corp. Financ.*, **72** (2022), 102165. https://doi.org/10.1016/j.jcorpfin.2022.102165
32. W. Yue, Human capital and firm innovation: evidence from China's higher education expansion in the late 1990s, *Emerg. Mark. Financ. Tr.*, 2023, 1–19. https://doi.org/10.1080/1540496X.2023.2242568
33. M. F. Leung, A. Jawaid, S. W. Ip, C. H. Kwok, S. Yan, A portfolio recommendation system based on machine learning and big data analytics, *Data Sci. Financ. Econ.*, **3** (2023), 152–165. https://doi.org/10.3934/DSFE.2023009
34. Z. Li, B. Mo, H. Nie, Time and frequency dynamic connectedness between cryptocurrencies and financial assets in China, *Inte. Rev. Econ. Financ.*, **86** (2023), 46–57. https://doi.org/10.1016/j.iref.2023.01.015
35. S. Orazi, L. B. Martinez, H. P. Vigier, Determinants and evolution of financial inclusion in Latin America: a demand side analysis, *Quant. Financ. Econ.*, **7** (2023), 187–206. https://doi.org/10.3934/QFE.2023010
36. C. Bandera, E. Thomas, The role of innovation ecosystems and social capital in startup survival, *IEEE Trans. Eng. Manage.*, **66** (2018), 542–551. https://doi.org/10.1109/TEM.2018.2859162
37. X. Zhao, Y. Xu, L. Vasa, U. Shahzad, Entrepreneurial ecosystem and urban innovation: contextual findings in the lens of sustainable development from China, *Technol. Forecast. Soc. Change*, **191** (2023), 122526. https://doi.org/10.1016/j.techfore.2023.122526
38. Y. Zhong, F. Xu, L. Zhang, Influence of artificial intelligence applications on total factor productivity of enterprises—evidence from textual analysis of annual reports of Chinese-listed companies, *Appl. Econ.*, 2023, 1–19. https://doi.org/10.1080/00036846.2023.2244246
39. Y. Chen, Y. Wang, D. Hu, Z. Zhou, Government R&D subsidies, information asymmetry, and the role of foreign investors: evidence from a quasi-natural experiment on the shanghai-Hong Kong stock connect, *Technol. Forecast. Soc. Change*, **158** (2020), 120162. https://doi.org/10.1016/j.techfore.2020.120162

40. T. Kong, R. Sun, G. Sun, Y. Song, Effects of digital finance on green innovation considering information asymmetry: an empirical study based on Chinese listed firms, *Emerg. Mark. Financ. Trade*, **58** (2022), 4399–4411. https://doi.org/10.1080/1540496X.2022.2083953
41. K. Albitar, K. Hussainey, Sustainability, environmental responsibility and innovation, *Green Financ.*, **5** (2023), 85–88. https://doi.org/10.3934/GF.2023004
42. X. Jiang, W. Fu, G. Li, Can the improvement of living environment stimulate urban innovation?—analysis of high-quality innovative talents and foreign direct investment spillover effect mechanism, *J. Clean. Prod.*, **255** (2020), 120212. https://doi.org/10.1016/j.jclepro.2020.120212
43. X. Lao, H. Gu, H. Yu, F. Xiao, Exploring the spatially-varying effects of human capital on urban innovation in China, *Appl. Spat. Anal. Policy*, **14** (2021), 827–848. https://doi.org/10.1007/s12061-021-09380-9
44. J. Zhong, Y. Zhong, M. Han, T. Yang, Q. Zhang, The impact of AI on carbon emissions: evidence from 66 countries, *Appl. Econ.*, 2023, 1–15. https://doi.org/10.1080/00036846.2023.2203461
45. M. Huang, C. Xing, X. Cui, Does college location affect the location choice of new college graduates in China, *China World Econ.*, **30** (2022), 135–160. https://doi.org/10.1111/cwe.12421
46. D. Acemoglu, P. Restrepo, Robots and jobs: evidence from US labor markets, *J. Polit. Econ.*, **128** (2020), 2188–2244.
47. S. Yang, Z. Li, J. Li, Fiscal decentralization, preference for government innovation and city innovation: evidence from China, *Chin. Manag. Stud.*, **14** (2020), 391–409. https://doi.org/10.1108/CMS-12-2018-0778
48. J. Guinot, Z. Barghouti, I. Beltrán-Martín, R. Chiva, Corporate social responsibility toward employees and green innovation: exploring the link in the tourism sector, *Green Financ.*, **5** (2023), 298–320. https://doi.org/10.3934/GF.2023012
49. Y. Gao, S. Jin, Corporate nature, financial technology, and corporate innovation in China, *Sustainability*, **14** (2022), 7162. https://doi.org/10.3390/su14127162
50. V. Chernozhukov, D. Chetverikov, M. Demirer, E. Duflo, C. Hansen, W. Newey, et al., Double/debiased machine learning for treatment and structural parameters, *Econ. J.*, **21** (2018), C1–C68. https://doi.org/10.1111/ectj.12097
51. Z. Liao, M. Hu, L. Gao, B. Cheng, C. Tao, R. Akhtar, Is air pollution detrimental to regional innovation? An empirical heterogeneity test based on Chinese cities, *Front. Public Health*, **10** (2022), 981306. https://doi.org/10.3389/fpubh.2022.981306
52. J. Cheng, J. Zhao, D. Zhu, X. Jiang, H. Zhang, Y. Zhang, Land marketization and urban innovation capability: Evidence from China, *Habitat Int.*, **122** (2022), 102540. https://doi.org/10.1016/j.habitatint.2022.102540
53. L. He, E. Yuan, K. Yang, D. Tao, Does technology innovation reduce haze pollution? An empirical study based on urban innovation index in China, *Environ. Sci. Pollut. Res.*, **29** (2022), 24063–24076. https://doi.org/10.1007/s11356-021-17448-9
54. Y. Tian, W. Song, M. Liu, Assessment of how environmental policy affects urban innovation: evidence from China's low-carbon pilot cities program, *Econ. Anal. Policy*, **71** (2021), 41–56. https://doi.org/10.1016/j.eap.2021.04.002
55. Z. Li, J. Zhong, Impact of economic policy uncertainty shocks on China's financial conditions, *Financ. Res. Lett.*, **35** (2020), 101303. https://doi.org/10.1016/j.frl.2019.101303
56. L. Grassini, Statistical features and economic impact of Covid-19, *Natl. Account. Rev.*, **5** (2023), 38–40. https://doi.org/10.3934/NAR.2023003
57. R. Nymoen, Economic Covid-19 effects analysed by macro econometric models—the case of Norway, *Natl. Account. Rev.*, **5** (2023), 1–22. https://doi.org/10.3934/NAR.2023001

58. Y. Liu, Y. Xie, K. Zhong, Impact of digital economy on urban sustainable development: Evidence from Chinese cities, *Sustain. Dev.*, 2023. https://doi.org/10.1002/sd.2656
59. N. Nunn, N. Qian, US food aid and civil conflict, *Amer. Econo. Rev.*, **104** (2014), 1630–1666. https://doi.org/10.1257/aer.104.6.1630
60. L. Liu, Y. Meng, D. Wu, Q. Ran, J. Cao, Z. Liu, Impact of haze pollution and human capital on economic resilience: evidence from prefecture-level cities in China, *Environ. Dev. Sustain.*, **25** (2023), 13429–13449. https://doi.org/10.1007/s10668-022-02625-8
61. X. Sun, H. Li, V. Ghosal, Firm-level human capital and innovation: evidence from China, *China Econo. Rev.*, **59** (2020), 101388. https://doi.org/10.1016/j.chieco.2019.101388
62. X. Shi, Y. Chen, M. Xia, Y. Zhang, Effects of the talent war on urban innovation in China: a difference-in-differences analysis, *Land*, **11** (2022), 1485. https://doi.org/10.3390/land11091485
63. L. Wei, B. Lin, Z. Zheng, W. Wu, Y. Zhou, Does fiscal expenditure promote green technological innovation in China? Evidence from Chinese cities, *Environ. Impact Asses. Rev.*, **98** (2023), 106945. https://doi.org/10.1016/j.eiar.2022.106945
64. Q. Tan, C. Li, Z. Qin, S. Yu, Y. Pan, M. H. Andrianarimanana, Impact of fiscal education expenditure on innovation of local listed enterprises: evidence from China, *Financ. Res. Lett.*, **57** (2023), 104192. https://doi.org/10.1016/j.frl.2023.104192
65. Z. Tu, T. Hu, R. Shen, Evaluating public participation impact on environmental protection and ecological efficiency in China: evidence from PITI disclosure, *China Econ. Rev.*, **55** (2019), 111–123. https://doi.org/10.1016/j.chieco.2019.03.010
66. Z. Li, G. Liao, K. Albitar, Does corporate environmental responsibility engagement affect firm value? The mediating role of corporate innovation, *Bus. Strategy Environ.*, **29** (2020), 1045–1055. https://doi.org/10.1016/j.chieco.2019.03.010
67. S. Cai, H. Wang, X. Zhou, Do city size and population density influence regional innovation output evidence from China, *Wirel. Commun. Mob. Com.*, **2021** (2021), 3582053. https://doi.org/10.1155/2021/3582053