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Does Government-Biased Talent Allocation Hinder Innovation? Evidence from China

Shirong Zeng

School of Economics, Zhejiang University. West Quad, 866 Yuhangtang Road, Hangzhou, 310058, China
zeng0717@zju.edu.cn

Abstract

This paper examines the relationship between talent allocation pattern and innovation in China. We use census data from 2005, 2010, and 2015 to estimate the concentration of talent in government departments at city level, representing the pattern of talent allocation. We find that the current talent allocation pattern negatively impacts corporate innovation. A one standard deviation increase in government talent concentration leads to 3.1% decrease in the average number of patent applications by industrial enterprises within the jurisdiction over the following three years. This negative effect is primarily driven by non-state-owned enterprises and small and medium-sized enterprises. The government-biased talent allocation pattern results in lower quality of R&D personnel in enterprises. Additionally, government departments with higher talent concentration have stronger tax collection abilities, leading to an increased real tax burden on enterprises and crowding out R&D expenditure, while failing to provide effective support for corporate innovation through public goods provision.

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1. Introduction

Talent allocation is widely recognized as playing a critical role in shaping economic development (Baumol, 1990; Murphy et al., 1991; Acemoglu, 1995; Hsieh et al., 2019). The diversion of talent into unproductive or rent-seeking activities reduces aggregate productivity (Baumol, 1990), and countries with a disproportionate share of talent engaged in such activities tend to experience markedly slower economic growth (Murphy et al.,1991). This issue is particularly salient in developing countries, where the overall stock of human capital is limited, making the efficient allocation of talent especially important.

However, the public sector—as the typical non-productive sector—continues to attract considerable interest in the labor market due to its advantages in compensation, job security, and occupational prestige (Shao et al., 2018; Cavalcanti and Santos, 2021). In developing countries such as China, the public sector remains highly attractive to top graduates. According to the 2021 Annual Report on Graduate Employment Quality released by Tsinghua University, one of China's top universities, approximately 46.1% of its graduates chose to enter government agencies and public service. This has drawn attention to talent misallocation and raised concerns that insufficient investment in scientific and technological talent may constrain innovation performance. Such concerns are especially pressing as China strives to overcome the middle-income trap, with the sustainability of its economic growth increasingly dependent on innovation. This raises a critical question: does the government-biased talent allocation pattern hinder innovation in China, and if so, to what extent? However, micro-level empirical evidence on this issue remains limited.

This paper addresses above limitations and examines how the concentration of government-employed talent affects innovation with firm-level panel data. Using census data from 2005, 2010, and 2015, we construct a proxy for city-level government talent concentration to capture the allocation pattern between government and non-government sectors. We find that the current pattern

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of talent allocation in government departments significantly suppresses enterprise innovation: a one-standard-deviation increase in government talent concentration at the city level is associated with a 3.1% decline in the average number of patent applications by industrial enterprises over the following three years. After controlling for the personal characteristics of mayors, as well as whether turnover at the year, the results remain highly significant. This negative effect is more pronounced for utility model patents and is primarily driven by non-state-owned and small to medium-sized enterprises,

I conduct a detailed examination of the underlying mechanisms. On the one hand, the concentration of talent in government departments leads to a significant decline in the quality—rather than the quantity—of R&D personnel within firms. On the other hand, it affects state capacity in a dual manner. As talent shifts toward the public sector, the “grabbing hand” of government—its tax extraction capacity—is strengthened, resulting in heavier tax burdens on firms and crowding out R&D investment. Meanwhile, the “helping hand”—public goods provision—fails to improve accordingly.

These findings carry important policy implications for promoting enterprise innovation in China. It requires not only alleviating the excessive concentration of talent in the public sector to release human capital for innovation, but also incentivizing existing public-sector talent to support firms through improved public service provision rather than through taxation.

2. Literature Review

This study speaks to three strands of the literature. First, it relates to researchs on talent or human capital allocation and its economic consequences (Baumol, 1990; Murphy et al., 1991; Acemoglu, 1995; Hsieh et al., 2019), with particular attention to the distribution of talent between the public and private sectors (Gomes, 2018; Albrecht et al.2019; Cavalcanti and Santos, 2021; Geromichalos and Kospentaris, 2022). These studies emphasize that excessive talent allocation to the public sector may reduce aggregate output, employment, and total factor productivity. Extending this perspective to the domain of innovation, Pan et al. (2020) develop an endogenous growth model and find that the overexpansion of the public sector reduces the inflow of R&D talent into the private sector in China. This negative impact outweighs the positive effects of public services, ultimately hindering the transition from imitation-based innovation to independent innovation. Chen (2022) provides empirical evidence, based on city-level cross-sectional data, that government-biased talent allocation significantly suppresses innovation. This paper complements the empirical literature on talent allocation and innovation (Chen, 2022) by utilizing detailed firm-level panel data. It contributes by providing new insights into firm-level heterogeneity—regarding ownership type and firm size—as well as exploring underlying mechanisms and conducting comprehensive robustness checks.

Second, this study contributes to the literature on bureaucratic quality and state capacity (He and Wang, 2017; Xu, 2018; Besley et al., 2021; Moreira and Pérez, 2024). A high-quality bureaucracy is widely recognized as essential for the effective functioning of public institutions (Evans and Rauch, 1999; Leaver et al., 2021; Besley et al., 2021). Public sectors staffed with more skilled personnel may be better positioned to deliver high-quality public services, thereby enhancing firm productivity. However, when talent is excessively concentrated in the public sector, these potential benefits may be outweighed by the negative effects of diverting talent from productive activities. This paper contributes to this line of inquiry by analyzing how talent concentration in government affects state capacity along two dimensions: taxation and public goods provision. The findings reveal that while tax extraction capacity increases with talent concentration, the provision of public goods does not improve accordingly.

In addition, this study relates to the substantial body of literature on human capital and innovation (Romer, 1990; Gennaioli et al., 2012; Squicciarini and Voigtländer, 2015), particularly empirical studies (McGuirk et al., 2015; Sun et al., 2020; Moretti,2021; Zhang and Guo, 2025). This paper adds to this literature by providing evidence that excessive concentration of talent in the public sector directly reduces the quality of R&D personnel in firms. I highlight that, for developing countries, achieving a balanced allocation of talent between the public and private sectors—and

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ensuring that sufficient human capital is directed toward innovation—may be more critical than merely expanding the overall stock of human capital.

The paper is structured as follows: Section 3 presents the theoretical framework; Section 4 describes data sources, variable definitions and descriptive statistics; Section 5 presents the empirical strategy and empirical results, including baseline regression results, endogeneity treatment, robustness checks and heterogeneity analysis; Section 6 presents mechanism analysis. Finally, Section 7 provides a summary.

3. Theoretical Framework

This paper examines the impact of talent allocation patterns on innovation through three main mechanisms: including (1) the quantity and quality of R&D talent within firms and state capacity, which can be divided into two aspects: (2) the government's grabbing hand through tax collection and its crowding-out effect on enterprise R&D investment; and (3) the government's helping hand through the provision of public goods.

Quantity and Quality of R&D personnel: Endogenous growth theory posits that technological progress is the fundamental driver of economic growth (Romer 1990). Human capital is the key production factor in generating new knowledge and technologies. Innovation activities require a minimum threshold of human capital, as only individuals with a certain level of educational attainment are qualified to engage in R&D—referred to in this study as talent. Firms, as the principal agents of technological innovation, rely heavily on such talent. However, government departments require talented civil servants to ensure effective administration and high-quality public service delivery. Given the relatively inelastic supply of skilled labor in the short term, both government and firms compete for the same talent pool, making talent allocation a zero-sum game.

Attractive benefits—such as wage premium and generous pensions and job stability (Gomes, 2018; Albrecht et al. 2019; Cavalcanti and Santos, 2021), as well as occupational prestige (Shao et al., 2018; Xu and Adhvaryu, 2023)—make civil service positions highly appealing. Additionally, merit-based recruitment allows government agencies to select top candidates (Geromichalos and Kospentaris, 2022), leading to a talent allocation pattern skewed toward the public sector. Although not all private-sector talent engages in R&D, an excessive inflow of skilled workers into the public sector shrinks the pool available to firms and raises recruitment costs. Consequently, firms may be forced to reduce the size or quality of their R&D teams. Thus, excessive talent allocation to the government sector undermines both the quantity and quality of research talent available to firms.

Grabbing hand, tax burden and R&D investment: Government departments are not only major employers in the labor market but also play a critical role in policy implementation and public service delivery. State capacity hinges on the quality of its civil service workforce (Besley et al., 2021). This study focuses on two core government functions frequently emphasized in the literature: tax collection and the provision of public goods. For firms, the former represents the grabbing hand, while the latter constitutes the helping hand.

From the perspective of tax collection, a higher-quality bureaucracy enhances the government's capacity to enforce taxation (Xu, 2018). Holding the size of the public workforce and nominal tax rates constant, an inflow of more capable individuals into government strengthens tax enforcement and reduces the scope for tax evasion and avoidance by firms. However, for enterprises, a heavier tax burden may crowd out expenditures otherwise allocated to R&D investment. Therefore, as talent becomes increasingly concentrated in government departments, tax enforcement capacity rises, actual tax burdens increase, and firms' R&D expenditures decline accordingly.

Helping hand and provision of public goods: However, what enterprises value more is the government's helping hand—its capacity to provide essential public goods and services. Public infrastructure, such as communication networks and transportation systems, promotes the flow of people and information (Acemoglu, 2015; Agrawal et al.,2017; Yang et al, 2022). Additionally, public services in education and healthcare can reduce labor-related costs for firms. In this sense, a more capable bureaucracy enhances the government's ability to deliver high-quality public services (He and Wang, 2017; Dahis et al.,2023), thereby indirectly promoting firm innovation. The greater the concentration of talent in government departments, the more abundant the provision of public goods and the higher the quality of services firms can rely on.

In conclusion, the concentration of talent in government departments can have both positive and negative effects on enterprise innovation. Theoretically, this implies an inverted U-shaped relationship and there exists an optimal level of government talent concentration that maximizes innovation output. When talent allocation surpasses this optimal point and becomes excessively concentrated in government departments, the negative effects outweigh the positive ones. Consequently, the greater the concentration of talent in the public sector, the more enterprise innovation is inhibited and vice versa. In the following sections, I use firm-level data from China to first analyze the impact of the government-biased talent allocation pattern on innovation and empirically test the mechanisms discussed above.

4. Data Sources and Descriptive Statistics

4.1. Allocation Pattern of Talent

I construct an index to characterize the allocation pattern of talent between government and non-government sectors. Following the literature on human capital distribution between government and enterprises (Li and Yin, 2017), we define **Government Department Talent Concentration (GDTC)** as the ratio of the proportion of talent in government departments to that in all non-agricultural employment sectors. The calculation is presented in equation (1).

$$\mathrm{GDTC} = \frac{\text{Proportion of talent in government departments}}{\text{Proportion of talent in non}-\text{agricultural employees}} \quad (1)$$

The data used to calculate talent concentration in government departments are drawn from the subsample of 1% Population Sampling Survey of 2005, the 2010 Population Census, and the 1% Population Sampling Survey of 2015, which are currently the most comprehensive micro-survey data covering almost all cities nationwide and with the largest sample size. In this study, employees[1] with a bachelor's degree or higher are defined as talent, and the intersection of individual industry and occupation information is used to define government department employees (i.e., civil servants[2]) and non-agricultural employees[3]. To mitigate sampling bias from small city samples, I exclude outliers and cities with fewer than 20 sampled government employees, resulting in a final sample of 819 observations across 273 cities for the period 2005–2015.

The first row of Panel A in Table 1 reports the descriptive statistics of talent concentration in government departments at the city level, with an average value of 5.072, indicating that, on average, the proportion of talents in government departments is more than five times that of the overall non-agricultural employed population. Figure A1 illustrates both the cross-city variation in government department talent concentration (GDTC) and its evolution from 2005 to 2015. In 2005, the highest

[1] The employed population is defined as workers aged 16-64 who were in a working state during the previous week.

[2] Government employees (or civil servants) are defined as those working in the sectors of public administration, social security, and public management organizations, whose occupations include managers of enterprises and institutions, professional and technical personnel, and clerical staff. Industry and occupation classifications across different survey years are adjusted to the 2015 standards (industry classification code according to GB/T 4754-2011, occupation classification code according to GB/T 6565-2015)

[3] Agricultural employees are defined as those engaged in industries such as agriculture, forestry, animal husbandry, and fisheries, with occupations related to production in agriculture, forestry, animal husbandry, fisheries, and water conservancy, and whose household registration is classified as agricultural; non-agricultural workers are those engaged in occupations other than agricultural employment.

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levels of GDTC were primarily observed in the eastern coastal regions, likely reflecting the earlier adoption of merit-based recruitment mechanisms. By 2010, the national average GDTC had risen, and by 2015, the highest concentrations were found in parts of central and southwestern China.

Table 1. Descriptive Statistics of City and Firm Characteristics Variables.

Variables	Definition	Obs	Mean	SD	Min	Max
Panel A. City-level variables						
GDTC	Government departments talent concentration	819	5.072	2.211	1.009	17.267
per_gdp	GDP per capita (Yuan)	819	10.073	0.811	7.612	12.239
pop	Permanent population (in ten thousands)	819	5.879	0.676	3.303	8.029
ind2_gdp	Output value of the secondary industry /GDP	819	0.458	0.105	0.151	0.859
ind3_gdp	Output value of the tertiary industry /GDP	819	0.382	0.090	0.111	0.854
inno_city	Innovative pilot city(dummy)	819	0.096	0.295	0	1
pub_pop	Official-to-civilian ratio	819	0.014	0.006	0.004	0.052
uni_ratio	proportion of employees with a bachelor's degree or higher among non-agricultural employment	819	0.041	0.036	0.001	0.311
nonfar_em	Proportion of non-agricultural employment	819	0.578	0.204	0.111	0.999
Panel B. Firm-level variables						
asset	Total assets(million)	76,380	565.304	6022.920	0.116	1150000
com_em	Number of employees	76,380	579.130	2888.475	8	513195
age	Firm age	76,380	12.199	7.123	0	68
oa	Total profit / Total assets	76,380	0.052	0.120	-0.984	1.000
debt_ratio	Total debt / Total assets	76,380	0.606	5.198	0.000	1433.441
soe	State-Owned Enterprise(dummy)	76,380	0.055	0.228	0	1
exporter	Exporting enterprise(dummy)	76,380	0.555	0.497	0	1

4.2. Firm-Level Data

To align with the years of the population census data, this study uses industrial enterprise samples from 2005, 2010, and 2015. The 2005 data are drawn from the China Industrial Enterprise Database (CIED), while the 2010 and 2015 data are obtained from the National Tax Survey Database (NTSD)[4]. Following the matching method for industrial enterprise databases by Brandt et al. (2012),

[4] There are two considerations for matching the industrial enterprise samples from two databases: firstly, a single database cannot fully cover the time span from 2005 to 2015, and the two databases complement each other in terms of time coverage; secondly, the 2010 industrial enterprise data lacks sufficient variable information for the empirical analysis required by this study, and the quality of post-2009 CIED data is

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I match and merge the enterprise samples from the two databases sequentially according to corporate legal codes and enterprise names. Then I clean the data[5] and check operating status[6]. Finally, I get a balanced panel consisting of 25,460 continuously operating enterprises from 2005 to 2019, with a total of 76,380 observations. Table 1 Panel B presents summary statistics for the firm-level control variables, including total assets, number of employees, firm age, debt-to-asset ratio, return on total assets, and dummy variables indicating whether a firm is state-owned or an exporting enterprise.

4.3. Innovation Data

I use the number of invention patents and utility model patents as measures of firm-level innovation output, excluding design patents that are less related to technological innovation. The patent data is sourced from the incoPat Database, which provides global intellectual property data services. Following the matching procedure of Kou et al. (2020), I match firm names and abbreviations from the industrial enterprise dataset to patent applicants, retaining only exact matches to ensure accuracy. The matched data cover patent applications filed between 2005 and 2019, yielding a total of 1,446,507 patent applications, of which 736,675 are invention patents. Figure 1 illustrates the trend in patent applications (by first applicant) from 2005 to 2019. It is noteworthy that the majority of patent applications are concentrated among a small group of large firms. Even in 2019, less than one-quarter of the sample firms filed a patent application in that year. indicating considerable heterogeneity in innovation performance across firms.

I use census years (2005, 2010, and 2015) as base years and examine firms' patent applications in subsequent years. Table 2 Panel A reports the total number of patent applications filed over the following n years (log-transformed, plus one), where n = 1, 2, 3, 4. Panel B reports a binary indicator for whether a firm filed any patents. On average, sample firms filed 10.679 patents over the next three years, while 29.6% of firms filed at least one patent.

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significantly problematic, while the NTSD data provides more information, including financial status, R&D expenditures, and tax payments.

[5] I cleaned the data following these steps: (1) deleting samples with missing values or outliers for variables such as total assets, number of employees, and total profit; (2) deleting samples with fewer than 8 employees; (3) deleting samples located in different cities between 2005 and 2015; and (4) deleting samples with missing values for core explanatory variables and control variables.

[6] Since this study examines corporate innovation until 2019, to avoid the issue of sample enterprises exiting after 2015 causing data incomparability across different years, I matched the industrial registration information of sample enterprises through Qichacha to check the operating status, and keep the sample of firms that were continuously operating from 2005 to 2019.

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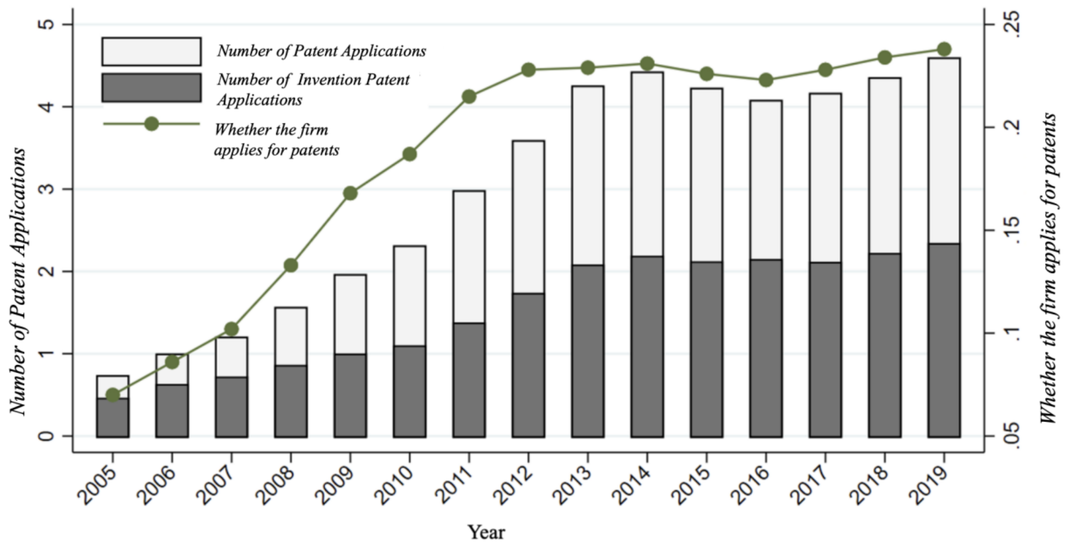

Figure 1. Patent Application of Sample Industrial Enterprises from 2005 to 2019.

Table 2. Descriptive Statistics of Patent Applications for Industrial Enterprises.

Variables	Obs	Mean	SD	Min	Max
Panel A. Number of Patent Applications					
Number of patent applications in the next year (t+1)	76,380	3.154	94.107	0	21,019
Number of patent applications in the next two years (t+2)	76,380	6.698	186.374	0	39,983
Number of patent applications in the next three years (t+3)	76,380	10.679	285.429	0	54,891
Number of patent applications in the next four years (t+4)	76,380	14.922	395.320	0	68,477
Panel B. Whether the Firm Applies for Patents					
Whether the firm applies for patents in the next year (t+1)	76,380	0.181	0.385	0	1
Whether the firm applies for patents in the next year (t+2)	76,380	0.248	0.432	0	1
Whether the firm applies for patents in the next year (t+3)	76,380	0.296	0.457	0	1
Whether the firm applies for patents in the next year (t+4)	76,380	0.337	0.473	0	1

5. Allocation Pattern of Talent and Innovation

5.1. Empirical Model

Based on the theoretical framework and data structure, I specify the baseline regression as a two-way fixed effects model, as shown in Equation (2):

$$Inno_{i,\ c,\ t+n} = \alpha + \beta GDTC_{ct} + \gamma X_{ct} + \delta Z_{ict} + \mu_i + \lambda_t + \varepsilon_{ict} \quad (2)$$

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$Inno_{i,c,t+n}$ denotes the innovation output of firm i in city c, measured by patent applications over the next n years from base year *t* (*t=2005, 2010, 2015*). There are two forms of dependent variable, the number of patent applications (logarithm of total number plus one) and whether a firm filed any patents (1 for yes, 0 for no).

This setting accounts for the time lag between R&D investment and the realization of patent outputs (Carlino, 2007). For instance, patents filed in year t+3 may stem from R&D activities initiated in year t, particularly for complex technologies requiring longer development cycles. Moreover, the data indicate that, unlike a few large firms with sustained innovation activities (e.g., Huawei, Gree), most small and medium-sized enterprises (SMEs) display irregular and intermittent innovation patterns. For example, if Firm A files no patents in year *t+1*, three in *t+2*, and one in *t+3*, relying on a single year's data may introduce measurement error. Using cumulative patent applications over multiple years helps smooth short-term volatility, better capture innovation output, and reduce measurement error. It also mitigates concerns about reverse causality to some extent. Accordingly, this paper primarily uses the cumulative number of patent applications over the next three years as the dependent variable.

$GDTC_{ct}$ is the core explanatory variable of this study, representing the concentration of talent in government departments in city c during year t, μ_i denotes the firm level fixed effects to control for unobserved time-invariant effects, while λ_t represents year fixed effects. X_{ct} includes a set of city-level control variables: per capita GDP (log-transformed), resident population (log-transformed), the share of secondary and tertiary industry output[7], the proportion of non-agricultural employment and the proportion of non-agricultural workers with a bachelor's degree or higher.[8] Additionally, a dummy variable is included to indicate whether the city was designated as a national innovation pilot city in year *t*, capturing the potential influence of regional innovation policies[9]. At the firm level, control variables include firm age (log-transformed), number of employees (log-transformed), total assets (log-transformed), return on assets, debt-to-assets ratio, ownership type (state-owned or non-state-owned), and whether the firm is an exporter. Descriptive statistics are presented in Table 1. Furthermore, acknowledging significant industry differences in patent applications (Hu et al., 2017), I control for industry-year trends using two-digit industry codes. ε_{ict} is error term, which is clustered at the city-industry level.

5.2. Baseline Results

Table 3 presents the baseline regression results. Columns (1) to (3) sequentially add city-level control variables, firm-level control variables, and industry-year trends. Across all specifications, the coefficients on government department talent concentration are consistently negative and statistically significant at the 1% level, suggesting that a higher concentration of talent in government departments significantly dampens firm-level innovation output. We take column (3) as the baseline regression, which suggests that a one standard deviation increase in talent concentration in government departments would result in a 3.1% decrease in the number of patent applications filed by firms over the following three years.

Considering that patent applications are the behavior of a minority of firms, columns (5) to (7) employ a binary indicator for whether a firm files any patent applications over the subsequent three years as the dependent variable. The results remain robust, indicating that higher talent concentration in the public sector reduces the probability of firms engaging in patenting activities.

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[7] The data primarily comes from the CEIC Database, with a few missing values supplemented from the China City Statistical Yearbook.

[8] Calculated based on data from the subsample of the 1% Population Sampling Survey of 2005, the 2010 Population Census, and the 1% Population Sampling Survey of 2015.

[9] The data is sourced from the official website of the Ministry of Science and Technology of China.

Table 3. GDTC and Industrial Enterprises' Patent Applications within the Following 3 Years.

Panel A. Number of Patent Applications within the Following 3 Years				
	(1)	(2)	(3)	(4)
GDTC	-0.016***	-0.153***	-0.014***	-0.016***
	(0.004)	(0.004)	(0.004)	(0.006)
GDTC_2				0.002
				(0.001)
R-Square	0.707	0.716	0.719	0.719
Panel B. Whether the Firm applies for Patents within the Following 3 Years				
	(5)	(6)	(7)	(8)
GDTC	-0.007***	-0.007***	-0.007***	-0.002
	(0.002)	(0.002)	(0.001)	(0.004)
GDTC_2				-0.0003
				(0.0002)
City-level control variables	YES	YES	YES	YES
Firm-level control variables	NO	YES	YES	YES
Industry trends	NO	NO	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R-Square	0.648	0.653	0.655	0.655
N	76380	76380	76380	76380

Notes: Control variables include city-level control variables and firm-level control variables; Standard errors clustered are clustered at the city-industry level; *, *, *** *denote significance at the 10%, 5%, and 1% levels, respectively.*

As previously discussed, the relationship between talent concentration in government departments and firm innovation is theoretically expected to follow an inverted U-shape. In columns (4) and (8), I include the quadratic term of talent concentration in government departments. The results show that both the linear and quadratic terms are negative and insignificant, suggesting that the hypothesized inverted U-shaped relationship is not supported empirically.

Two possible explanations are proposed: first, the concentration of talent in government departments has already surpassed the optimal point, with the negative effects outweigh the positive effects; second, the hypothesized positive effects through improved public goods provision (Hypothesis 4) may be absent or insignificant. These possibilities will be further explored in the mechanism analysis. This will be examined further in the mechanism analysis.

Columns (1) to (4) of Table 4 use cumulative patent applications over the following 1 to 4 years (from t+1 to t+4) as dependent variables, while columns (5) to (8) use annual patent applications in each subsequent year (t+n) as the dependent variable. Across all specifications, the coefficients on government talent concentration are negative, indicating a consistent negative impact on firm innovation output. However, the magnitude and significance of this effect gradually diminish over time and become statistically insignificant after four years. These findings provide indirect support

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for using three-year forward patent applications as the primary outcome variable in the main analysis.

Table 4. GDTC and Industrial Enterprises' Patent Applications Within the Following n Years and in the nth Year.

	Patent Applications Within the Following n Years				Patent Applications in the nth Year			
	T+1	T+2	T+3	T+4	T+1	T+2	T+3	T+4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. *Number of Patent Applications*								
GDTC	-0.014***	-0.024***	-0.035***	-0.035***	-0.014***	-0.013***	-0.019***	-0.007**
	(0.003)	(0.004)	(0.005)	(0.006)	(0.003)	(0.004)	(0.004)	(0.004)
R-Square	0.653	0.691	0.719	0.743	0.653	0.648	0.657	0.668
Panel B. Whether the Firm Applies for Patents								
GDTC	-0.009***	-0.012***	-0.014***	-0.012***	-0.009***	-0.007***	-0.009***	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R-Square	0.601	0.633	0.655	0.671	0.601	0.597	0.605	0.616
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry trends	YES	YES	YES	YES	YES	YES	YES	YES
N	76380	76380	76380	76380	76380	76380	76380	76380

Notes: Control variables include city-level control variables and firm-level control variables; Standard errors clustered are clustered at the city-industry level; *, *, *** *denote significance at the 10%, 5%, and 1% levels, respectively.*

5.3. Endogeneity

Although forwarding the dependent variable helps mitigate concerns of reverse causality, and the regressions control for firm fixed effects, year fixed effects, and industry-specific trends, the results may still be subject to bias from unobserved time-varying factors, such as regional employment preferences, or cultural and political institutional factors like government rent-seeking, may have biased the results. To address this issue, I adopt an instrumental variable (IV) approach. Institutional environments often exhibit path dependence, and I use the talent concentration of the older generation of civil servants as an instrument. Parental career choices can influence those of their offspring, and persistent institutional inertia in government recruitment systems contributes to the intergenerational correlation in public-sector talent concentration. Importantly, the talent concentration of the previous generation is unlikely to directly affect firm-level innovation outcomes decades later, thereby satisfying the exclusion restriction required for a valid instrument.

Table 5. Endogeneity—Instrumental Variable Estimation.

	(1)	(2)	(3)	(4)

	T+1	T+2	T+3	T+4
	Panel A. First-stage estimation			
GDTC	0.457***	0.457***	0.457***	0.457***
	(0.046)	(0.046)	(0.046)	(0.046)
	Panel B. Second-stage estimation：Number of Patent Applications within the Following 3 Years			
GDTC	-0.023**	-0.035***	-0.040***	-0.033**
	Panel C. Second-stage estimation：Whether the Firm Applies for Patents within the Following 3 Years			
GDTC	-0.017***	-0.018***	-0.018***	-0.015***
	(0.005)	(0.005)	(0.005)	(0.005)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry trends	YES	YES	YES	YES
KP F-statistic	109.262	109.262	109.262	109.262
N	76338	76338	76338	76338

Notes: Control variables include city-level control variables and firm-level control variables; Standard *errors clustered are clustered at the city-industry level; *, *,* *** denote significance at the 10%, 5%, and 1% levels, respectively.

I use the data from 1% subsample of the 1990 census, defining the parent generation of civil servants as those aged 40-60, 35-55, and 30-50, corresponding to the years 2005, 2010, and 2015, respectively. The talent concentration of this cohort is calculated and used as the instrumental variable. Table 6 Panel A reports the first-stage estimation results, showing a significant positive correlation between the instrumental variable and the GDTC, with a KP F-statistic of 109.262, well above the conventional threshold of 10, thus passing the weak instrument test. Panels B and C report the second-stage estimation results, where the dependent variables are the number of patent applications and whether file any patents in subsequent years, respectively. The IV estimates are slightly larger than the baseline OLS estimates, and the level of statistical significance remains robust. These findings provide further evidence that the current concentration of talent in government departments in China significantly dampens firm-level innovation within local jurisdictions.

5.4. Robustness Check

Control for the personal characteristics of the mayor. Considering the personal characteristics of political leaders, such as educational background (Besley et al.,2011; Yao and Zhang, 2015), age and tenure, have impact on regional economic development. I further control the mayor's educational background, which is categorized into five levels: high school and below, associate degree, bachelor's degree, master's degree, and doctoral degree. In regression, I take the high school and below group as the reference. I also control for the mayor's age and gender characteristics, as well as their tenure in office[10].Table 6 reports the estimation results: columns (1)-(2) present the results from the two-

[10] The data on the personal characteristics of mayors comes from is sourced from the CPED database, which conducted by Jiang J. "Making Bureaucracy Work: Patronage Networks, Performance Incentives, and Economic Development in China," published in *American Journal of Political Science*, 2018, 62(4): 982-999

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way fixed effects model, while columns (3)-(4) display the corresponding instrumental variable estimates.

Table 6. Robustness check — Control for the Personal Characteristics of the Mayor.

	FE Estimation		IV Estimation	
	(1)	(2)	(3)	(4)
	Number of Patent Applications within the *Following* 3 Years	Whether the Firm Applies for Patents within the *Following* 3 Years	Number of Patent Applications within the *Following* 3 Years	Whether the Firm Applies for Patents within the *Following* 3 Years
GDTC	-0.016***	-0.007***	-0.044***	-0.020***
	(0.004)	(0.002)	(0.015)	(0.005)
mayor*associate degree	-0.001	-0.003	-0.031	-0.017
	(0.030)	(0.013)	(0.035)	(0.014)
mayor*bachelor's degree	0.023	-0.006	0.017	-0.008
	(0.018)	(0.008)	(0.020)	(0.008)
mayor*master's degree	0.044**	0.004	0.057***	0.010
	(0.017)	(0.007)	(0.019)	(0.008)
mayor*doctoral degree	0.020	-0.001	0.031	0.005
	(0.020)	(0.008)	(0.021)	(0.008)
mayor's age	0.001	-0.0002	0.002	-0.0001
	(0.002)	(0.001)	(0.002)	(0.0006)
mayor's gender(male=1)	0.024	0.016*	0.006	0.007
	(0.023)	(0.009)	(0.025)	(0.010)
mayor's tenure	0.003	0.002	0.005	0.002
	(0.003)	(0.001)	(0.003)	(0.001)

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Control variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry trends	YES	YES	YES	YES
KP F-statistic	-	-	156.777	156.777
R-Square	0.722	0.659	-	-
N	74322	74322	74274	74274

Notes: Control variables include city-level control variables and firm-level control variables; Standard *errors clustered are clustered at the city-industry level;* *, *, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Compared to the baseline regression, the magnitude and significance of the core explanatory variables remain robust. It also indicates that the mayor's educational background may have a positive impact on firm innovation within the jurisdiction, with the impact of a master's degree being the largest and most significant (although this effect is not significant when using patent applications as the dependent variable). Although, the personal characteristics of local leaders, especially their educational background, may have some influence on firm innovation in their jurisdictions, this does not change the conclusion that the concentration of talent in government departments tends to inhibit firm innovation.

Other robustness check. Although identifying the enterprise as the first applicant reflects its primary contribution to technological innovation, approximately 14% of patents in the sample involve multiple applicants. As a robustness check, I relax the restriction on first-applicant status and instead count all patents in which the enterprise is listed as a participant (Table 7, Panel A). Columns (1) and (2) report the estimated effects of government talent concentration on the number of patents applied for and the likelihood of participation in patent applications over the next three years, based on the two-way fixed effects model. Columns (3) and (4) present the corresponding IV estimates. The magnitude and significance of the coefficient for the concentration of talent in government departments are almost identical to those in the baseline regression.

Table 7. Robustness Check.

	FE Estimation		IV Estimation	
	(1)	(2)	(3)	(4)
	Number of Patent Applications within the *Following* 3 Years	Whether the firm applies for patents within the *Following* 3 Years	Number of Patent Applications within the *Following* 3 Years	Whether the firm applies for patents within the *Following* 3 Years
Panel A. Participating in patent applications				
GDTC	-0.039***	-0.007***	-0.039***	-0.032***
	(0.014)	(0.001)	(0.018)	(0.007)
KP F-statistic	-	-	156.777	156.777

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N	76380	76380	76338	76338
Panel B. Talents with associate degree or higher				
GDTC	-0.025***	-0.011***	-0.048***	-0.022***
	(0.005)	(0.002)	(0.016)	(0.006)
KP F-statistic	-	-	63.974	63.974
N	76380	76380	76338	76338
Panel C. Recalculating GDTC by average years of education				
GDTC	-0.447***	-0.198***	-1.109***	-0.569***
	(0.110)	(0.042)	(0.452)	(0.170)
KP F-statistic	-	-	83.998	83.998
N	76380	76380	76338	76338
Panel D. Excluding the sample of enterprises located in municipalities				
GDTC	-0.014***	-0.009***	-0.041**	-0.018***
	(0.004)	(0.002)	(0.018)	(0.007)
KP F-statistic	-	-	77.015	77.015
N	62973	62973	62931	62931
Control variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry trends	YES	YES	YES	YES

Notes: Control variables include city-level control variables and firm-level control variables; Standard errors clustered are clustered at the city-industry level; *, *, *** *denote significance at the 10%, 5%, and 1% levels, respectively.*

Additional robustness checks are presented as follows: first, relaxing the definition of talent to include those with an associate degree or higher education (Panel B); second, substituting educational qualifications with average years of education and redefine talent concentration as the ratio of the average education years of government employees to that of the non-agricultural workforce (Panel C); third, excluding firms located in municipalities from the sample (Panel D). Across all specifications, the results remain consistent with the baseline findings. Coefficients are statistically significant at the 1% level in Panels B and C, and at the 5% level in Panel D. These results further confirm the negative impact of talent concentration in government departments on enterprise innovation within the jurisdiction.

5.5. Heterogeneity Analysis

Heterogeneity of patent types. I begin by examining the effects of government department talent concentration on different types of patent applications. Invention patents, characterized by higher application thresholds, stringent review standards, and long protection period, are generally viewed as reflecting higher levels of technological sophistication. Table 8 Panel A, Columns (1)-(2) and Columns (3)-(4) report the effects of government talent concentration on the number of invention and utility model patent applications filed by firms over the next three years, based on fixed effects (FE) and instrumental variable (IV) estimations, respectively.

The results show that the coefficients for invention patents is not significant under both FE and IV estimations, while the coefficients for utility model patents are significant at the 1% level. However, in Panel B, where whether a patent application was filed within the next three years is used as the dependent variable, the coefficients for both types of patents are negative and significant at the 1% level. This may be due to greater variation in invention patent activity across firms and the higher technical complexity of invention patents, which makes the innovation process more multifaceted and susceptible to various factors. Overall, talent concentration in government departments seems to inhibit more utility model patent applications rather than invention patents.

Table 8. Heterogeneity of Patent Types.

	FE Estimation		IV Estimation	
	(1)	(2)	(3)	(4)
	Invention Patent	Utility Model Patent	Invention Patent	Utility Model Patent
Panel A. Number of Patent Applications Within the Next 3 Years				
GDTC	-0.003	-0.145***	-0.014	-0.033***
	(0.003)	(0.003)	(0.010)	(0.012)
Panel B. Whether patents are applied for Within the Next 3 Years				
GDTC	-0.004***	-0.006***	-0.022***	-0.017***
	(0.001)	(0.001)	(0.007)	(0.005)
Control variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry trends	YES	YES	YES	YES
KP F-statistic			109.262	109.262
N	76380	76380	76338	76338

Notes: Control variables include city-level control variables and firm-level control variables; Standard errors clustered are clustered at the city-industry level; *, *, *** *denote significance at the 10%, 5%, and 1% levels, respectively.*

Heterogeneity in Enterprise ownership and Enterprise Size. Existing studies consistently find substantial heterogeneity in innovation behavior across firms of different ownership types and sizes—a pattern also evident in our sample. In our sample, state-owned enterprises (SOEs), which account for 5.5% of the total, are responsible for approximately 12% of patent applications. Table 9 Panel A presents heterogeneity in the effect of government talent concentration on innovation between SOEs and non-SOEs. In Column (1), the coefficient for SOEs is positive but statistically insignificant. In contrast, Column (2) shows a significantly negative coefficient for non-SOEs. These findings remain robust under instrumental variable estimation. Overall, talent concentration in government departments does not appear to hinder innovation among SOEs and may even be beneficial. The observed negative effect is predominantly driven by non-SOEs.

Table 9. Heterogeneity in Enterprise Ownership and Enterprise Size.

	Number of Patent Applications within the Following 3 Years		Whether the Firm Applies for patents within the *Following* 3 Years	
Panel A. Enterprise ownership				
	(1)	(2)	(3)	(4)

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	Invention Patent	Utility Model Patent	Invention Patent	Utility Model Patent
GDTC	-0.002	-0.016***	-0.002	-0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
GDTC*SOE	0.004	0.019*	0.004	0.019*
	(0.008)	(0.010)	(0.008)	(0.010)
Panel B. Enterprise Size				
	(5)	(6)	(7)	(8)
	Invention Patent	Utility Model Patent	Invention Patent	Utility Model Patent
GDTC	-0.002	-0.016***	-0.004***	-0.007***
	(0.003)	(0.003)	(0.001)	(0.003)
GDTC*large	-0.002	0.019***	0.005**	0.011***
	(0.005)	(0.007)	(0.003)	(0.003)
Control variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry trends	YES	YES	YES	YES
N	76380	76380	76380	76380

Notes: Control variables include city-level control variables and firm-level control variables; Standard errors clustered are clustered at the city-industry level; *, *, *** *denote significance at the 10%, 5%, and 1% levels, respectively*.

Additionally, large enterprises—although accounting for less than 20% of the sample—are responsible for approximately 74% of total patent applications. I further explore the heterogeneous effects of government talent concentration on large enterprises versus small and medium-sized enterprises (SMEs) [11](Table 9 Panel B). In Columns (5) and (7), the coefficients for large enterprises are negative but statistically insignificant. By contrast, Columns (6) and (8) show that for SMEs, the coefficients are significantly negative at the 1% level under both fixed effects and IV estimations. These results indicate that excessive talent concentration in government departments significantly inhibits innovation among SMEs, with the negative impact being more pronounced for smaller firms.

6. Mechanism Analysis

How does the concentration of talent in government departments impact the innovation output of enterprises in China? This section explores the underlying mechanisms. First, I investigate whether the talent concentrating in government departments reduce the high-skilled workers needed for corporate innovation. Second, I assess how government talent concentration affects government capabilities. Specifically, I consider two aspects: (1) the grabbing hand-whether enhanced tax collection capacity increases firms' tax burdens, thereby constraining R&D investment; and (2) the helping hand, whether a government with more concentrated talent contributes to corporate innovation by improving public goods provision.

GDTC and investment in research personnel of firms. Innovation relies heavily on the investment in human capital. However, in the short term, the talent pool within a city is relatively inelastic. When

[11] I classify firms by total assets, with firms having total assets of 400 million yuan or more considered large enterprises, and those with total assets less than 400 million yuan classified as small and medium-sized enterprises (SMEs).

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government departments in a city concentrate a larger share of talent, enterprises face the challenges of insufficient R&D personnel and a decline in the average quality of R&D personnel. Due to the lack of firm-level data on R&D personnel, I use census data to estimate the employment scale and quality of enterprise technical personnel at the city level. Enterprise employees are defined as non-agricultural workers outside the public sector [12], and technical R&D personnel are identified as those engaged in professional and technical occupations. The scale of enterprise R&D talent is measured by the share of technical R&D personnel employed in enterprises relative to the total technical workforce in the city. The quality of enterprise R&D talent is proxied by the proportion of enterprise R&D personnel holding a bachelor's degree or above.

As shown in column (1) of Table 10, the coefficient of government talent concentration on the employment scale of enterprise R&D personnel is –0.002 and statistically insignificant. However, column (2) reveals that the coefficient on the quality of enterprise R&D personnel is –0.004 and statistically significant at the 1% level. This suggests a trade-off in talent allocation: when government departments absorb a disproportionate share of talent, firms experience a decline in the average quality of their R&D workforce, which in turn suppresses innovation output.

Table 10. GDTC and Firms' R&D Talent Investment and R&D Efficiency.

	Scale of R&D personnel	Quality of R&D personnel	R&D Efficiency
	(1)	(2)	(3)
GDTC	-0.002	-0.004***	-0.008
	(0.002)	(0.001)	(0.005)
GDTC *R&D			-0.004
			(0.006)
R&D			0.189***
			(0.039)
City-level control variables	-	-	YES
Firm-level control variables	YES	YES	YES
City FE	YES	YES	-
Firm FE	-	-	YES
Year FE	YES	YES	YES
Industry trends	YES	YES	YES
KP F-statistic	-	-	
N	819	819	43760

Notes: Columns (1) and (2) use city-level panel data for 2005, 2010, and 2015 and standard errors are clustered at the city level; Columns (3) and (4) use firm-level panel data for 2005 and 2010 and standard errors are clustered at the city-industry level. *, *, *** *denote significance at the 10%, 5%, and 1% levels, respectively.*

Moreover, insufficient investment in R&D talent may lead to lower R&D efficiency. In column (3), I include R&D expenditure, measured as a binary variable indicating whether a firm reports any spending on new product or technology development. Due to extensive missing data in 2015, the analysis is restricted to 2005 and 2010. The interaction term between government talent concentration

[12] The public sector, as defined by industry, includes government departments, education, and healthcare industries.

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and R&D expenditure is negative but insignificant. This result provides indicative evidence that excessive talent concentration in government departments may lower the quality of R&D personnel in firms, potentially reducing R&D efficiency and ultimately leading to lower innovation output.

GDTC, Grabbing Hand of the Government and Firm's R&D expenditure. As the government attracts more talent, its capacity may also be strengthened. I further examine the relationship between talent concentration and government capacity, beginning with the government's most fundamental function—taxation capacity（Xu, 2018）—which also has a significant impact on firms' productive and innovation activities(Chen et al.2021; Fang et al.,2023).

Among various taxes, corporate income tax is one of the most important levies imposed on industrial enterprises in China. Unlike value-added tax (VAT), income tax offers greater scope for tax avoidance and evasion, as firms can underreport profits to shrink the tax base. Consequently, effective income tax collection depends more heavily on the enforcement capacity of local tax authorities (Fan and Tian, 2016). Following Fan and Tian (2013), I measure government tax collection capacity using the effective tax rate (ETR) of industrial enterprises, defined as income tax payable divided by pre-tax profit.

Columns (1) and (2) of Table 11 report the regression results of government talent concentration on tax capacity. The findings indicate that higher talent concentration in government departments is associated with stronger tax enforcement. A heavier tax burden—acting as a government's grabbing hand—may crowd out firms' R&D investment. Columns (3) and (4) of Table 11 examine the relationship between government talent concentration and firms' R&D investment. The results show that the higher the concentration of talent in government departments, the lower the likelihood of firms investing in R&D. Overall, the underlying transmission mechanism is as follows: greater talent concentration enhances the government's tax enforcement capacity, which increases firms' effective tax rates and consequently suppresses their R&D investment.

Table 11. GDTC, Grabbing Hand of the Government and Firm's R&D expenditure.

	Tax collection capacity		R&D expenditure		Rent-seeking	
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	IV	FE	IV	FE	IV
GDTC	0.004***	0.015***	-0.004**	-0.018**	-0.009	0.020
	(0.001)	(0.003)	(0.001)	(0.007)	(0.007)	(0.028)
Control variables	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	-	-
Year FE	YES	YES	YES	YES	-	-
Industry trends	YES	YES	YES	YES	-	-
Province FE	-	-	-	-0.018**	YES	YES
Industry FE	-	-	-	(0.007)	YES	YES
KP F-statistic		113.611		153.66		134.565
N	75001	74960	50894	50892	24920	24548

Notes: Control variables include city-level control variables and firm-level control variables; Columns (1) and (2) use firm-level panel data from 2005 and 2010. Columns (3) and (4) use firm-level panel data from 2005, 2010, and 2015. Columns (5) and (6) use firm-level cross-sectional data from 2010 and additionally control for Province FE and Industry FE; Standard errors clustered at the city-industry level; *, *, *** denote significance at the 10%, 5%, and 1% levels, respectively.

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In addition to tax collection, the government's *grabbing hand* may also manifest through rent-seeking by officials (Chen, 2022). Moreover, Murphy et al. (1993) and Li and Yin (2014) argue that the returns to rent-seeking increase with the rent-seeker's ability. Based on this, I hypothesize that a higher concentration of talent in government departments may lead to more extensive rent-seeking activities.

I define the sum of externally paid business entertainment and travel expenses as a proxy for rent, and use the ratio of rent to operating revenue to measure the scale of government rent-seeking activities. This information is available from the 2010 NTSD. Given the use of cross-sectional data, I additionally control for industry characteristics and provincial fixed effects. The regression results in Columns (5) and (6) of Table 11 indicate that higher talent concentration in government departments does not lead to larger-scale rent-seeking activities. Therefore, the reduction in firms' R&D investment is not attributable to government rent-seeking activities.

GDTC and Helping Hand of the Government. However, compared to the government's *grabbing hand*, enterprises are more eager to benefit from its *helping hand*—namely, the provision of public goods that support innovation. Does a higher concentration of talent in government departments also strengthen this helping hand? I begin by examining infrastructure investment at the city level, using the ratio of fixed asset investment to GDP as a proxy for public infrastructure provision. The results presented in Column (1) of Table 12 show that government talent concentration is significantly positively associated with fixed asset investment at the 5% level. This suggests that cities with a higher concentration of talent in government departments tend to have greater public infrastructure investment.

Table 12. GDTC and Public Services.

	Fixed Asset Investment	Public R&D expenditure	Environmental protection	Healthcare	Education
	(1)	(2)	(3)	(4)	(5)
GDTC	0.011**	-0.0001*	0.390	-0.232	-0.317
	(0.05)	(0.00003)	(0.968)	(0.246)	(0.422)
City-level control variables	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	828	828	671	746	749

Notes: Standard errors clustered are clustered at the city level; *, *, *** *denote significance at the 10%, 5%, and 1% levels, respectively.*

Column (2) examines public scientific research investment by using the share of R&D expenditure in public fiscal spending as the dependent variable. The results reveal a significant negative correlation at the 10% level, suggesting that a higher concentration of government talent at the city level does not correspond with increased support for scientific research. On the contrary, public R&D investment appears insufficient in such settings. Columns (3) to (5) examine the provision of public goods using indicators such as sewage treatment rate, hospital beds per capita, and the number of primary and secondary school teachers per 10,000 residents—capturing aspects of environmental protection, healthcare, and education, respectively. With the exception of the sewage treatment rate, which shows a positive but modest effect, other coefficients are negative and statistically insignificant. These findings suggest that a higher concentration of talent in government

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departments does not translate into greater provision of public goods. In short, the government's *helping hand* has not strengthened in tandem with its *grabbing hand*.

Overall, government departments with higher talent concentration tend to allocate more fiscal resources to infrastructure investment while reducing spending on public research. This trade-off may offset the potential benefits of infrastructure on innovation. Moreover, government departments do not demonstrate superior performance in delivering public goods such as environmental protection, healthcare, and education. These findings suggest that the expected positive effect of government talent concentration on innovation—via improved public goods provision—has not been realized, which helps explain the absence of the theoretically predicted inverted U-shaped relationship in the baseline regressions.

7. Conclusions

This study investigates the impact of government talent concentration on corporate innovation using firm-level panel data from China. The results reveal that higher talent concentration in government departments significantly inhibits corporate innovation. Specifically, a one standard deviation increase in city-level government talent concentration is associated with a 3.1% reduction in the average number of patent applications filed by industrial firms over the subsequent three years. This result remains robust when using patent application status as an alternative dependent variable and after controlling for the personal characteristics and tenure of mayors. The negative effect of government talent concentration on corporate innovation is observed for both invention and utility model patents, with a more pronounced impact on utility model patents. Heterogeneity analysis by firm type and size reveals that this negative impact is primarily driven by non-state-owned enterprises and small to medium-sized enterprises.

To further explore the mechanism behind this negative impact, I find that, on one hand, the talent concentration in government departments crowds out the talent needed for corporate R&D, leading to lower quality of R&D personnel and reduced R&D efficiency. On the other hand, a government with more concentrated talent has stronger tax collection capabilities, which increases the real tax burden on companies, thereby squeezing out corporate R&D investments. The insufficient investment in both qualified R&D personnel and R&D expenditure hinders corporate innovation. Meanwhile, a higher concentration of talent in government departments does not translate into stronger support for corporate innovation. While it is associated with increased fixed asset investment, it coincides with a reduction in public research funding. Additionally, there is no significant improvement in public services such as environmental protection, healthcare, or education. These findings suggest that the government has not effectively exercised its supportive role in fostering innovation.

As China seeks to overcome the middle-income trap and pursue sustainable economic growth, fostering innovation has become increasingly critical. Beyond strengthening industrial policy support for firms, this study underscores following policy implications. First, it is vital to balance talent allocation between the public and private sectors to ensure sufficient investment in corporate R&D personnel. Second, the substantial human capital within the public sector should be fully utilized and converted into higher-quality public services. Moreover, while enhancing the government's legitimate tax enforcement capacity, innovation-targeted tax incentives should be implemented to reduce the financial burden on enterprises and stimulate R&D investment. In developing countries, particularly in transitional economies, the concentration of national talent within government departments is a common phenomenon. China's experience also offers valuable insights for these countries.

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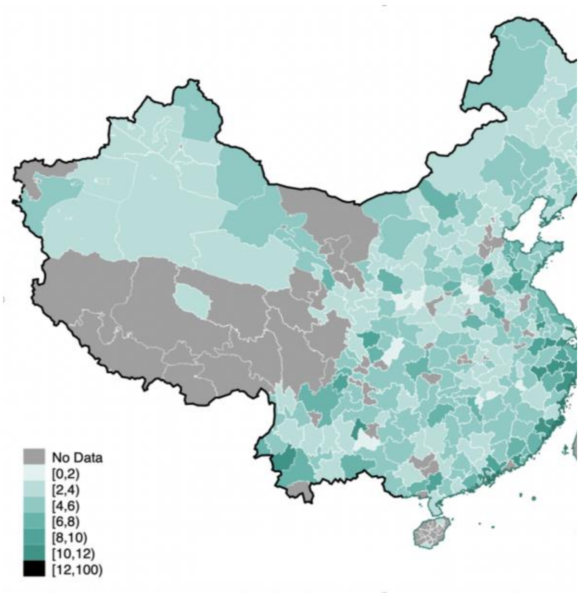
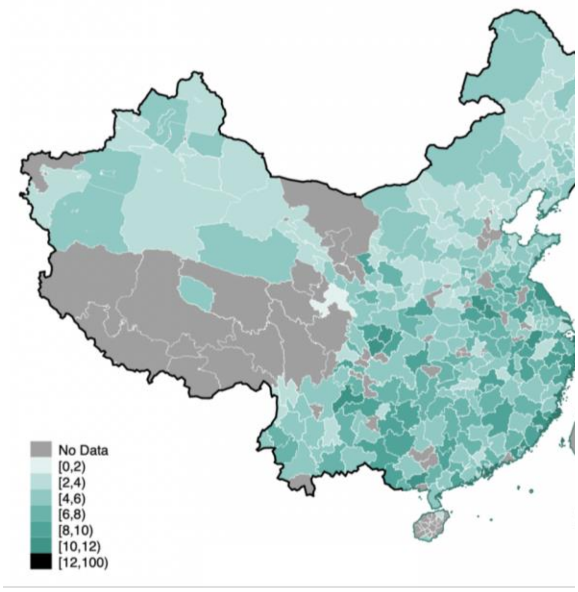


(a)2005



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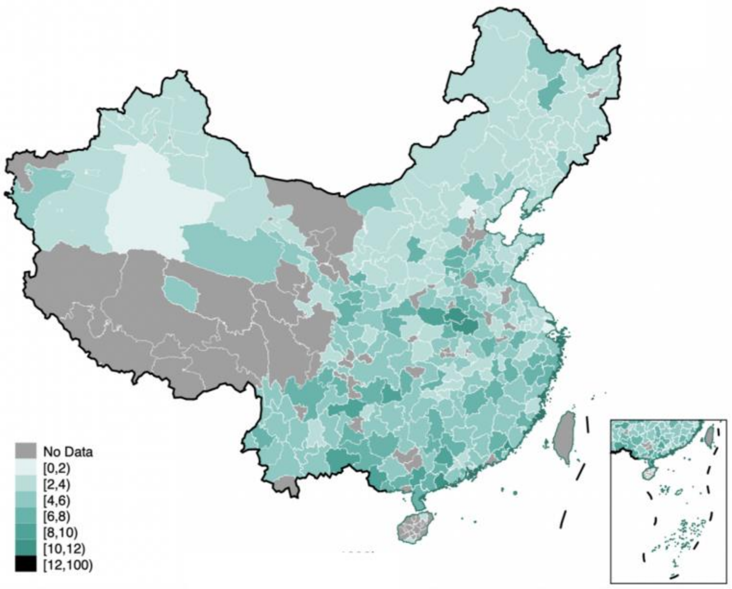

(c)2015

Figure A1. Government departments talent concentration（GDTC）across cities in 2005, 2010, and 2015.

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