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Heterogeneous Effects of the Talent Competition on Urban Innovation in China: Evidence from Prefecture-Level Cities

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Abstract: With in-depth efforts in the national strategy of innovation-driven development, the demand for talent in cities is burgeoning. Cities in China have released a large number of preferential policies to attract talent as these cities look to gain an edge in increasing talent competition. This study empirically studied the effect of talent competition on urban innovation using a panel data set of 298 prefectural-level cities in China from 2010 to 2019 based on the difference-in-difference model and an event study method. The results show that there are heterogeneous effects of talent competitions on urban innovation, which may widen the gap between urban innovation in different cities. The effect of talent competition in different cities showed a significant positive correlation with the level of urban development, and there is a "head effect" of talent competition on urban innovation. Moreover, the results of the mechanism analysis indicate that the effect of talent competition on urban innovation is mainly through talent flow. These findings can help policymakers formulate scientific and reasonable talent policies to promote the strategy of innovation-driven development.

Keywords: talent competition; urban innovation; heterogeneous effects; human capital agglomeration

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1. Introduction

It has been a consensus that innovation is the source of economic and social development around the world [1]. Since the reform and opening-up, China has been developing rapidly for more than 40 years. However, with the gradual disappearance of a demographic dividend and the increasing marginal cost of production factors, the development pattern driven by factors and investment is unsustainable in China [2]. Meanwhile, China's carbon peaking and neutrality goals have also provided higher requirements for economic development [3]. In this context, the strategy for innovation-driven development is an optimal choice to promote high-quality social and economic development [4]. The agent of innovation is talent, and innovation-driven development is essentially talent-driven development [5]. Since the 21st century, national and regional prosperity has increasingly become dependent on the role of humans. The greater the human capital reserve, the greater the innovation capacity and the faster the progress of science and technology [6,7]. Currently, the competition between countries and regions has shifted from development competition to talent competition [8,9]. Additionally, talent competition is essentially an institutional competition or policy competition [10].

China has been stressing the importance of talent resources for years. This can be traced back to 1978. After China adopted the reform and opening-up policy, the government took economic construction as the central task, which led to increasing demand for talent. "Respecting knowledge and talents" became one of the basic national policies in China. The government successively implemented a series of talent policies such as government special allowances to professionals and "hundred, thousand and ten thousand" talent projects. The strategy to reinvigorate China through human resources development was formulated in 2002 after the country's entry into the World Trade Organization (WTO). Since 2012, China's development has entered a new era, where innovation has become the primary driving force for development, and talent has become a priority in the country's development [11]. The State Council issued its opinions on further promoting the reform of household registration in 2014. These opinions relax the restrictions for urban household registration, which means that the main body of talent competition can shift away from countries to cities increasingly. Talent competitions between cities intensify as the demand for talent burgeons and the "talent war" gradually comes into being. According to the Peking University Law Database, from 2014 to 2019, the local governments in China launched more than 7000 talent policies involving nearly 200 cities at the prefecture level and above. By 2022, the local governments launched an accumulated 18,000 talent policies. Despite cities beginning to attach importance to talent and innovation, there is still a large gap in urban innovation between cities in China [12]. Therefore, evaluating the effect of talent competition will help cities formulate effective policies and promote urban innovation.

The difference-in-differences (DID) model is usually conducted to evaluate the causal effects of public policy [13–15]. Generally speaking, DID is based on four assumptions: strict exogeneity assumption, no anticipation assumption, stable unit treatment values assumption, and the homogeneous treatment effect assumption. It is difficult to accurately judge the actual effect of public policy before it is implemented, so countries and regions often gradually expand relevant policies through pilot policies to ensure their rationality [16]. In this case, staggered DID is widely used by scholars to evaluate the effect of public policy [17]. However, there are three limitations to staggered DID when evaluating the effect of the talent competition. First, many scholars, such as Chaisemartin and D'Haultfœuille [18], Callaway and Sant'Anna [19], and Goodman-Bacon [20], have stressed that treatment effect estimates based on staggered DID can only be interpreted as the weighted averages of causal effects between different treated and comparison groups. That is, the estimates are problematic owing to the neglect of homogeneous treatment effect assumptions. Second, urban innovation activities are not completely independent in the context of talent competition [21,22]. There is a clear spillover effect of talent policies, so the implementation of talent policies in one city can also affect innovation activities in other cities [23]. A talent policy in one city can either promote urban innovation in neighboring cities through positive externalities, or it can restrain urban innovation in neighboring cities due to its siphon effect. As pointed out above, most cities in China have released talent policies, resulting in all cities being more or less affected by talent competition. In this case, the application of DID with multiple time periods contradicts the assumption of stable unit treatment values. Third, talent policies relate to the registered residence policy, subsidy policy, housing policy, etc. There are pretty clear differences in the tools and strengths of talent policy in different cities. According to the Peking University Law Database, from 2014 to 2019, Shanghai launched 186 policies related to talent, including providing permanent resident permits for talent, giving subsidies to talent and other measures, covering scientific research talent, educational talent, health talent, and legal talent. In the same period, however, Ya'an in Sichuan province only launched one talent policy, which was mainly related to public health talent. Evidently, the effects of talent competition on these two cities are different. Moreover, the same measures of talent policy may have different effects on different cities. For example, preferential policies for household registration are more attractive in first-tier cities than in other cities [24]. In other words, it is incorrect to distinguish the treatment group and the comparison group by whether a city has released a talent policy.

Due to the spillover effects of talent policies, and the differences between talent policies in different cities, it is difficult to define the treatment for evaluating the effect of talent competitions on urban innovation using the staggered DID model. Under such a circumstance, a method called the generalized difference-in-difference model can solve these problems. This method can distinguish treatment groups from comparison groups by the extent to which public policy shocks the subjects when all subjects are more or less affected by public policy. Vikrant Vig classified firms based on the value of their tangible assets, i.e., groups with more tangible assets were set as the treatment group and the effect of the secured transactions law on the use of secured debt by corporations was investigated [25]. Campello and Larrain distinguished treatment groups from comparison groups by forms that demand movable assets and found that firms operating with more movable assets benefited more from credit reforms in Eastern European countries [26]. According to the seventh national census of China, the Eastern region saw its weighting in the nation's population rise by 2.15 percentage points over the levels in 2010. This means that there was a tendency for the population to move to the east between 2010 and 2020, probably as a result of the talent competition. That is, the effect of talent competition on urban innovation may vary owing to the economic region in which the city is located. This provides us with a promising way to define the treatment. According to the National Bureau of Statistics, the division of China's regions is not a geographic concept but an economic one that reflects the level of regional development. Therefore, we classified the cities or regions with higher development levels as the treatment group, while the cities or regions with lower development levels were the comparison groups.

Recent studies have discussed the causal effect of talent competition on innovation in different ways [27–29]. Many scholars have pointed out that human capital agglomeration resulting from talent competition has a positive effect on economic development [30,31]. Talent competition could promote regional or urban innovation through the attraction, retention, education, circulation, and utilization of talent, in which talent acts as a knowledge spillover agent [32]. Based on the data from 1536 A-share listed companies, Zhang et al. found that talent competition helped enterprises boost green technological innovation [33]. Shi et al. empirically verified the influence of talent competition on urban innovation at the prefecture level in China, and the results indicate that talent competition also has positively influenced urban innovation [34]. Notably, despite their contributions, these studies have two limitations. First, only a small study analyzed the heterogeneous effects of talent competition on different objects, especially at the city level. Shen et al. investigated the relationship between environmental policy and green innovation, and the results show that pollution charges played a positive role in promoting green process innovation but a negative role in green product innovation [35]. She et al. explored the effect of the River Chief Policy on surface water pollution and found that the River Chief Policy had heterogeneous effects on different cities [36]. Similarly, the effect of talent competition may vary from city to city. Second, owing to its heterogeneous effects, talent competition may impede the sustainable development of some cities [37]. Talent competition can promote the growth of human capital in some cities. At the same time, it leads to the outflow of human capital from other cities, which widens the gap in innovation capacity between cities. Simandan pointed out that competition is one of the fundamental processes shaping the dynamics of markets; any competitive strategies involve a number of unavoidable delays [38]. In the context of talent competition, the temporal gap between the implementation of talent policies and the improvement of urban innovation in different cities is often different and was defined as material delays by Simandan [38]. For example, talent policy systems are more complete in first-tier cities, and the target audience for these policies is broader than in other cities, allowing the talent to reach migration decisions more quickly. This process promotes urban innovation activities in a short period of time, which is expressed by the fact that first-tier cities benefit more from talent competition. Therefore, it is necessary to consider the different mechanisms by which talent competition affects urban innovation.

To compensate for these shortcomings, talent competition in this study is defined as the phenomenon of cities releasing talent policies to compete for talent. We assume that the talent policy implemented by one city will affect other cities. Thus, in the context of talent competition, a large number of talent policies originating from different cities have an impact on innovation activities in all cities. This impact depends on the development of the city. In other words, this study aimed to investigate the effect of talent competition on urban innovation, verify the heterogeneous effects of talent competition from the perspective of urban development, and further explore its mechanism. The conclusions of this study may provide a theoretical basis and practical guidance for cities to further improve talent policies.

2. Materials and Methods

2.1. Methods and Variable Definition

This study selected a difference-in-differences (DID) model to investigate the causal effect of talent competition on urban innovation. As the primary resource for technical progress and economic development, talent could not increase rapidly in the short run. The talent inflows of some cities were accompanied by the talent outflows of other cities [39]. In other words, the effect of talent competition on cities does not depend on whether cities promulgate talent policies but on the talent-gathering capability of the cities. Generally speaking, the talent-gathering capability of the city increased with its development of the city [40]. This study aims to estimate the heterogeneous effects of talent competition by contrasting the different impacts of talent competition on urban innovation in different cities. Additionally, we, thus, distinguished the treatment group and the comparison group through differences in urban development. Specifically, under the context of talent competition, relatively developed cities were set as the treatment group, and relatively undeveloped cities were set as the comparison group.

In order to verify whether there were heterogeneous effects of talent competition on urban innovation, we constructed a canonical DID model (here referred to as Model I), which was described by:

$$Innovation_{it} = \lambda_i + \gamma_t + \beta D_i \times T_t + \alpha X_{it} + \varepsilon_{it}, \quad (1)$$

where i and t represent the observational city and the year, respectively; $Innovation$ represents the level of urban innovation; λ_i represents the individual fixed effect which is a time-invariant; γ_t represents the time fixed effect which is an individual invariant; D_i is a dummy variable that distinguishes the treatment group and the comparison group. If city i belongs to the treatment group, D_i is set as one. Otherwise, it is set as zero. T_t is a dummy variable that distinguishes pre-treatment and post-treatment periods. If time t is later than the year when the talent competition starts, T_t is set as one. Otherwise, it is set as zero. The coefficient β denotes the relative effect of talent competitions on the urban innovation between cities in the treatment group and in the comparison group. X_{it} represents some control variables; α denote the coefficients for control variables; ε_{it} represents the random error term.

Then, on the basis of Model I, we constructed the following model (here referred to as Model II) to estimate how the effect of talent competition on urban innovation changed with the level of urban development.

$$Innovation_{it} = \lambda_i + \gamma_t + \sum_{j=2}^{10} (\beta_j Group_{ij} \times T_t) + \alpha X_{it} + \varepsilon_{it}. \quad (2)$$

In Equation (2), $Group_{ij}$ a dummy variable represented the level of urban development. If the city i belongs to the group with an urban development level j, $Group_{ij}$ is set as one. Otherwise, it is set as zero. The coefficient β_j denotes the relative effect of talent competition on urban innovation between cities in the group with urban development level j and in the comparison group. The meanings of the remaining variables are the same as in Equation (1).

In addition, as we noted above, the effect of talent competition on urban innovation is probably through human capital agglomeration. To further investigate the mechanism of how talent competition affects urban innovation, we constructed Model III referring to Baron and Kenny [41]. Model III contains three steps. First, the effect of talent competition on urban innovation is verified, which was conducted in Model II. Second, the effect of talent competition on human capital by replacing urban innovation in Equation (2) with human capital (as shown in Equation (3)) is verified. Third, whether talent competition promotes the growth of human capital and further improves urban innovation by adding human capital into Equation (2) (as shown in Equation (4)) is verified. The model is constructed as follows:

$$Human_{it} = \lambda_i + \gamma_t + \sum_{j=2}^{10}(\beta_j Group_{ij} \times T_t) + \alpha X_{it} + \varepsilon_{it}, \quad (3)$$

$$Innovation_{it} = \lambda_i + \gamma_t + Human_{it} + \sum_{j=2}^{10}(\beta_j Group_{ij} \times T_t) + \alpha X_{it} + \varepsilon_{it}, \quad (4)$$

where $Human_{it}$ represents the level of human capital. The meanings of the remaining variables are the same as in Equation (2). In Model III, if the estimates of coefficient β_j in Equation (4) are less than those in Equation (2), it proves that the effect of talent competition on urban innovation was brought about by the human capital agglomeration.

The definition of relevant variables in the models constructed above is as follows:

The urban innovation. Patents are usually considered proxy variables for innovation in most previous studies [42–44]. Similarly, this study used the number of authorized patents to measure urban innovation. The patents were divided into three types: patents for inventions, patents for utility models, and patents for appearance designs. Some examples in the literature point to differences in the difficulty and value of innovation between those patents [45,46]. Thus, we constructed a composite index by assigning different weights to different types of patents as a measure of urban innovation. The composite index is described by:

$$Innovation_{it} = 0.5P_{1it} + 0.3P_{2it} + 0.2P_{3it}. \quad (5)$$

In Equation (5), P_{1it}, P_{2it}, and P_{3it} represent the authorized number of patents for inventions, the patents for utility models, and patents for appearance designs, respectively.

The human capital. This study selected the number of employed persons in each city to measure the human capital. There were two reasons for this. First, the number of employed persons is a better representation of the actual level of labor in each city than the total population. Second, the talent policy aims more at attracting talent to work rather than to live in the city.

The identification of the start time of the talent competition. From what we have discussed above, talent competition refers to the process by which most cities promulgate talent policies to introduce talents. The beginning of this process was the promulgation of opinions in the State Council on further promoting the reform of household registration in 2014 [47]. Thus, this study sets 2014 as the start time of the talent competition. That is to say, T_t is set as to one when year t is later than 2014. Otherwise, it is set as zero.

The distinction between the treatment group and the comparison group. Due to the differences in natural resources and economic development, regional disparities have become universal economic phenomena [48]. In Model I, we divided the cities concerned in this study into three parts according to regional disparities, namely the eastern, central, and western regions. Any two parts of these cities were compared to each other. Cities in the more developed part were set as the treatment group and the remaining part as the comparison group. For example, when we compared the different effects of talent competition on urban innovation between eastern and western regions, cities in the eastern region were set as the treatment group and those in the western region as the comparison group. In Models II and III, we equally divided the cities concerned in this study into ten groups according to the level of urban development and set the group with the lowest urban development level as the comparison group. As in the related literature [49], this study used GDP as a proxy variable for the level of urban development.

The control variables. In order to control the individual characteristics of cities that changed with time, we referred to the previous studies [22,34,50] and selected four factors that could affect urban innovation as control variables. (1) Industrial structure. This study utilized the proportion of value-added for the secondary and tertiary industry in GDP to measure the industrial structure. (2) The degree of city openness. We used the actual foreign direct investment in each city to measure the degree of city openness. (3) Investment in education. Investment in education was measured by the education spending per capita provided by the government. (4) The income level. The income level is measured by the average wage of employed persons in each city.

2.2. Data Source

This study selected the panel dataset for China's 298 prefecture-level cities from 2010 to 2019 as the fundamental data, and the cities that underwent an adjustment in administrative areas during the study period were not included. The authorized number of patent data for each city was collected from the Chinese Research Data Services (CNRDS) database. The GDP, the number of employed persons, and the control variables data of each city were collected from the China Urban Statistical Yearbook (2011–2020). The geographic vector data for cities used in this study were downloaded from the National Geomatics Center of China (http://www.ngcc.cn, accessed on 5 January 2023) and the Standard Map Service System (http://bzdt.ch.mnr.gov.cn, accessed on 5 January 2023). We modified the colors of some map elements on the basis of the standard map (approval number: GS (2019) 1822) for the readability of this paper.

Table 1 presents the specific descriptions of the variables used in this study. Figure 1 shows the distribution level of urban innovation in 2019 and for three regions in Model I. It can be seen that the level of urban innovation in 2019 was higher in the eastern region than in the central and western regions. Additionally, the purpose of Model I was to verify whether this gap resulted from talent competition.

Table 1. Description of the variables used in the study.

Symbol	Variable	Definition	Measurement Unit
Innovation	Level of urban innovation	The composite index of authorized patents	none
Human	Human capital	The number of employed persons in each city	10,000 people
INS	Industrial structure	The proportion of value-added for the secondary and tertiary industry in GDP	%
FDI	The degree of city openness	The actual foreign direct investment	10,000 dollars
EDU	Investment in education	The education spending per capital provided by the government	yuan per person
WAG	The income level	The average wage of employed persons	yuan
Group	Relative level of urban development	The grouping variable based on the GDP in each city	none

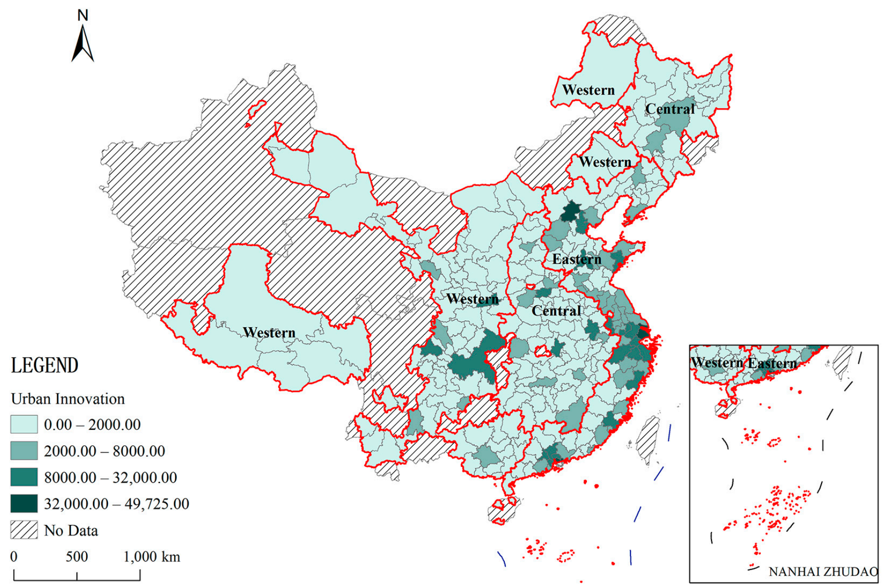

Figure 1. The distribution of the level of urban innovation in 2019.

3. Results and Discussion

3.1. Verification of the Heterogeneous Effects of Talent Competition

This study used a two-way fixed effect model to regress Model I. The regression results for Model I consist of three parts. The first part shown in column (1) of Table 2 represents the relative effect of talent competition on urban innovation between cities in the eastern and western regions. The coefficient of the interaction term in column (1) is significant at the 1% significance level, indicating that talent competition promoted urban innovation in the eastern region more than in the western region. Similarly, the second part shown in column (2) indicates that talent competition also promoted urban innovation in the eastern region more than in the central region. However, even though the coefficient of the interaction term in columns (3) is significant at the 10% significance level, its value is much less than the values of the coefficient in columns (1) and (2); this result implies that there is little difference in the effect of talent competition on urban innovation between cities in the central and western regions. More precisely, talent competition widened the urban innovation gap between cities in the eastern and central/western regions, while the gap between cities in the central and western regions did not widen. Generally speaking, the regression results for Model I indicate that there are heterogeneous effects of talent competition on urban innovation.

Table 2. Estimated results of Model I.

Symbol	(1)	(2)	(3)
Treatment group	Eastern region	Eastern region	Central region
Comparison group	Western region	Central region	Western region
$D_i \times T_t$	1198.78 ***	251.95 **	−29.09
	(120.05)	(126.53)	(78.93)
Constant	−3114.39	2861.85 **	−1075.13 **
	(2946.27)	(1410.76)	(486.33)
Control variables	Yes	Yes	Yes
Observations	1717	1968	1689
adj. R^2	0.900	0.909	0.894

Notes: Standard errors of coefficients reported in parentheses. **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

The application of the DID model relies on a parallel trend assumption: in the absence of the treatment, the average changing trends of the treatment and comparison groups remain parallel [51]. This study requires the average changing trends of urban innovation in different regions to remain consistent before the talent competition. Therefore, we used the event study method to verify whether Model I satisfied the parallel trend assumption. The method is constructed as follows:

$$Innovation_{it} = \lambda_i + \gamma_t + \sum\nolimits_{j=2010, j \neq 2014}^{2019} (\beta_j D_i \times T_{tj}) + \alpha X_{it} + \varepsilon_{it}, \quad (6)$$

where T_{tj} is a dummy variable that represents a specific year. If the year t is equal to j, T_{tj} is set as one. Otherwise, it is set as zero. The coefficient β_j denotes the differences between cities in treatment and comparison groups in year j. The meanings of the remaining variables are the same as in Equation (1). We chose the year 2014, when the talent competition started, as the base year. If the coefficients of interaction terms were not significant before 2014, then the parallel trend assumption was considered satisfied. Figure 2 shows the results of the parallel trend test of Model I.

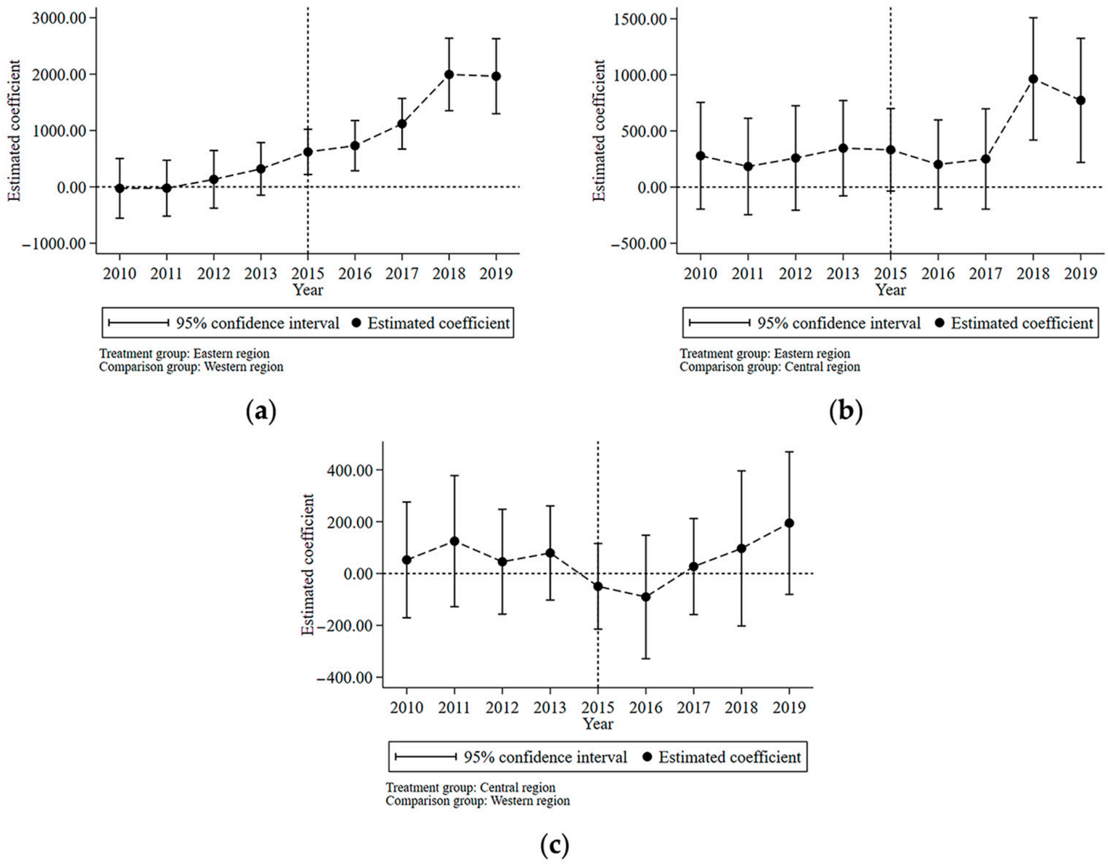

Figure 2. Parallel trend test of Model I. (**a**) Parallel trend test between cities in the eastern and western regions; (**b**) Parallel trend test between cities in the eastern and central regions; (**c**) Parallel trend test between cities in the central and western regions.

As shown in Figure 2a, zero is in the 95% confidence interval of the estimated coefficients from 2010 to 2013. It might be argued that the gap between urban innovation in eastern and western regions did not change significantly prior to the talent competition. However, this gap gradually widened after the start of the talent competition, which means that the heterogeneous effects of talent competition on urban innovations intensified over time. Thus, the parallel trend assumption was satisfied for the first part of Model I. The results in Figure 2b also reveal that the parallel trend assumption was also satisfied for the second part of Model I. Unlike the former two, the results in Figure 2c show that the 95% confidence interval of the estimated coefficients always covers zero during the research period. This has two implications. First, the parallel trend assumption is also satisfied for the third part of Model I. Second, the talent competition did not widen the gap between urban innovation in central and western regions, which indirectly supports the findings in the third part of Model I. In summary, it is appropriate to use the DID model to assess the effect of talent competition on urban innovation.

3.2. Analysis of the Heterogeneous Effects of Talent Competition

Based on the findings of Model I, Model II discusses how the effect of talent competition on urban innovation changes with the level of urban development. Figure 3 displays the estimated results of Model II. In order to describe the significance of the estimated coefficients more clearly, the image of the coefficients from groups 2 to 9 is blown up. As shown in the right part of Figure 3, we found that the estimated coefficients gradually increased with the number of groups. This suggests that the effect of talent competition on urban innovation was positively related to the level of urban development. In other words, the faster the city developed, the higher the benefits of the talent competition. There are two possible reasons for this. One reason is that talent competition drives the flow of talent, and developed cities have sufficient fiscal revenue for policy subsidies to provide additional talent benefits, which leads to a corresponding clustering of talent and an improvement in urban innovation. The other possible reason is that the innovation environment and public infrastructure are more perfect in developed cities, so talent is more efficient in innovation [52]. In the left part of Figure 3, the estimated coefficients from groups 2 to 4 are not significant, which means that the effect of talent competition on urban innovation was not significantly different between the first four groups. In addition, the estimated coefficient of group 10 is significantly more than the other coefficients, which indicates that there is a "head effect" of talent competition; that is, talent competition only greatly promotes innovation in a minority of cities; for others, the effect of talent competition on urban innovation is similar. This could be explained by the "material delays". In the context of talent competition, talent, especially the high-end talent that is not limited by the cost of migration, is more capable and willing to flow to first-tier cities [53,54]. Talent responds preferentially to the talent policies released by first-tier cities and flows to them. Other cities will only be considered if first-tier cities become less attractive. This leads to shorter material delays between the implementation of talent policies and the improvement of urban innovation in first-tier cities than in other cities. These talents are the first productivity of urban innovation, and thus, the results show that innovation in first-tier cities is significantly promoted.

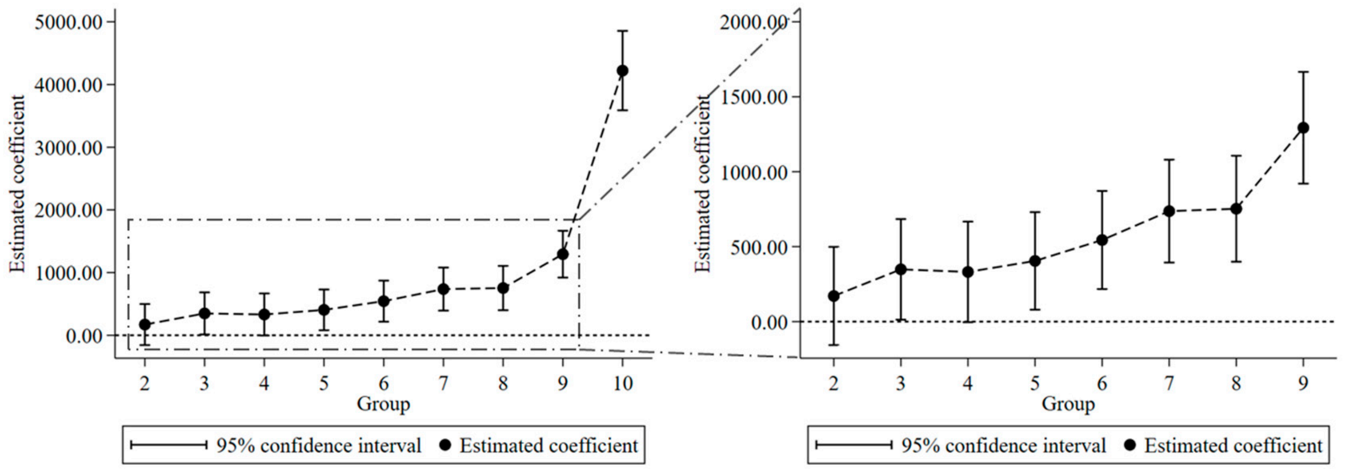

Figure 3. Estimated results of Model II.

Similarly, Figure 4 shows the results of the parallel trend test in Model II. We sequentially tested the parallel trends of urban innovation between Group 1 and the other groups. The results shown in Figure 4 suggest that the parallel trend assumption was satisfied in all groups except Group 9. The 95% confidence interval of the estimated coefficients for 2010 and 2011 does not cover zero in Figure 4h. This may be due to the fact that some policymakers in Group 9 cities placed a high value on innovation in 2014, leading to a larger gap in urban innovation between Group 1 and Group 9 cities in 2014. In addition, we found that the estimated coefficients tended to increase slowly before 2014 in Figure 4f–i, which suggests that the urban innovation gaps may increase slowly before the talent competition, but this trend was not significant. Correspondingly, the estimated coefficients increased rapidly after 2014, indicating that the process was accelerated by talent competition. In general, the parallel trend assumption was satisfied for Model II.

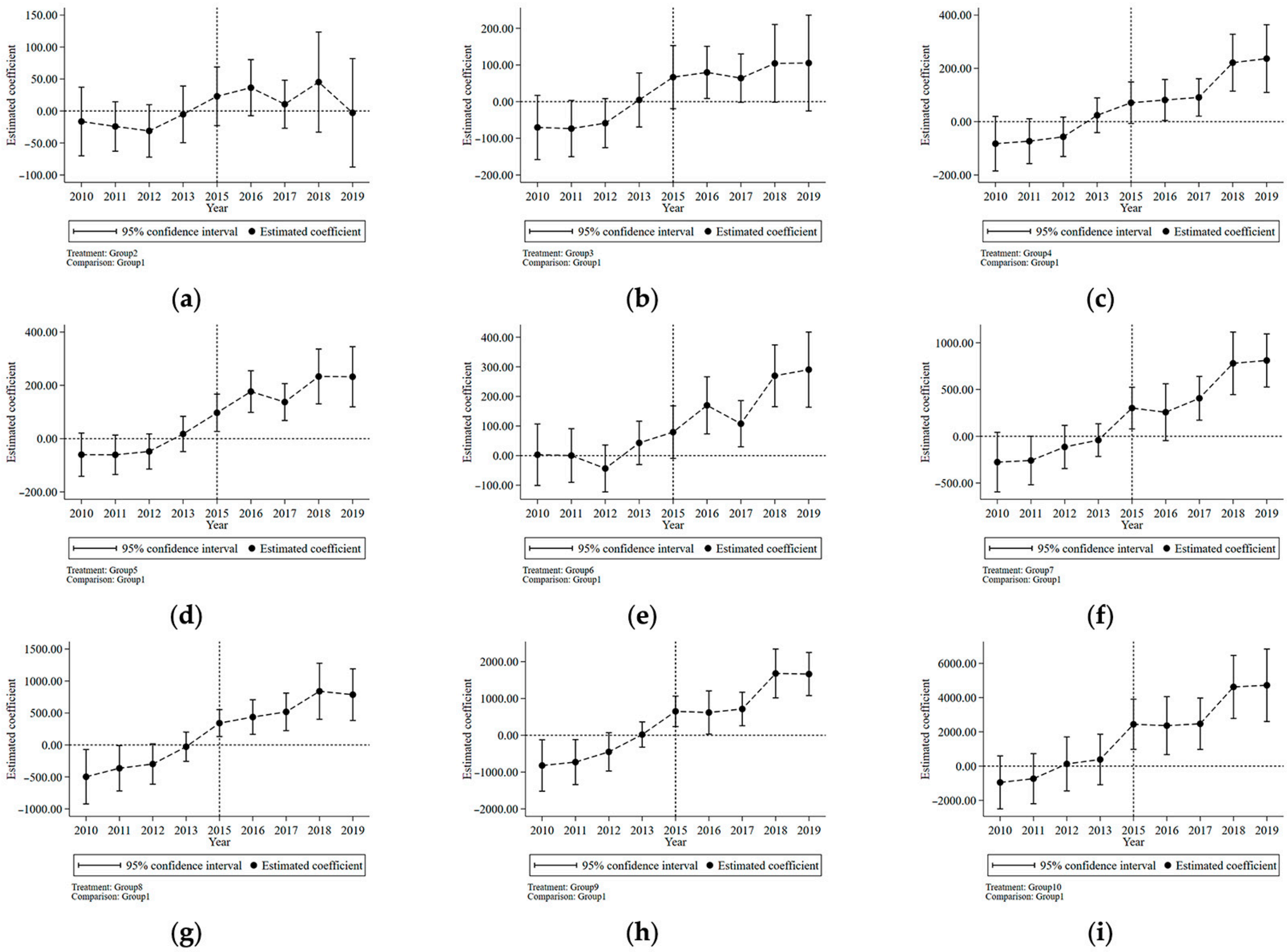

Figure 4. Parallel trend test for Model II. (**a**) Parallel trend test between cities in Group1 and Group 2; (**b**) Parallel trend test between cities in Group1 and Group 3; (**c**) Parallel trend test between cities in Group1 and Group 4; (**d**) Parallel trend test between cities in Group1 and Group 5; (**e**) Parallel trend test between cities in Group1 and Group 6; (**f**) Parallel trend test between cities in Group1 and Group 7; (**g**) Parallel trend test between cities in Group1 and Group 8; (**h**) Parallel trend test between cities in Group1 and Group 9; (**i**) Parallel trend test between cities in Group1 and Group 10.

3.3. Mechanism of Talent Competition on Urban Innovation

From the empirical results of Model I and Model II, we can see that talent competition has different effects on urban innovation owing to the differences in the level of urban development. So, what is the mechanism of influence that talent competition has on urban innovation? Theoretical analysis shows that talent competition may promote the flow of talent, which then improves urban innovation. To verify this mechanism, Model III was estimated in steps. The results of the first step were the same as Model II. Figure 5 shows the estimated results of the second step of Model III (Equation (3)).

The trend of the estimated results in Figure 5 is similar to that of Figure 3, i.e., the estimated coefficients gradually increased with the number of groups. In other words, talent competition promotes the agglomeration of human capital, and its function has a positive correlation with the level of urban development. Again, there was no significant difference between Group 1 and Group 2, 3, 4, and 5. In addition, the estimated coefficient of group 10 is greater than the remaining coefficients in Figure 5, which indicates that there was also a "head effect" of talent competition on human capital. However, unlike the results in Figure 3, the relative differences between the estimated coefficients in Figure 5 are smaller than those in Figure 3. Human capital in this study was measured by the number of employed persons, which mainly reflects the quantity of human capital rather than the quality. As a result, the same number of employed persons in developed cities can better promote urban innovation due to the higher quality of human capital agglomeration compared to developing cities. These results indicate that there is a multiplier effect of talent competition on urban innovation through human capital agglomeration.

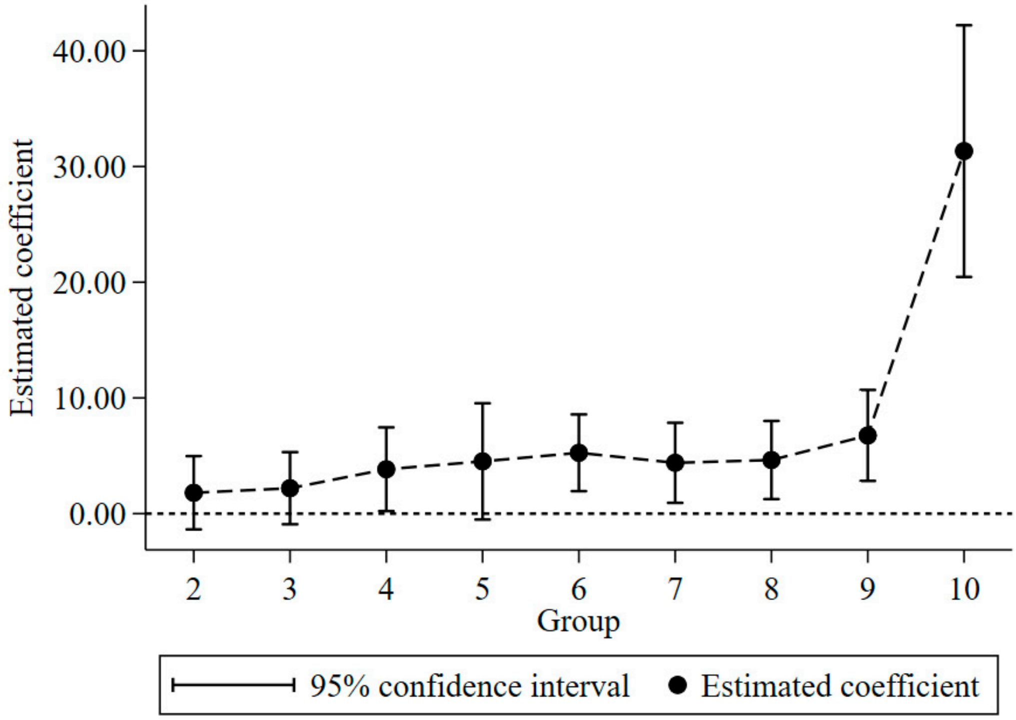

Figure 5. Estimated results of the second step of Model III.

Table 3 contrasts the results of three steps for Model III. It can be seen from columns (3) of Table 3 that the trend of the estimated results in the third step is also in line with that of the first and second steps. Namely, the basic conclusion of this study did not change. The significance level of estimated coefficients for Groups 3 and 4 changed from 5% in columns (1) to 10% in columns (3). Additionally, the estimated coefficients of Groups 5–10 in columns (3) were less than those in columns (1), which verifies the mechanism that talent competition promotes urban innovation through human capital agglomeration. According to the significance of the estimated coefficients, the effect of talent competition on urban innovation was mainly through human capital agglomeration in Groups 3–4, while in Groups 5–10, the effect could be generated by other means in addition to human capital agglomeration.

Next, we explain these results from the following. First, talent competition not only brings human capital to developed cities but also projects finance and technology. As regional centers, developed cities can often gather human capital with less cost. This high-quality human capital can lead to additional employment opportunities in developed cities by way of talent-leading projects, which further attract more talent [37]. This process provides positive feedback and can promote urban innovation in multiple ways. Second, cities at the mid-level of development pay a certain cost to attract and gather talent that is supported by talent policy, while the gathered talent does not promote the aggregation of other production factors. In this case, the relationship between urban innovation improvement and gathered talent is linear. Therefore, in these cities, the effect of talent competition on urban innovation is through the agglomeration of human capital. Third, cities at a low level of development are at an unfair disadvantage in talent competition [55], meaning that it is difficult to attract talent despite the implementation of talent policies. Even worse, the brain drain in developed cities has been a serious problem for these undeveloped cities [34].

As for the data set in this study, the average increase in the number of employed persons in Group 1 cities before 2014 was 8200 people per year, plummeted to −12,100 people per year after 2015. Additionally, the cost of talent policies may occupy the public funds for urban construction, further restricting urban sustainable development. In general, the heterogeneous effects of talent competition on urban innovation lead to an increasing gap in urban innovation between cities with different levels of development.

Table 3. Result comparison of the three steps of Model III.

Symbol	**(1) Step 1**	**(2) Step 2**	**(3) Step 3**
Explained Variable	$Innovation_{it}$	$Human_{it}$	$Innovation_{it}$
$Human_{it}$			11.70 *** (2.79)
$Group_{i2}$	170.94 (167.06)	1.80 (1.62)	149.85 (160.94)
$Group_{i3}$	348.53 ** (171.16)	2.20 (1.59)	322.82 * (164.31)
$Group_{i4}$	331.59 ** (171.17)	3.84 ** (1.85)	286.68 * (165.39)
$Group_{i5}$	404.93 ** (165.92)	4.51 * (2.56)	352.09 ** (160.50)
$Group_{i6}$	544.30 *** (166.93)	5.25 *** (1.69)	482.75 *** (161.79)
$Group_{i7}$	737.03 *** (174.97)	4.39 ** (1.76)	685.62 *** (169.01)
$Group_{i8}$	752.97 *** (180.27)	4.63 *** (1.72)	698.75 *** (173.25)
$Group_{i9}$	1293.27 *** (190.10)	6.76 *** (2.01)	1214.17 *** (187.09)
$Group_{i10}$	4222.17 *** (322.98)	31.33 *** (5.54)	3855.42 *** (321.92)
Constant	−1428.69 (1354.13)	−10.19 (23.07)	−1309.43 (1437.23)
Control variables	Yes	Yes	Yes
Observations	2687	2687	2687
adj. R^2	0.919	0.952	0.923

Notes: Standard errors of coefficients reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

4. Conclusions and Policy Implications

This study investigated the heterogeneous effects of talent competition on urban innovation in the context of household registration reform, using a panel dataset of 298 prefectural-level cities in China from 2010 to 2019. The DID model was used to analyze the effect of talent competition on urban innovation. Additionally, referring to the event study method, we discussed the relationship between the effect of talent competition and the level of urban development and verified the mechanism by which talent competition affects urban innovation. The main conclusions drawn from this study are as follows:

First, there are heterogeneous effects of talent competition on urban innovation. Talent competition plays a higher catalytic role in urban innovation in the eastern region than in the central/western region, which leads to increasing urban innovation gaps. Second, the effect of talent competition on urban innovation varies depending on the level of urban development. The more developed the city is, the stronger the effect. In addition, talent competition has a “head effect” on urban innovation. Its expansionary effect on urban innovation is significantly larger in a few first-tier cities than in other cities. Third, the effect of talent competition on urban innovation is mainly through talent flow. For = developed cities, talent competition can promote urban innovation in multiple ways beyond human capital agglomeration. As for cities at the mid-level of development, the mechanism that talent competition affects urban innovation primarily through human capital agglomeration.

Correspondingly, talent competition leads to brain drain in undeveloped cities, which may impede their sustainable development in the long term.

According to the main conclusions, some relevant policy implications can be raised. First, the coordinated development of cities can be promoted by adding financial subsidies for the central/western cities. From the above conclusions, talent competition will widen the urban innovation gap between cities in different regions. Consequently, the financial department of the central government should properly increase transfer payments for undeveloped cities to ensure regional coordinated development. Second, the construction of public service facilities should be strengthened to foster a favorable environment for innovation. The differences in public service facilities are one of the main driving forces of talent flow [37]. Talent can generate a multiplier effect only in developed cities, reflecting the weakness of the environment for innovation in other cities. Thus, it is necessary to strengthen the construction of public services to improve urban innovation. Third, cooperation on innovation should be deepened to avoid vicious talent competition. Cities should use their comparative advantages to implement differentiated talent policies based on their actual needs. The cooperation of innovation between cities could sufficiently bring into play the spillover effects of talent and avoid talent competition from becoming a zero-sum game.

This study contributes to the identification of the heterogeneous effects of the talent competition and the mechanisms by which it affects urban innovation in different cities. Meanwhile, these findings can help formulate reasonable talent policies for governments from the perspective of reducing regional disparities and promoting sustainable development. However, there are some limitations. The measurements of human capital in this study do not accurately reflect their quality. In order to investigate the flow of talent at different levels in the context of talent competition, future research works should consider the quality of human capital. The effect of talent competition on urban innovation is interpreted as human capital agglomeration in this study. Further research could explore the mechanisms by which talent competition affects urban innovation in multiple ways. Moreover, limited by data availability, this study uses longitudinal data from 2010 to 2019, covering a short time interval, which may have resulted in problematic causal inferences. Fujita and Mori point out that the evolutionary mechanisms of urban systems, in the long run, may be different from those in the short run [56]. Therefore, further research should verify the effect of talent competition on urban innovation using longer time intervals for more comprehensive and accurate causal inference.

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