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Does Task-Oriented Policy Dilute the Star Inventor Resources of Listed Companies? — Quasi-Experimental Evidence Based on Smart City Pilots

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Abstract. This paper examines whether China's National Smart City Pilot Program (NSCP) reduces the pool of star inventor resources in listed companies. Using a multi-period Difference-in-Differences model, it finds a significant decline in star inventors at pilot enterprises following policy implementation, with the effect more pronounced among firms reliant on government subsidies or with digital strategies misaligned with government plans. Mechanism analysis identifies tighter financing constraints and the crowding-out of corporate capital expenditures as key drivers. The study recommends optimizing resource allocation to avoid the "policy siphon effect" and expanding innovation support for non-pilot firms to sustain a balanced and efficient innovation ecosystem.

Keywords: Smart City Pilot Policy, Star Inventor Resources, Task-Oriented Policy, Resource Allocation, Innovation Ecosystem

1. Introduction

Global technological innovation is entering a vibrant new phase, with digital technology centered industrial transformation reshaping the economic landscape. China has taken developing innovative and high-quality productive capabilities as the core strategy for high-quality development, proposing to lead modern industrial system construction through technological innovation. Against this backdrop, mission-oriented policies have become crucial for guiding resources to strategic sectors, a typical case being the NSCP Policy—implemented in 2012 and covering over 300 cities nationwide—to advance urban governance modernization and industrial upgrading via digital innovation.

The resource allocation logic of mission-oriented policies has sparked controversy: direct support tools like fiscal subsidies and tax incentives may create a "policy siphoning effect" to attract talent and capital to pilot regions, while non-pilot sectors or enterprises may face diluted resources and weak innovation motivation. Two opposing views exist on such policies: resource siphoning, where support for specific sectors drains talent and capital from non-pilot areas, and innovation spillover, where improved infrastructure and knowledge sharing attract talent inflows. This raises a core question: does the Smart City Pilot (SCP) policy dilute listed companies' star inventor resources?

While the SCP policy targets digital innovation, industrial upgrading, and green development [1], existing research has three limitations: it focuses on macro-level effects, lacking micro-enterprise

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analysis [2]; it fails to compare the intensity of siphoning versus spillover effects [3]; and it neglects heterogeneous responses across industries and city sizes [4].

Using a multi-period DID model on Chinese A-share data (2007–2024), this study assesses the policy's impact on star inventor resources.

2. Review of existing literature and theoretical examination

2.1. Policy-induced resource misallocation: "mission-oriented" squeezing out "exploratory" R&D

Mission-oriented policies drive major technological breakthroughs and social transformations, yet their biased resource allocation may distort corporate innovation resource distribution. While such policies effectively direct resources to specific sectors via clear technological objectives and evaluation metrics, they also induce firms to overinvest in short-term policy-related projects, neglecting high-risk, long-term exploratory R&D [5]. For example, under the SCP Policy, firms prioritize resources for urban digital governance and intelligent transportation—areas with explicit indicators and quick visible results—while cutting investment in basic or frontier technology R&D. Exclusive government focus on mission-oriented projects (without supporting exploratory R&D) will prompt firms to shift resources from the latter to the former, causing innovation resource misallocation that undermines firms' long-term innovation capabilities and global technological competitiveness [6].

2.2. Sensitivity Of "superstar inventors" to resource stability

Superstar inventors' productivity relies heavily on sustained, predictable internal funding and organizational commitment [7]. Forced funding for short-term projects shifts top scientists' patent output from high-impact breakthroughs to low-value iterative innovations, reducing their marginal output. Stronger mission-oriented resource allocation within firms lowers core inventors' organizational commitment and raises turnover risk [8].

2.3. Compliance-focused effect of organizational attention

Policy shocks divert executives from long-term innovation to compliance, eroding support for star inventors [9]. Under the NSCP's short-term mandates, this shift fosters strategic rigidity, suppresses breakthrough research, and heightens turnover risk by neglecting inventors' personalized needs [10].

2.4. Technology trajectory lock-in and loss of knowledge diversity

Policy-induced technical paths shift firms from exploratory to exploitative search, reducing knowledge diversity [11]. nnovation relies on uncertain knowledge recombination; fixed technical frameworks increase matching risks, prompting firms to reduce support for cross-domain projects, leading star inventors to leave when undervalued [12].

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3. Analytical framework

3.1. Model construction

This study employs a multi-period DID model to evaluate the impact of the NSCP on the star inventor resources of listed companies.

The particular model is configured in the following manner:

$$\mathrm{Y_{it}} = \beta_0 + \beta_1 \times \text{Smart City Pilot}_{\mathrm{it}} + \beta_2 \times \text{Control Variables}_{\mathrm{it}} + \gamma_{\mathrm{t}} + \mu_{\mathrm{i}} + \epsilon_{\mathrm{it}}$$

Where Y_{it} represents the number of superstar inventors in firm i in year t.

Smart City Pilotit is the core explanatory variable, indicating whether firm i is within the scope of the SCP in year t.

Control Variablesit include government subsidies, firm size (size), return on assets (roa), debt-to-asset ratio (leverage), and sales revenue (sale).

γ_t represents year fixed effects, μ_i represents FFE, and ϵ_{it} is the stochastic disturbance.

3.2. Data sources

The principal data employed in this research are mainly derived from the subsequent sources:

Listed company data: The number of superstar inventors, firm size, roa, leverage, and sales revenue are sourced from the CSMAR and Wind databases, covering relevant financial data of Chinese A-share listed companies from 2010 to 2022.SCP data: The list of cities and timing information for the Smart City Pilots are sourced from the Ministry of Housing and Urban-Rural Development and relevant government announcements, which detail the specific cities and implementation times for each batch of Smart City Pilots.

Government subsidy data: Government subsidy data are sourced from the "non-operating income" or "government grants" items in the annual reports of listed companies.

3.3. Variable selection

3.3.1. Dependent variable

Superstar Inventor Count (SIC) captures the number of top-tier inventors in a firm, identified by patent volume, quality, and innovative impact.

3.3.2. Core explanatory variable

SCP is a dummy variable indicating whether a listed firm is headquartered in a city designated as a National Smart City Pilot during the sample period.

3.3.3. Control variables

This paper introduces control variables to exclude other interfering factors.

Government Subsidy (GS): Affects firms' R&D, innovation capacity, and attraction/retention of star inventors, measured by government grant data from listed companies' annual reports.

Enterprise Size: Influences innovation capacity and resource allocation, measured by the natural logarithm of year-end total assets.

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ROA: Reflects asset utilization efficiency and R&D resource availability, calculated as net profit divided by average total assets.

DAR: Reflects debt levels and restricts R&D, measured as total liabilities divided by total assets.

Sales Revenue (SR): Reflects operating performance and provides R&D funds, measured by operating income from listed companies' annual reports.

Table 1. Variable definition table

Variable Type	Variable Name	Variable Symbol	Variable Description
Dependent Variable	Superstar Inventor Count	Npro	Measures the number of superstar inventors in listed companies
Explanatory Variable	SCP	post	If a city is selected as a national SCP, all listed companies within that city take a value of 1 for this variable;
Control Variables	Government Subsidy	GS	An important way for enterprises to obtain external financial support
	Enterprise Size	size	LN (1 + total assets at the end of the year)
	Return on Assets	ROA	Net profit / average total assets
	Debt to Asset Ratio	DAR	Total liabilities / total assets
	Sales Revenue	sale	Sales quantity × unit sales price
	Stock Code	stkcd	A unique code used to identify individual companies
	Year Variable	year	An annual dummy variable that takes a value of 1 if it belongs to that year, and 0 otherwise

4. Empirical results and analysis

4.1. Descriptive statistics

According to the empirical results, the mean value of the number of superstar inventors (Npro) in listed companies is 0.2502, with a standard deviation of 0.6798, indicating significant differences in the distribution of star inventors. The SCP policy (post) covers 42.95% of the sample firms, suggesting a broad impact of the policy.

Table 2. Descriptive statistics

Variable	Mean	Standard Deviation	Minimum	Median	Maximum	Sample Size
Npro	0.2502	0.6798	0	0	6.9256	27,971
post	0.4295	0.4950	0	1	1	27,971
GS	15.2668	4.1338	0	-	22.8756	27,965
size	22.1597	1.3393	17.8790	-	28.6365	27,971
ROA	0.0371	0.0881	-2.8706	-	0.9737	27,971
DAR	0.4204	0.2118	0.0071	-	3.5129	27,971
sale	21.4582	1.5212	8.4286	-	28.7183	27,971

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4.2. Benchmark estimation

The regression results in Table 3 show that the SCP policy has a coefficient of -0.0486649, significant at the 5% level. This suggests the policy reduces the number of superstar inventors in listed firms, consistent with the idea that task-oriented policies may crowd out star talent. By channeling resources to designated areas, such policies can weaken non-pilot firms' ability to attract top innovators, potentially undermining broader innovation capacity. The finding raises questions about whether targeted initiatives risk sacrificing resource balance for local gains.

Table 3. Baseline estimation

Variable	Npro
Post	-.0486649** (-2.69)
GS	.0034993** (2.49)
size	.0093272 (0.85)
ROA	.0698703** (2.18)
DAR	-.0409095 (-1.24)
sale	.0091036 (1.12)
constant	-.1710884 (-0.83)
stkcd	YES
year	YES
observation	27579

Note:***p<0.01,**p<0.05,*p<0.1.

4.3. Robustness check

4.3.1. Parallel trend test

This study uses a multi-period DID method for estimation, so it is first necessary to conduct a parallel trend test. Setting the year before the policy implementation as the baseline period, the test results are shown in Figure 1. Before the policy implementation, there was no significant difference in the change trend of the "number of superstar inventors" between the treatment group and the control group, satisfying the parallel trend assumption. After the policy implementation, the "number of superstar inventors" in the treatment group was significantly lower than that in the control group, and the effect persisted. The results of the parallel trend test support the research hypothesis and provide robust empirical evidence for dynamic analysis of policy effects and causal inference.

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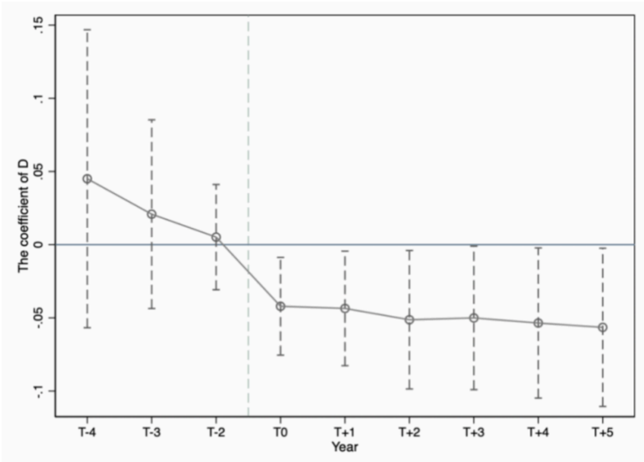

Figure 1. Parallel trend test

4.3.2. Placebo test

A placebo test (500 random permutations, Figure 2) excludes other variables and randomness. Results show the real coefficient (-0.0487, p=0.0000) deviates from the permutation distribution center (extreme left tail), confirming the SCP's negative effect on superstar inventors is not random, with robust control variables and permutation results supporting baseline regression reliability.

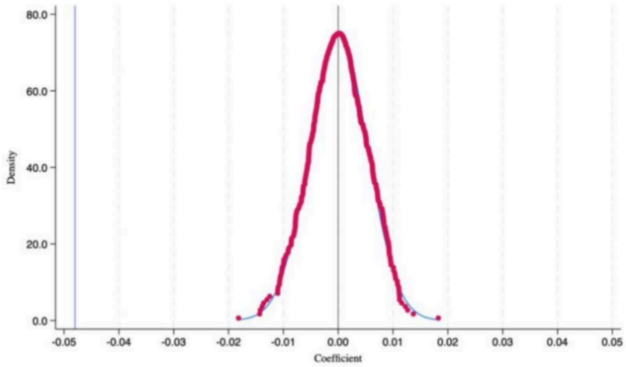

Figure 2. Placebo test

4.3.3. PSM-DID test

To address selection bias from non-random SCP selection, we use PSM-DID (1:1 nearest-neighbor matching, caliper 0.05, Logit-estimated propensity scores) with matched samples. Table 4 shows the pilot policy is significantly negatively correlated with superstar inventor numbers (0.5% level, coefficient 0.05), confirming no self-selection bias and robust conclusions.

4.3.4. Double machine learning test

To further verify whether the impact of the SCP, a task-oriented policy, on the star inventor resources of listed companies is robust, a double machine learning method was used for testing. With the "number of superstar inventors" as the dependent variable and the "smart city pilot" as the core explanatory variable, variables such as government subsidies and enterprise size, as well as time and individual fixed effects, were controlled. Table 4 reports a significant negative coefficient

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for SCP (-0.075, p<0.01), confirming its dilution effect on star inventor resources. This result aligns with the baseline findings and corroborates the robustness of the analysis.

Table 4. Robustness tests

Variable	PSM-DID Test		Double Machine Learning Test
	(1) Before Sample Exclusion	(2) After Sample Exclusion	(3)
	Npro	Npro	Npro
Post		-.0505114 *** (-2.79)	-0.075*** (-3.678)
GS	0.0021455 (0.69)	.0035347** (2.50)	
size	0.2782832*** (14.03)	.008813 (0.80)	
ROA	-0.3081864 (-2.01)	.0699357 (2.17)	
DAR	-0.5961149 (-8.10)	-.0447597 (-1.35)	
sale	-0.1106628 (-6.14)	.0091628 (1.11)	
constant	-3.561986 (-15.95)	-.01642903 (-0.79)	0.008***
stkcd	YES	YES	YES
year	YES	YES	YES
observations	27965	27492	27965

Note:***p<0.01,**p<0.05,*p<0.1.

4.4. Mechanism analysis

4.4.1. The influence of SCP initiatives on capital allocation direction: an empirical examination based on the financing constraints perspective

The SCP policy may tighten firms' financing constraints, as shown in Table 5, limiting their ability to fund high-risk R&D and retain top talent. This financial pressure reduces the appeal to superstar inventors, ultimately lowering their count in affected firms.

4.4.2. The SCP policy has a significant crowding-out effect on capital expenditures

SCP crowds out firm capital spending, as shown in Table 5, supporting the crowding-out hypothesis. Reduced capital expenditure undermines R&D capacity and innovation infrastructure, shrinking the pool of star inventors within affected firms.

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Table 5. Mechanism analysis

Variable	(1)	(2)
	FC	CE
Post	0.0067765*** (1.94)	-1.344116*** (-3.80)
GS	-0.0000456*** (-0.01)	-0.0363308* (-1.46)
size	-0.0087291** (-1.81)	0.4485512** (2.07)
ROA	0.0122201*** (1.25)	-1.464745 (-2.28)
DAR	-0.0358055* (-3.94)	3.590011 (5.94)
sale	-0.0015876*** (-0.53)	0.5040157 (3.02)
constant	-3.548699 (-29.55)	-10.1047 (-2.53)
stkcd	YES	YES
year	YES	YES
observations	27492	27492

Note:***p<0.01,**p<0.05,*p<0.1.

4.5. Heterogeneity analysis

4.5.1. Impact of government subsidy orientation on enterprise star inventor resources

The SCP policy reduces star inventors more sharply in firms with high subsidy dependence (coef. significant in Table 6, col. 1). These firms likely reallocate resources toward policy-aligned areas, diverting focus from core R&D. Low-dependence firms show no significant effect (col. 2). The findings suggest that while steering resource allocation, the policy may inadvertently undermine long-term innovation capacity in subsidy-reliant firms.

4.5.2. Impact of digital route fixation on enterprise star inventor resources

The SCP policy reduces star inventors only in firms whose digital path misaligns with the government's roadmap (Table 6, col. 3). For aligned firms, the effect is insignificant and even positive (col. 4). This suggests policy effectiveness hinges on strategic synergy. Policymakers should avoid one-size-fits-all mandates that risk talent loss.

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Table 6. Heterogeneity analysis

Variable	Government Subsidy Heterogeneity		Digital Route Fixation Heterogeneity	
	(1) Dependent on Government Subsidies	(2) Not Dependent on Government Subsidies	(3) the solidification of digitalization path	(4) The digital transformation route is not rigid.
	Npro	Npro	Npro	Npro
Post	-0.0970837 (-3.12)	-0.012571 (-0.74)	-0.0562061 (-2.84)	.0602701 (0.61)
GS	.0048316 (0.46)	.002541 (2.43)	.0046596 (2.50)	.0025321 (1.00)
size	-.0015569 (-0.07)	.0148191 (1.47)	.01257 (0.83)	.0125628 (0.75)
ROA	.1468395 (1.72)	-.0061253 (-0.23)	.0873301 (1.81)	-.0249141 (-0.59)
DAR	-.0144863 (-0.21)	-.0666207 (-2.28)	-.0070919 (-0.16)	-.1461923 (-3.10)
sale	.0293698 (1.33)	-.0005562 (-0.01)	-.0065569 (-0.55)	.0275404 (1.99)
constant	-.3268901 (-0.66)	-.1589515 (-0.90)	.0729344 (0.26)	-.658489 (-2.02)
stkcd	YES	YES	YES	YES
year	YES	YES	YES	YES
observations	13460	13402	16344	10665

Note:***p<0.01,**p<0.05,*p<0.1.

5. Conclusions

The SCP policy led to an average 5.05% decline in star inventors at listed firms, a conclusion that holds across various robustness checks. Notably, this impact is more pronounced for companies with high subsidy dependence or digital strategies out of step with government priorities, suggesting the policy may worsen resource imbalances for firms on divergent development paths. The underlying mechanism points to capital reallocation: the policy inadvertently crowds out firms' long-term investment, making it harder to attract and retain top inventive talent even as it sends positive market signals.

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