Human Capital and Innovation: The Effect of Talent Introduction Policy

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Abstract: Using the prefectural-level data in China, this paper investigates the role of human capital agglomeration in the regional innovation activities using the implementation of prefectural Talent Introduction Policy (TIP) as a quasi-natural experiment to estimate its impacts and the underlying mechanism. Using a staggered Difference in Difference methodology, this paper found that the TIP had a positive impact on the local innovation activities measured by patent through the agglomeration of human capital. The impact is the strongest for those innovation activities with above-average difficulties, and is stronger when combined with a more preferrable locational characteristics. The policy mainly affects the innovation in the industry not in the academia. The results provide strong evidence to the role of human capital in regional innovation and economic development.

Keywords: Talent Introduction Policy, Human capital, Innovation

JEL：O15; O31; R58

人力资本与创新：人才引进政策的影响

内容提要：本文使用中国地市级数据，通过实施地市人才引进政策 (TIP) 作为准自然实验，研究人力资本集聚在区域创新活动中的作用，以估计其影响和潜在机制。本文采用交错差分法，发现 TIP 通过人力资本集聚对用专利衡量的地方创新活动产生了积极影响。对于那些难度高于平均水平的创新活动，这种影响最为强烈，并且在与更好的区位特征相结合时会更强。政策主要影响的是产业界的创新，而不是学术界的创新。本文的结果为人力资本在区域创新和经济发展中的作用提供了强有力的证据。

关 键 词：人才引进政策 人力资本 创新

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Introduction

Human capital plays a central role in the innovation and modern economic development, and many countries and regions have designed various policies to boost the accumulation and agglomeration of human capital. This paper investigates the role of human capital agglomeration in the regional innovation activities using the implementation of prefectural Talent Introduction Policy as a quasi-natural experiment to estimate its impacts and the underlying mechanism.

The background of this research is the transformation of the Chinese economy from being labor-intensive to capital-intensive. As a result of this transformation, the mass quantity of low-skilled labor is becoming a less comparative advantage in regional economic development. On the contrary, the stock of high-skilled human capital and talents is becoming more important because it is the key to the creative destruction of innovation and the operation of high technology production. With the realization of this trend, it is pointed out in the report of the CCP's 20th National Congress that innovation is the first force of development, and is the strategic foundation of constructing a modern economic system.

The common way to accumulate human capital is to invest in education. However, it takes a long time for its positive effect to emerge. Alternatively, in the 2010s, many cities in China have adopted various Talent Introducing Policy (TIP), which once-and-for-all specifies all the categories and subsidies for different kinds of talents (such as Master, PhD, entrepreneurs, researchers, high-skilled workers) targeted at the whole society in the form of governmental official document. This trend of incentive programs has been summarized by the Chinese media as "a war for talent". The design of such policy is to attract the talents to the local area and contribute to the local innovation and potential economic development. The contents of such policies are similar in terms of providing financial and various subsidies, but the timing of implementation in different prefectural cities is different. This creates a useful variation to exploit and a quasi-natural experiment in which we can investigate the policy effect and subsequently the role of human capital agglomeration in the local innovation activity.

This paper uses the variation of the implementation of TIP to estimate its impact on local innovation activity, and investigates into the channel which is the agglomeration of human capital. The main econometric methodology is a staggered Difference in Difference identification. Through this identification, I was able to identify a positive causal impact of the TIP policy on the local innovation activity measured by patents. By decomposing the patent data into its three categories according to innovation difficulty (invention, practical, and design), I found that the TIP has most of the impact on the practical patent, which requires less original but still above-average intellectual inputs. To ensure the correctness of my causal inference, I conducted the check of parallel trend assumption and the event study, in which I found that the policy has no anticipatory impact, no pre-trend in innovation, and an increasing post-implementation effect. This strengthened my results that the TIP's impact on the local innovation activity is positive and increasing with time. I also conducted a check for exogenous implementation of TIP to ensure that there is no reverse causality problem that leads to biased estimation.

To ensure the robustness of my results, I did several robustness checks. The PSM-DID is ensure that the result doesn't suffer from severe selection bias. The placebo test is to ensure that the policy implementation and the results are not driven by other unobserved prefectural characteristics. As for heterogeneity, I investigated whether the effect is different between cities with different administrative hierarchy and different locational characteristics. Different administrative hierarchy didn't lead to the difference in the policy effect, while the effect is stronger in cities with better locational characteristics. To investigate the mechanism of the policy effects, I constructed an intermediate effect model in which I use the indicators of talent agglomeration as the intermediate variable. Through the estimation of this model, I confirmed that the TIP fulfilled its design, which is to boost the agglomeration of talents and contributed to the local innovation activity and potential economic development. Through this intermediate model, I also find that the impact is mainly in the industry not in the academia.

The results of this paper may have three implications. First, it was effective to use financial and other incentives for local governments to attract the talents and the high-skilled human capital.

My results not only confirmed the effectiveness but also estimated the magnitude of such effect in terms of the patent data. Second, the magnitude of such incentive effects may be strengthened by the advantage in locational characteristics but not the political hierarchy. This might because that it is more of the locational characteristics such as weather and infrastructure that determined the attractiveness to the talent. Third, such incentive policy may be most effective to those who have above-average skills and talents but not among the highest rank of skillfulness, as indicated by the detailed regression using categorized patent data.

The core idea of this paper, that human capital contributes to the innovation and the economic development, is developed from Lucas (1988), which views human capital as the central factor of production, which sustained growth due to its non-decreasing retuCrns. It also echoes with the model in Mankiw et al. (1992) which extended the neoclassical growth model by including human capital as an accumulable factor. The centric role of human capital in the innovation is systematically analyzed by Romer (1990). In this literature, higher level of human capital facilitates the generation or diffusion of new technologies, or to a more efficient adoption of a given technology, thereby shifting the production possibility frontier outwards (Benhabib and Spiegel, 1994; Nelson and Phelps, 1966). Lucas (2009) further developed the model in which he explained how ideas can generate innovation and growth.

For the empirical study about how human capital and innovation affects economic development, Badinger and Tondl (2003) documented that a high innovation rate permitted a high growth using EU data from the 1990s. Similarly, Gennaioli et al. (2012) found that human capital played a paramount role in accounting for regional differences in development using data from 110 countries. Given that the ultimate goal of the TIP policy is to boost the local economic development, this paper is highly related to this strand of literature.

There already exists many studies on the role of human capital in the innovation. Dakhli and Cledcq (2004) found that human capital is an antecedent to innovation activity at the society level by using data from 59 countries. In supplementation, both Ma et al. (2018) and Sun et al. (2020) documented the importance of human capital in innovation at the firm level by using firm level micro data. A thorough study about the impact and the mechanism of human capital is conducted by Cinnirella (2007), in which the author used the Prussian data in the second Industrial Revolution to find that the stock of literate people (human capital) was associated with high-tech innovations, by enabling more people to read and then facilitating transregional knowledge spillover. This paper contributes to this strand of literature by providing evidence of the role of human capital in innovation from modern China.

As for the study on human capital and innovation in China, Li (2007) first documented that the investment in education and the government support are two significant factors in increasing the innovation efficiency. Li et al. (2010) and Liu et al. (2018) found that there are spatial correlation and agglomeration towards eastern region of the innovation in China, due to the better socioeconomic circumstances and differences in human capital structure. The contribution of the agglomeration of human capital to the regional innovation is heavily documented using provincial level data (Bai and Jiang, 2015; Yu, 2011; Qian et al., 2010; Wu, 2006). As for the impact of policy on innovation, Liu and Tian (2020) found that the backing of firm-level talent policy boosted the firm-level innovation by connecting firms to government and1 market resources. Bai et al. (2022) found that the innovative city pilot policy had a positive impact on the city-level innovation activity. This paper contributes to this strand of literature by identifying the impact of a talent introducing policy on innovation using a detailed city-level panel data and explicitly establish the link between the agglomeration of human capital and the increase in innovation activity.

The rest of the paper is arranged as follows. Section 2 presents the data and descriptive analysis. Section 3 and section 4 presents the empirical methodology and the baseline results, including all necessary robustness check. Section 5 provides the analysis of heterogeneous effects and section 6 analyzes the mechanism of the effect. Section 7 provides further discussions, and section 8 concludes the paper.

2 Data and Descriptive Analysis

This section presents the data sources, the construction of the data set, and the descriptive analysis. To estimate the effect of the Talent Introduction Policy on local innovation activity, the data is gathered on the timing of policy implementation, the patent, and other prefectural-level characteristics. The sample includes 275 prefectural-level cities from 2012 to 2019, which forms a balanced panel for the empirical analysis.

2.1 Talent Introduction Policy (TIP)

The policy implementation data is manually collected and verified from prefectural government Red-Headed policy files (Hong Tou Wen Jian) in all the prefectural cities from 2012 to 2019. To avoid confusion with other similar innovation policies, the Talent Introduction Policy studied in this paper specifically specifies the terms of financial incentives and institutional convenience for people with higher education degrees or with specific skills to settle and work in the city. Once implemented, the content of each city's TIP policy is open to the whole nation. Thus, when constructing the policy implementation data set, only those containing specific identifiers, such as housing or per-month life subsidies for Ph.D./Master/high-skilled people from the whole nation, are counted as the proper treatment policy.

There are two concerns with this construction that might cause measurement errors in the policy implementation. First, many cities provided different kinds of yearly-based subsidies and convenience for a specific group of talents throughout the whole sample period, as part of their basic institutional plan. This may make the TIP in this paper hard to be accurately identified. To deal with this issue, I restrict the definition of TIP to be period-based (for example, 5-year based according to the local economic development plan), and targeted at the whole society not one specific group, thus creating a group of approximately homogeneous TIP to be the treatment. Second, different cities provide different levels of financial incentives and institutional convenience, based on their economic performance and development strategies. This might put the homogeneous effect of TIP into question. To mitigate this concern, the interpretation of the estimation results should be more focused on the sign, that is, whether there is a significant positive or negative effect, rather than the magnitude of the coefficient.

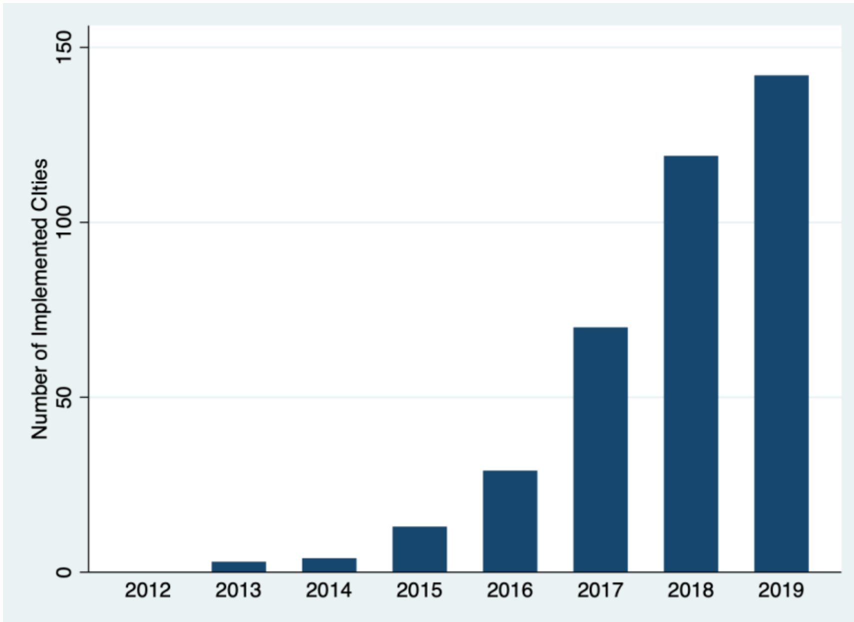

Figure 1: Number of Implemented Cities by Year

Figure 1 shows the accumulated number of cities in our sample that implemented the Talent Introduction Policy from 2012 to 2019. Overall, there is an increasing trend. The number of implemented cities experienced the sharpest increase from 2016 to 2017 after the central government announced the guiding policy document (Opinions of Deepening the Reform of the System and Mechanism for Talent Development)[1]. By the end of 2019, over half of the cities in the sample have adopted the TIP policy. In contrast, there are approximately half of the cities that never adopted the TIP, which forms the control group of this study.

2.2 Patent: Measurement of Innovation Activity

This paper follows the convention of literature and measures the innovation activity directly using patent data (Badinger and Tondl, 2003; Cinnirella, 2007; Sun et al., 2020; Liu and Tian, 2020). There are two categories of patent data, which are patent applied and patent granted. Within

[1] For more details about this document, see 中共中央印发《关于深化人才发展体制机制改革的意见》 滚动新闻 中国政府网 (www.gov.cn)

each category, the patent is divided into three subgroups, that is, invention, practical innovation, and outlook design. The patent applied reflects the innovation result of this year and a shorter period of the previous time, while the patent granted reflects both the innovation result of a longer period of the previous time and the strictness of the patent reviewing process. The dataset contains all those measurements of patent data. The patent data comes from Chinese City Statistical Yearbook.

2.3 Other Control Variables

The data for other prefectural-level characteristics come from the Chinese City Statistics Yearbook from 2012 to 2019, which includes over 400 indicators for 330 cities. Considering that there are other prefectural-level characteristics that might affect innovation activities, this paper uses the following variables as control. First, the log level of GDP per capita is controlled as an indicator of local economic development level, as it usually has a positive relationship with local innovation. Second, the industrial structure is used to reflect differences in the endowment and inputs for innovation activity. The measurement is constructed following Wang (2015)'s method,

$$IndustStru = \sum Indust_i \times i \ (1 \leq i \leq 3)$$

where $Indust_i$ is the proportion of the output of i^{th} industry in the total output. Third, financial support is essential in providing capital and splitting risk for innovation activity. Thus, this paper uses the ratio of the total amount of debt of financial institutions to the regional GDP as a control for the external financial support available in the city. Fourth, access to the internet usually has a positive correlation with the activeness of regional innovation, since it generates knowledge spillover effects by facilitating information flow and transparency (Han et al., 2019). This paper uses the number of households with access to broadband as the control for the internet access level. Fifth, this paper uses the ratio of local GDP and government budget to control the government intervention in the market, which indicates the marketization level. Lastly, this paper controls the number of universities in the city, which stands for the strength of the academic forces.

3 Empirical Methodology

Considering that different cities implemented the TIP at different times, this paper uses a staggered Difference in Differences specification to estimate the impact of TIP on local innovation activities. The regression setup is the following:

$$Y_{it} = \alpha + \mu_i + \lambda_t + \theta TIP_{it} + \beta \boldsymbol{X}_{it} + \varepsilon_{it}$$

$$i \in [1, 275];\ t \in [2012, 2019]$$

where Y_{it} is the innovation outcome in city i and year t. μ_i is the city fixed effect variable that controls for time-invariant, unobserved city characteristics that affect innovation, and λ_t is the year fixed effect variable that controls for nationwide shocks and trends that shapes the overall innovation level. $\boldsymbol{X}_{it}$ is a vector of control variables that includes city characteristics. The variable of interest is TIP_{it}, a dummy that equals to one if the city i implemented the TIP in year t. A positive and significant θ indicates that the implementation of the Talent Introduction Policy has a positive impact innovation activity. In total, the sample contains 275 cities over nine years, so the total number of observations is 2200. Standard errors are clustered at a provincial level to allow for within-province serial correlation.

The Difference-in-Differences specification relies on the crucial assumption of parallel trend, that is, the treatment group should have the same trend as the control group without the implementation of the policy. In this setting where the control group consists of the cities which never implemented TIP and the cities in the treatment group implemented TIP in different years, it is difficult to draw a graph with two lines representing the two groups' outcomes. Thus, this paper relies on another commonly-used method to test whether there exist pre-treatment differences by the following specification,

$$Y_{it} = \alpha + \mu_i + \lambda_t + \theta_1 TIP_{it}^{-4} + \theta_2 TIP_{it}^{-3} + \cdots + \theta_7 TIP_{it}^{2} + \beta \boldsymbol{X}_{it} + \varepsilon_{it}$$

This event-study version of the benchmark model not only provides a test for parallel trend assumption but also examines the dynamic effects of the policy. We can infer whether the effect is increasing or decreasing after the implementation of the policy. When estimating the model, the year of implementation is excluded, so that the dynamic effect of TIP on innovation activity is estimated relative to the year of implementation.

4 Baseline Results

4.1 Baseline Estimation Results

Table 1 provides the estimates of θ in our benchmark regression model and shows that the implementation of TIP policy at a prefectural level has a significant positive effect on innovation activity, indicated by the average number of patents per ten thousand people. The first column reports the simplest OLS regression in which we only have TIP as the explanatory variable and do not control for city characteristics and fixed effects. Thus, we can only interpret the estimate as a positive correlation. The second column adds the city and year fixed effects to the model, while the third column adds the control variables for city characteristics. In the fourth column, we include both fixed effects and control variables to give a proper estimate of the Difference-in-Differences specification. Through (2) to (4), the results are fairly stable and are positively significant at a 5 percent level, which strengthened the robustness of our result.

The point estimate in column (4) indicates that the implementation of the Talent Introduction Policy causes an average increase of 8 patent applications per ten thousand people in the affected city, which is the Average Treatment Effect of the Treated (ATT). Although this estimation of the magnitude is under debate, we can still draw credible inferences based on its sign. The positive sign shows the increase in innovation activity in the affected cities after controlling for time-invariant city characteristics (such as economic development level) and common shocks (such as macroeconomic fluctuations). Overall, the TIP policy is effective in terms of boosting the innovation activity. However, due to the huge differences between Chinese cities, the effect may be different in different regions. Further analysis on this heterogeneity will be discussed in the next session.

Table 1: Baseline Results

	(1)	(2)	(3)	(4)
VARIABLES	Avg_Patent	Avg_Patent	Avg_Patent	Avg_Patent
TIP	39.4402***	9.3972**	7.2976***	8.1304**
	(13.1616)	(2.4501)	(2.8151)	(2.1771)
ln_AGDP			33.4136***	4.4090
			(17.0911)	(1.2639)
Indust_Stru			0.0686	-0.1285
			(0.8186)	(-0.9757)
Finance			0.0008***	0.0001
			(5.5041)	(0.8728)
Market			-7,122.5176***	-2,493.1261
			(-2.8413)	(-1.4097)
Internet			0.3385***	0.0601**
			(25.3581)	(2.3183)
University			-1.3400***	1.7153**
			(-14.0086)	(2.2499)
Constant	32.2195***	25.2515***	-372.4617***	-7.5332
	(26.2293)	(12.0560)	(-15.0067)	(-0.1255)
Observations	2,190	2,190	2,080	2,080
R-squared	0.0734	0.3103	0.4491	0.3373
city fe	no	yes	no	yes
year fe	no	yes	no	yes
Number of city		275		273

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2 Decomposition of the Effects

To see how the TIP influences different kinds of innovation activity, we can decompose the effects into three parts by utilizing the detailed information provided by the dataset of patent applications. The total patent applications include three types, which are invention, practical, and design patents.[2] By regressing the benchmark model on the average applications per ten thousand people of these three types, we can see the relative impact of the policy on each type of the patent

[2] According to the Law of Patent, an invention patent is a patent in which one propose a new technical methodology to a specific product, production method, or their refinement; a practical patent is a patent in which a new technical methodology is proposed to the shape or construction of a product; a design patent is a patent in which one propose a new design to the product's color, shape, or other aesthetic features. According to this instruction, the difficulty ranking of these three patents are: invention, practical, design.

application.

Table 2: Decomposition of the Effects

	(1)	(2)	(3)
VARIABLES	Invent_Patent	Pract_Patent	Design_Patent
TIP	2.7436*	5.1833**	0.2035
	(1.8834)	(2.7321)	(0.1324)
ln_AGDP	1.3948	1.7739	1.2403
	(1.0729)	(0.9387)	(1.4437)
Indust_Stru	-0.0595	-0.1454	0.0763
	(-1.1037)	(-1.3583)	(1.3314)
Finance	-0.0000	0.0001	0.0001
	(-0.1741)	(0.9646)	(1.0807)
Market	-670.7987	-1,534.5451	-287.7824
	(-0.8434)	(-1.4188)	(-0.7548)
Internet	0.0293*	0.0651*	-0.0343
	(2.0282)	(1.8712)	(-1.1845)
University	0.4189	1.0311***	0.2653
	(1.4430)	(2.8787)	(1.1298)
Constant	0.8118	14.4262	-22.7713
	(0.0371)	(0.3548)	(-1.2594)
Observations	2,080	2,080	2,080
R-squared	0.2229	0.4098	0.0410
Number of city	273	273	273
city fe	yes	yes	yes
year fe	yes	yes	yes

Robust t-statistics in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The estimated coefficients θ from column (1) to (3) in the last table sums up to be equal to the coefficient in the benchmark regression (2.7436 + 5.1833 + 0.2035 = 8.1304). The effect on practical innovation patent application takes up the largest proportion (approximately 72%) of the total impact and is significant at a 5% level. The effect on invention patents is smaller but still significant. Given that the application of an invention patent has a higher requirement of quality and originality than the application of a practical innovation patent, we can infer that the Talents

Introduction Policy mainly boosted the invention activities that require less original or groundbreaking work but still enough intellectual inputs. This might be caused by the inflow of mostly medium and some high-end talents attracted by the favorable policy. Further examination of the channels of the effect will be discussed in the mechanism section.

4.3 Parallel Trend Assumption and Dynamic Effects

To examine the parallel trend and to study the dynamic trend of effects, an event-study version of the benchmark model is estimated using indicators to and from the implementation of TIP. Specifically, the following is estimated,

$$Y_{it} = \alpha + \mu_i + \lambda_t + \theta_1 TIP_{it}^{-4} + \theta_2 TIP_{it}^{-3} + \cdots + \theta_7 TIP_{it}^{2} + \beta \boldsymbol{X}_{it} + \varepsilon_{it}$$

where $\{TIP_{it}^{j}\}_{j=-4}^{2}$ is the set of indicators that take the value of one if the implementation of TIP is j years away for city i. The year of implementation is set as the benchmark for the comparison.

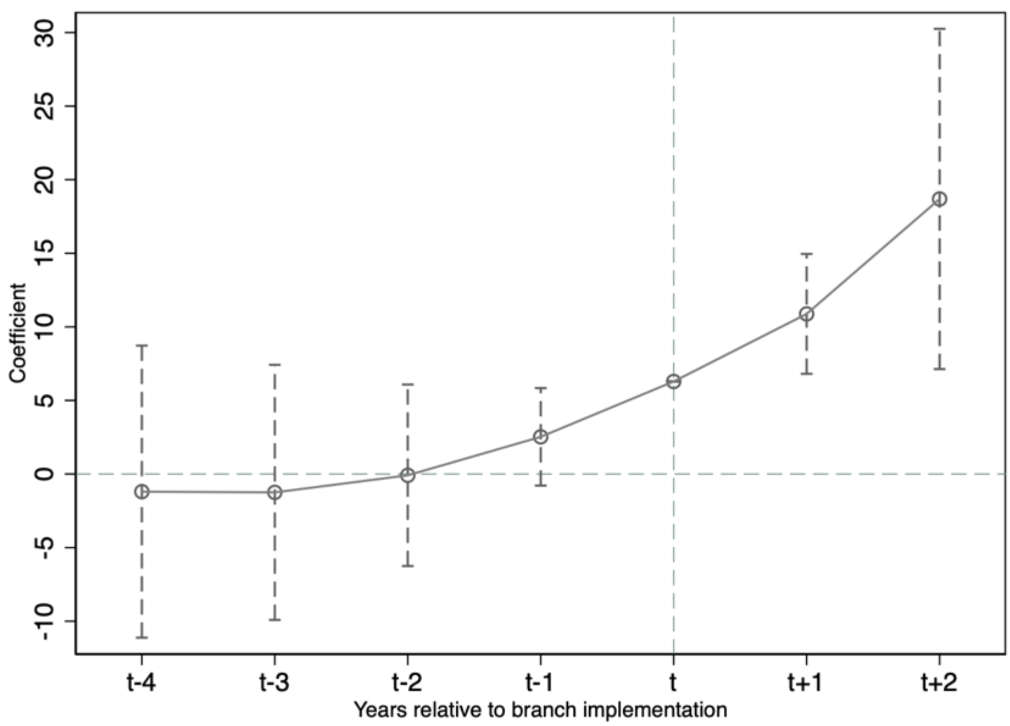

Figure 2: Parallel Trend and Event Study

Figure 2 presents the point estimates of each of the indicators' coefficient and the 95%

confidential interval. The coefficients for the four pre-period are arbitrarily small and not significantly from zero, and only experience a slight but insignificant increase before the implementation. This indicates that the parallel trend assumption is plausible in general, with little anticipatory effect in the innovation activities just before the implementation. The estimates also show that the effect of TIP increases with time for the post two periods. There are two ways of explanations for this result. The first is that innovation is usually a long-term process, and the attracted talents generally need more than one year to settle down and put their talents into full use. The second is that the patent reviewing process is becoming less strict so that more patents are granted. This paper leans in favor of the first explanation since the TIP policy is aimed at generating an inflow of human capital which could boost innovation activity, given the fact that the patent reviewing is actually becoming stricter.

4.4 Exogenous Implementation

One might argue that the implementation of the Talent Introduction Policy is decided by the city's endowed innovation ability, which can be measured by the patent applicated in the past period. This could cause serious reverse causality and bias our benchmark result. To rule out this possibility, this paper uses a probit model and regresses the future-period policy dummy on past-period average patent application and the control variables. The coefficients should be statistically insignificant to satisfy the exogenous policy implementation assumption. The specification is

$$\Pr\left(TIP_{i,t+1} \middle| AvgPatent_{i,t},, X\right) = \Phi(\gamma_0 + \gamma_1 AvgPatent_{i,t} + \beta X)$$

where Φ is the cumulative density function of a standard normal distribution. Table 3 shows the estimation results. The coefficients for average patent applications from columns (1) to (5) are insignificant, indicating that the previous innovation activities have no power to explain the implementation of TIP in the next year. Although the point estimates in column (6) and (7) turn significant, they are negligibly small. Also, the policy implementation mainly happened before 2018, so the bias from the sample in 2018 and 2019 should not plague our benchmark estimation very seriously.[3]

[3] The "significant" estimation for the year 2018 and 2019 maybe driven the spill-over effects. Specifically, the cities who haven't

Table 3: Exogenous Implementation

VARIABLES	(1) 2013	(2) 2014	(3) 2015	(4) 2016	(5) 2017	(6) 2018	(7) 2019
Avg_Patent	-0.0010	-0.0027	0.0041	0.0048	0.0020	0.0045**	0.0043**
	(-0.1611)	(-0.4115)	(1.0531)	(1.5920)	(0.9689)	(2.4206)	(2.1539)
ln_AGDP	-0.0417	0.4417	-0.1392	-0.1998	0.2627	-0.0057	0.2813
	(-0.0666)	(0.9068)	(-0.4062)	(-0.6227)	(1.2148)	(-0.0315)	(1.2051)
Indust_Stru	-0.0006	0.0132	-0.0061	-0.0046	-0.0145*	-0.0087	-0.0010
	(-0.0272)	(0.6411)	(-0.4699)	(-0.3998)	(-1.6586)	(-1.0060)	(-0.1183)
Finance	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000
	(1.1159)	(1.3405)	(1.5666)	(0.8610)	(1.4301)	(-0.2814)	(-0.7371)
Market	463.5467	-6.6689	-646.7146	-553.6030	-433.0849	-181.1429	-99.2742
	(0.7836)	(-0.0107)	(-1.0263)	(-1.0209)	(-1.1924)	(-0.5600)	(-0.5496)
Internet	0.0008	0.0006	-0.0008	0.0020	0.0024	0.0013	0.0003
	(0.2245)	(0.2103)	(-0.2842)	(1.0085)	(1.5471)	(0.9067)	(0.2115)
University	-0.0069	-0.0015	0.0164	0.0160	0.0185*	0.0301**	0.0260**
	(-0.2818)	(-0.0825)	(1.2202)	(1.3822)	(1.7933)	(2.4664)	(2.0051)
Constant	-2.6077	-10.5339	0.9621	1.4960	-0.5475	1.5788	-3.0299
	(-0.3538)	(-1.6101)	(0.2338)	(0.4124)	(-0.1894)	(0.5952)	(-1.0480)
Observations	259	267	265	263	262	261	257

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.5 Other Robustness Checks

The implementation of TIP is not random assigned to the treated cities, and it is selected by the city itself. Thus, the estimation of the ATT may suffer from the selection bias., which might positively bias the benchmark result. To mitigate this concern, I constructed a Propensity Score Matching - Difference in Difference (PSM-DID) model to check if the result is robust with a more balanced treatment and control group. There are two common methods of PSM. The first method of PSM is to treat the dataset as a cross-sectional data and then do the matching between observations, that is, to find the best control for each of the treated city under the common support

adopted the TIP enjoyed a positive knowledge and skill spill-over from other cities who adopted TIP and had a positive patent growth already before their adoption of TIP. This caused an increase in their innovation activity in advance to the TIP implementation. So, their adoption of TIP is not driven by the pre-growth in their own endowed innovation ability.

condition using the neighborhood matching method. The second method of PSM is to match the cities within each year and then merge the datasets for each year into the final dataset. The drawback of the first method is that it may cause the self-matching problem, and the drawback of the second method is that the matched observations might be for different individuals before and after the policy. However, despite those caveats, these two methods are still good methods to perform PSM in my setting of staggered DID. Based on the new datasets generated by these two methods, I re-estimated the benchmark staggered DID model. The results are reported in the column (1) and (2) in table 4. The estimated coefficients of TIP remain significant and positive, with little change in the magnitude. This indicates that the benchmark result suffers little from the selection bias, and is robust in general.[4]

Table 4: PSM-DID Estimation

	(1)	(2)
VARIABLES	PSM-DID-1	PSM-DID-2
TIP	6.7140*	6.3626*
	(1.7358)	(1.7790)
Constant	-14.4539	-16.3970
	(-0.2491)	(-0.2844)
Observations	2,009	1,943
R-squared	0.3104	0.3280
controls	yes	yes
city fe	yes	yes
year fe	yes	yes
Number of city	270	265

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Although we have controlled many important prefectural-level characteristics in our benchmark model, the estimation effect could still be affected by other unobservable characteristics. I

[4] To see the detailed effect of PSM-DID in balancing the treatment and control groups and in mitigating the selection bias, please refer to Appendix A.

implemented a placebo test to ensure that these unobservable characteristics are not driving the results. Because the implementation of the policy is at different years in our staggered DID setting, we must simultaneously generate the pseudo-treatment group variable ($Group^{random}$) and the pseudo-policy shock variable ($Post^{random}$), that is, assign a random treatment period for every sample to be its policy implementation period. To ensure that the policy could not have impact on the innovation activity in our placebo test, I construct the pseudo-policy implementation and let it generate 500 random shocks to the 275 cities in the sample. In each shock, there are 145 cities that form the treatment group, and I generate 500 dummies ($TIP^{random} = Group^{random} * Post^{random}$). Therefore, 500 θ^{random} are estimated. The kernel density and the p-value of these 500 θ^{random} are plotted in Figure 3. The results of the placebo test indicates that the estimates for θ^{random} are mostly close to zero, and have a p-value that is higher than 0.1. Compared to the actual estimated effect of the policy (8.1304), these results are small and insignificant. Overall, the placebo test indicates that the benchmark results are not driven by the city characteristics that is unobserved and not included in the regression model.

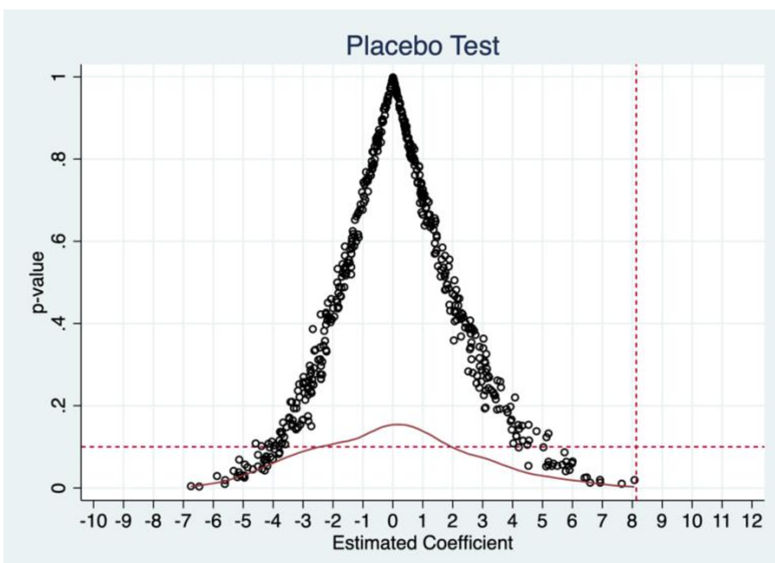

Figure 3: Placebo Test

To further affirm the effect of TIP on the innovation activity, I change the dependent variable to be the number of patents granted. As is mentioned before, the number of patents granted reflects the innovation activity for a longer period of time and also reflects the strictness of patent approval. Given that China have been making the patent approval stricter in order to increase the quality,[5] if the implementation of the TIP policy had a causal effect on the innovation activity given a stricter approval process, then we should see a significant positive and increasing effect by lagging the policy dummy for one period, and we shouldn't see any significant pre-implementation impact by leading the policy dummy for one period. The estimation results on the altered model are

Table 5: Effect of TIP with Different Dependent and Independent Variables

	(1)	(2)	(3)
VARIABLES	Avg_Granted	Avg_Granted	Avg_Granted
TIP_lead	2.1566		
	(1.3279)		
TIP		3.9668*	
		(1.7903)	
TIP_lag			5.7122*
			(1.9953)
Constant	-33.7794	-41.0329	-39.7660
	(-1.0421)	(-1.1775)	(-1.1511)
Observations	1,834	2,080	2,080
R-squared	0.2345	0.2748	0.2785
Number of city	273	273	273
controls	yes	yes	yes
city fe	yes	yes	yes
year fe	yes	yes	yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

By leading the policy implementation one year ahead of the actual year, the estimation becomes insignificant. By lagging it one year after the actual year, the estimation increases in magnitude and is still significant. This means that the implementation of TIP has a positive and

[5] To see the details of the strengthening of the enforcement of patent granting, see 国家知识产权局 公告 关于规范专利申请行为的若干规定(2017)(第 75 号) (cnipa.gov.cn)

increasing impact on the innovation activity measured by the patent granted, even if the granting approval is becoming stricter than before.

5 Heterogeneous Effects

5.1 Difference in the Administrative Hierarchy

Cities with a higher administrative rank, that is, a closer link with the central government, have more bargaining power in the allocation of factors and resources. They may also have a more developed environment to attract capitals and labor, and is more favored by the policy. Thus, it is natural to reason that the implementation of TIP may have a stronger effect on the innovation activity measured by patent. To test this, I include the interaction of the policy dummy (TIP_{it}) and a dummy indicating the administrative rank ($rank_{it}$) in the benchmark model. The administrative dummy ($rank_{it}$) equals to one if the city is the provincial capital[6], a city with independent planning status (Jihua Danlie Shi)[7], or a city of special economic zone[8]. Although the estimated coefficient for the interaction term has a high magnitude (22.28), it is not statistically significant. This suggests that the policy effect is not significantly different between the high-ranked cities and the low-ranked cities. One explanation is that many cities without a high administrative rank also have very compatible infrastructure and specific advantages that can attract capital and labor (for instance, Wenzhou and Suzhou are very competitive in terms of economic development). The political ranking is not necessarily correlated with the economic development. Thus, the effect of a high administrative rank is mitigated, and the political rank of the city has little deterministic role in the effect of the TIP.

[6] These cities include: Heilongjiang, Changchun, Shenyang, Shijiazhuang, Taiyuan, Jinan, Nanjing, Hangzhou, Fuzhou, Guangzhou, Nanning, Zhengzhou, Wuhan, Changsha, Nanchang, Hefei, Xi'an, Chengdu, Guiyang, Kunming, Huhehaote, Yinchuan, Gansu, Lasa, Xining, Wulumuqi.
[7] These cities include: Dalian, Qingdao, Ningbo, Xiamen, Shenzhen
[8] These cities include: Shenzhen, Shantou, Zhuhai, Xiamen, Haikou, San'ya

Table 6: Heterogeneous Effects

VARIABLES	(1) Avg_Patent	(2) Avg_Patent
TIP	3.8477	8.4955**
	(0.9733)	(2.1702)
TIPrank	22.2760	
	(1.3634)	
TIPHu_Line		-7.9201*
		(-1.7551)
Constant	-18.5853	-8.3748
	(-0.3354)	(-0.1397)
Observations	2,080	2,080
R-squared	0.3542	0.3379
Number of city	273	273
controls	yes	yes
city fe	yes	yes
year fe	yes	yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2 Difference in the Locational Characteristics

Cities differ significantly in their locational characteristics, such as topography, climate, historical heritages, and transportation condition. Based on these locational characteristics, the geologist Hu Huan Yong proposed a straight line that connected Heihe in Heilongjiang province with Tengchong in Yunnan province. The territory in the southeast side on this line has significantly better locational characteristic, and it contains 94% of the Chinese population and most of the economic centers. In contrast, the territory in the northwest side of this line has worse condition for inhabitation and economic development. I investigate whether the effect of the TIP is different between these two regions by adding an interaction term of policy dummy and a dummy that equals to one if the city is in the northwest part of the line (Hu_Line_{it}) into the benchmark model. The estimated coefficient for the interaction dummy ($TIPHu\_Line_{it}$) is negative and significant, which implies that the TIP policy effect is systematically smaller in those cities with a worse condition for inhabitation and economic development.

6 Mechanism Analysis

Following Bai (2022)'s method, I construct the following intermediate effect model.

$$Intermediate_{it} = \alpha + \mu_i + \lambda_t + \delta TIP_{it} + \beta \boldsymbol{X}_{it} + \varepsilon_{it}$$

$$Y_{it} = \alpha + \mu_i + \lambda_t + \theta TIP_{it} + \varphi Intermediate_{it} + \beta \boldsymbol{X}_{it} + \varepsilon_{it}$$

The hypothesis of this paper is that the TIP policy causes an inflow of high-skilled talent and the accumulation of human capital, thus boosting the innovation activity. To test whether this hypothesis is true, I set the intermediate variable to be an indicator of talent in the city, and the Y_{it} to be the innovation outcome. If the coefficient δ and φ are both significant, then we can conclude that the intermediate effect exists. Moreover, if the sign of θ is the same as the sign of $\delta \times \varphi$, then we can confirm that the contribution rate of the intermediate variable to the outcome variable is $\frac{\delta\varphi}{\theta+\delta\varphi}$. Based on the accessibility of the data, I sum up the number of talents in the science & technology sector and IT sector and divide the sum by the population of the city in that year to construct an approximate measure of the agglomeration level of talents. Given that the nature of IT is more of an applied field and that the research in science & technology is mostly done in the academia, he science & technology sector and the IT sector can be seen as good representatives of the innovation power from the academia and the industry, respectively.

6.1 Human Capital Agglomeration

The results in column (1) and (2) of table 7 confirmed the hypothesis. We can see that the implementation of TIP has a positive impact on the agglomeration of talents, and through this channel it contributes to the increase in innovation activity measured by patent application. The contribution rate based on the available data is, by calculation, 6.68%. Comparing column (3), (4), and (5), we can also see that the intermediate channel has the strongest effect on the practical patent, as it has the largest and the most significant estimated coefficients. This result supports the inference drawn from the effect decomposition section that the TIP policy has the strongest impact on the innovation activities with above-average difficulties, through the channel of talent agglomeration.

Table 7: Mechanism Analysis

VARIABLES	(1) Talent	(2) Avg_Patent	(3) Invent_Patent	(4) Pract_Patent	(5) Design_Patent
TIP	11.1376**	10.8696**	2.8110	6.4839***	1.5747
	(2.4218)	(2.2239)	(1.6257)	(3.1045)	(0.6057)
Talent		0.0699*	0.0352**	0.0404***	-0.0058
		(1.8570)	(2.4635)	(2.9574)	(-0.2406)
Constant	-369.2138***	-3.2954	12.9087	9.8707	-26.0748
	(-4.9526)	(-0.0628)	(0.4821)	(0.3370)	(-1.3467)
Observations	1,302	1,302	1,302	1,302	1,302
R-squared	0.1260	0.2552	0.2468	0.3076	0.0258
Number of city	273	273	273	273	273
controls	yes	yes	yes	yes	yes
city fe	yes	yes	yes	yes	yes
year fe	yes	yes	yes	yes	yes

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

6.2 Impact in the Industry and the Academia

We can also investigate how this intermediate effect differs in between the innovation in the industry and in the academia. I use the agglomeration of IT talents and the science & technology as two different intermediates in the regression and check each's channel. Table 8 reports the estimation result. The TIP has a significant positive impact on the agglomeration of IT talents, and through the agglomeration of IT talents it boosts the innovation activity. In contrast, the effect on the agglomeration of science & technology talents is not significant. Given that these two categories of talents roughly represent two different fields, we can infer from this result that the intermediate effect of the agglomeration of talents mainly happen through the channel in the industry, not in the academia.

Table 8: Mechanism Analysis with Different Types of Talents

	(1)	(2)	(3)	(4)
VARIABLES	IT_Talent	Avg_Patent	Sci_Talent	Avg_Patent
TIP	5.4151**	6.6618**	0.8484	11.6070**
	(2.5617)	(2.0654)	(0.3937)	(2.1584)
IT_Talent		0.2390**		
		(2.2217)		
Sci_Talent				0.0921
				(1.4579)
Constant	-114.9461***	17.6834	-163.3890***	-12.9273
	(-2.8010)	(0.2991)	(-4.1967)	(-0.2474)
Observations	2,061	2,061	1,308	1,308
R-squared	0.0874	0.3808	0.0819	0.2458
Number of city	273	273	273	273
controls	yes	yes	yes	yes
city fe	yes	yes	yes	yes
year fe	yes	yes	yes	yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7 Discussion

In this section I will discuss the extends to which my results can help understand the effect of the Talent Introducing Policy and the role of human capital in innovation.

The major obstacle in generalizing my results come from the data availability. To obtain a continuous yearly measure of innovation, I can only access the patent data. However, there are many more measurement to consider, such as the number of legal disputes over intellectual property, which could be reasonably assumed to be positively correlated to the innovation level in a region. To construct a measurement of the agglomeration level of the talents, I use the proportion of high-tech sector employees with the total working population. If we use other measurement, such as the number of the annual inflow of the high-educated or high-skilled people (immigrants into the city), we can directly identify the impact of TIP in attracting the talents. Moreover, the construction of the policy dummy suffers from the heterogeneity in contents across different cities.

To mitigate these concerns, we can only draw safe inference on the sign and the causal direction based on my results, but we cannot trust the estimated numerical magnitude and to calculate the effect based on these numbers.

However, we can still safely conclude that the TIP positively contributed to the agglomeration of human capital and thus boosted the local innovation activity, because the estimation strictly follows the procedure of a staggered Difference in Difference and exploited the nature of the policy variation. We can also infer that such effect would be strengthened by a more favorable locational characteristics based on the heterogeneous analysis. The incentive system introduced by the TIP policy will perform as a plus if the location itself is attractive enough in terms of its locational characteristics such as weather and infrastructure. Also, based on the data of different categories of patent, we can conclude that the TIP lead to truly high-quality innovation.

Conclusion

In the 2010s, many cities in China have introduced the Talent Introduction Policy (TIP) which contains several incentives to attract the agglomeration of human capital, in order to boost the local innovation activity and the potential economic development. This paper exploited the variation caused by the different timing of policy implementation and established the causal effect of such policy on the local innovation level measured by patent. Specifically, this paper found that the implementation of TIP policy has a positive impact on the local innovation, through the channel of human capital agglomeration. This impact could be strengthened by favorable locational characteristics, and is more important in the industry not in the academia.

In general, the finding of this paper is in line with a broad literature discussing the role of human capital in innovation and in modern economic growth. This paper not only provides evidence of such role with the data from China but also provides empirical estimates of such effect that can be used by government agencies in the evaluation and the design of their economic policies.

Appendix A

Figure A1 and figure A2 provide inference for the balance test for the cross-sectional PSM. Figure A1 is the result of the balance test after the PSM when we treat the dataset as a cross sectional data. As we can see from the figure, most of the control variables have the standard bias below 20% after the matching. However, the strict balance condition requires that the standard bias should not be above 10%. Figure A2 shows that most of the sample in the treatment and control groups are within the common support. The samples that are not in the common support usually have an extreme value for their propensity score, either close to zero or close to one.

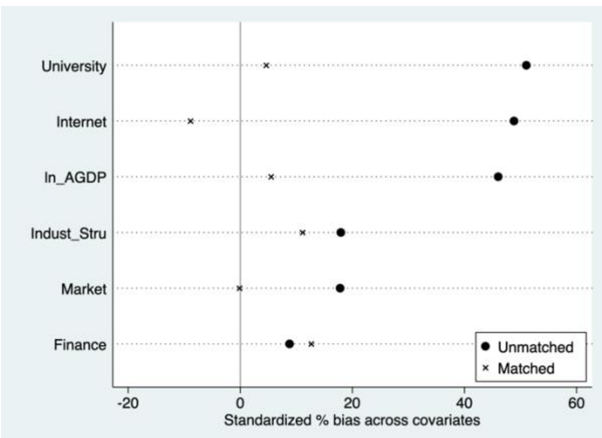

Figure A1: Balance Test One

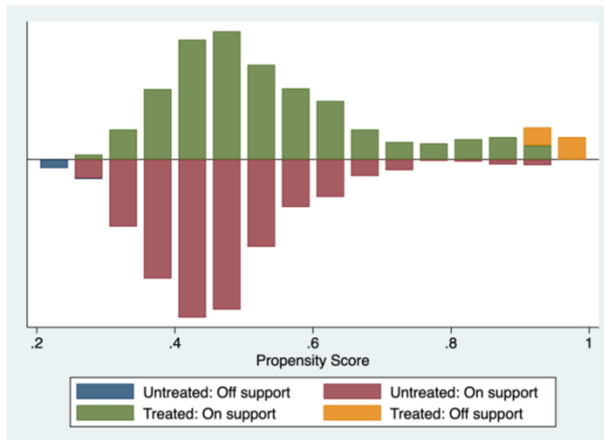

Figure A2: Balance Test Two

Table A1 and table A2 provides inference for the balance test for the year-by-year PSM. To see whether there exists systematical difference between the matched treatment and control group, we can only compare them within one year. There is no direct method to check this, so I compare the logit regression of the grouping dummy on the control variables before and after matching for each year, and then check the changes in the estimation. To form a balanced matching, the coefficients should change from large to small, and from significant to insignificant. As we can see from the comparison between table A1 and table A2, most of the coefficients change from large to small, and from significant to insignificant. Thus, we can conclude that the year-by-year PSM-DID method forms a balanced match between treatment and control.

Table A1: Balance Test One for Year-by-Year PSM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	2013b	2014b	2015b	2016b	2017b	2018b	2019b
ln_AGDP	0.2587	0.3142	0.8182**	0.6742**	0.3265	0.8343**	0.6891*
	(0.9451)	(1.0233)	(2.2544)	(1.9878)	(0.7378)	(2.3901)	(1.9363)
Indust_Stru	-0.0037	-0.0059	-0.0078	-0.0172	-0.0098	-0.0013	0.0011
	(-0.3175)	(-0.5266)	(-0.6760)	(-1.4543)	(-0.7160)	(-0.1021)	(0.0690)
Finance	-0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000
	(-0.5472)	(-0.5708)	(0.5053)	(1.2825)	(-0.4735)	(-0.2932)	(-1.2165)
Market	-2.1660	80.1519	-274.6794	-114.2171	48.6181	-222.3099	80.5240
	(-0.0049)	(0.1847)	(-0.5593)	(-0.2306)	(0.0833)	(-0.9134)	(0.1608)
Internet	0.0043	0.0029	0.0053*	0.0042*	0.0034*	0.0026	0.0015
	(1.0300)	(0.8629)	(1.7967)	(1.8859)	(1.7321)	(1.5380)	(0.7902)
University	0.0395*	0.0490*	0.0196	0.0239	0.0378	0.0320	0.0622*
	(1.6953)	(1.8010)	(0.9421)	(1.2129)	(1.5582)	(1.3223)	(1.9286)
Constant	-2.3431	-2.3986	-7.5107*	-3.9688	-1.6710	-9.1295**	-8.0102
	(-0.7270)	(-0.6485)	(-1.8275)	(-0.9671)	(-0.3410)	(-2.1073)	(-1.5883)
Observations	267	265	263	262	261	257	246

Table A2: Balance Test Two for Year-by-Year PSM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	2013a	2014a	2015a	2016a	2017a	2018a	2019a
ln_AGDP	0.0791	-0.2075	0.1688	0.1397	-0.1153	0.4487	0.0539
	(0.2767)	(-0.6044)	(0.4375)	(0.3893)	(-0.4276)	(1.0928)	(0.1312)
Indust_Stru	-0.0092	0.0189	0.0027	0.0001	-0.0093	0.0087	0.0094
	(-0.6756)	(1.1960)	(0.2026)	(0.0081)	(-0.6085)	(0.5925)	(0.5189)
Finance	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	-0.0000
	(-0.2236)	(0.4708)	(-0.5869)	(0.6964)	(0.8771)	(0.2091)	(-0.6767)
Market	-51.4876	-162.1670	19.6829	147.9760	-171.8359	-32.4899	69.0026
	(-0.1181)	(-0.2909)	(0.0361)	(0.2613)	(-0.3060)	(-0.0666)	(0.1130)
Internet	0.0017	-0.0017	-0.0006	0.0013	0.0016	-0.0002	-0.0009
	(0.5595)	(-0.5930)	(-0.1626)	(0.4251)	(0.6853)	(-0.0960)	(-0.3895)
University	0.0022	0.0149	0.0140	-0.0012	0.0045	-0.0045	0.0313
	(0.0998)	(0.6020)	(0.5292)	(-0.0467)	(0.1846)	(-0.1619)	(0.7183)
Constant	1.1970	-2.1759	-2.4160	-2.0104	3.0894	-7.0436	-2.7229
	(0.3285)	(-0.5250)	(-0.5632)	(-0.4598)	(0.7123)	(-1.4167)	(-0.4765)
Observations	192	172	190	190	173	191	174

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure A3 to Figure A6 compares the kernel density between the treatment and control group before and after matching using both cross-sectional and year-by-year PSM methods. As we can see for both methods, the kernel density curves have significant difference between the two groups before the matching, and this difference reduced significantly after the matching. Thus, we can infer that both the cross-sectional and the year-by-year PSM matching reduced the selection issue and reduced the selection bias in the estimation.

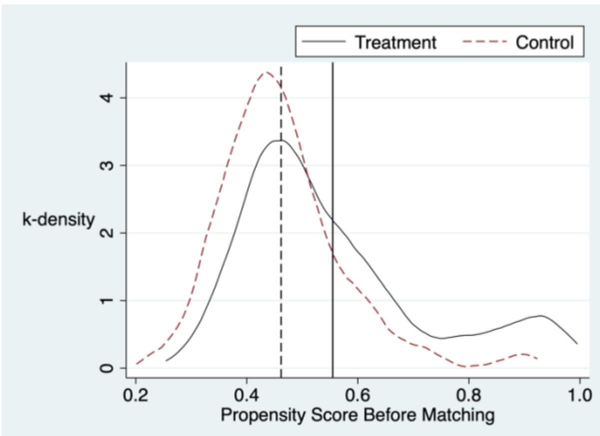

Figure A3: K-density for Cross-Sectional PSM: Before

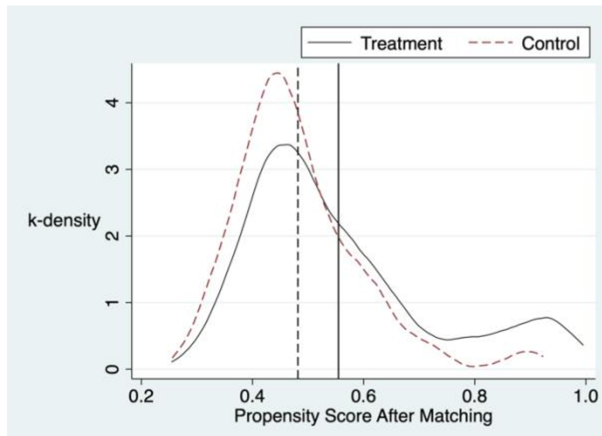

Figure A4: K-density for Cross-Sectional PSM: After

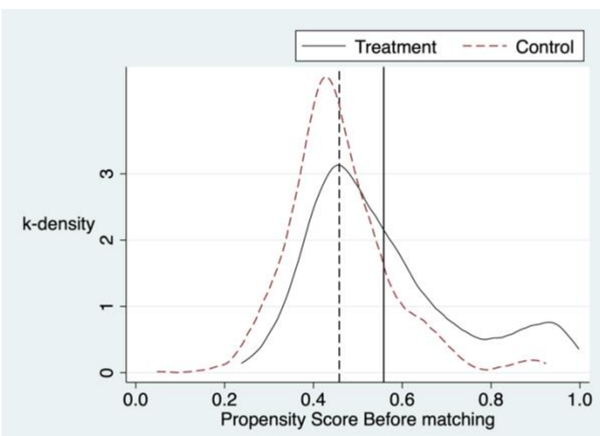

Figure A5: K-density for Year-b-Year PSM: Before

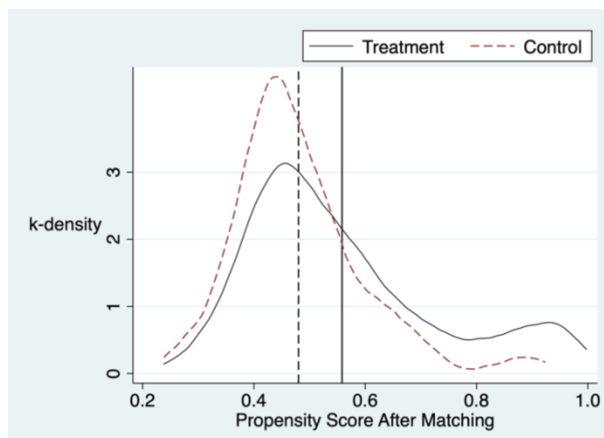

Figure A6: K-density for Year-b-Year PSM: After

References

[1] 白俊红，蒋伏心：《协同创新、空间关联与区域创新绩效》，《经济研究》，2015 年第 7 期，第 174-187 页。

[2] 白俊红、张艺璇、卞元超：《创新驱动政策是否提升城市创业活跃度——来自国家创新型城市试点政策的经验证据》，《中国工业经济》，2022 年第 6 期，第 61-78 页。

[3] 韩先锋，宋文飞，李勃昕：《互联网能成为中国区域创新效率提升的新动能吗》，《中国工业经济》，2019 年第 7 期，第 119-136 页。

[4] 鞠晓生，卢荻，虞义华：《融资约束、营运资本管理与企业创新可持续性》，《经济研究》，2013 年第 1 期，第 4-16 页。

[5] 李婧、谭清美、白俊红：《中国区域创新生产的空间计量分析——基于静态与动态空间面板模型的实证研究》，《管理世界》，2010 年第 7 期，第 43-55，65 页。

[6] 李习保：《区域创新环境对创新活动 z 效率影响的实证研究》，《数量经济技术经济研究》，2007 年第 8 期，第 13-24 页。

[7] 刘春、田玲：《人才政策"背书"能否促进企业创新》，《中国工业经济》，2021 年第 3 期，第 156-173 页。

[8] 刘智勇、李海峥、胡永远、李陈华：《人力资本结构高级化与经济增长——兼论东中西部地区差距的形成和缩小》，《经济研究》，2018 年第 3 期，第 50-63 页。

[9] 钱晓烨、迟巍、黎波：《人力资本对我国区域创新及经济增长的影响——基于空间计量的实证研究》，《数量经济技术经济研究》，2010 年第 4 期，第 107-121 页。

[10] 吴玉鸣：《空间计量经济模型在省域研发与创新中的应用研究》，《数量经济技术经济研究》，2006 年第 5 期，第 74-85，130 页。

[11] 余泳泽：《创新要素集聚、政府支持与科技创新效率——基于省域数据的空间面板计量分析》，《经济评论》，2011 年第 2 期，第 93-101 页。

[12] 邹薇，代谦：《技术模仿、人力资本积累与经济赶超》，《中国社会科学》，2003 年第 5 期，第 26-38，205-206 页。

[13] Abadie, A., 2005, Semiparametric Difference-in-Differences Estimators. *The Review of Economic Studies* 72(1), pp.1-19.

[14] Badinger, H., and G. Tondl, 2003, *Trade, Human Capital and Innovation: The Engines of European Regional Growth in the 1990s*. Springer Berlin Heidelberg.

[15] Beck, T., R. Levine, and A. Levkov, 2010, Big Bad Banks? The Winners and Losers from Bank Deregulation in the United States. *The Journal of Finance* 65(5), pp.1637-1667.

[16] Benhabib, J., and M. M. Spiegel, 1994, The Role of Human Capital in Economic Development Evidence

from Aggregate Cross-Country Data. *Journal of Monetary Economics* 34(2), pp.143-173.

[17] Bils, M., and P. J. Klenow, 2000, Does Schooling Cause Growth?. *American Economic Review* 90(5), pp.1160-1183.

[18] Braghieri, L, R. Levy, and A. Makarin, 2022, Social Media and Mental Health. *American Economic Review* 112(11), pp.3660-3693.

[19] Cinnirella, F., and J. Streb, 2017, The Role of Human Capital and Innovation in Economic Development: Evidence from Post-Malthusian Prussia. *Journal of Economic Growth* 22, pp.193-227.

[20] Dakhli, M., and D. D. Clercq, 2004, Human Capital, Social Capital, and Innovation: a Multi-Country Study. *Entrepreneurship & Regional Development* 16(2), pp.107-128.

[21] Gennaioli, N., R. La Porta, F. Lopez-de-Silanes, and A. Shleifer, 2013, Human Capital and Regional Development. *The Quarterly Journal of Economics* 128(1), pp.105-164.

[22] Lucas Jr, R. E., 1988, On the Mechanics of Economic Development. *Journal of Monetary Economics* 22(1), pp.3-42.

[23] Lucas Jr, R. E., 2009, Ideas and Growth. *Economica* 76(301), pp.1-19.

[24] Ma, L., X. Zhai, W. Zhong, and Z. Zhang, 2019, Deploying Human Capital for Innovation: A Study of Multi-Country Manufacturing Firms. *International Journal of Production Economics* 208, pp.241-253.

[25] Munjal, S., and S. Kundu, 2017, Exploring the Connection Between Human Capital and Innovation in the Globalizing World. *Human Capital and Innovation: Examining the Role of Globalization*, pp.1-11.

[26] Nelson, R. R., and E. S. Phelps, 1966, Investment in Humans, Technological Diffusion, and Economic Growth. *The American Economic Review* 56(1/2), pp.69-75.

[27] Romer, P. M., 1990, Endogenous Technological Change. *Journal of Political Economy* 98(5), pp.S71-S102.

[28] Sun, X., H. Li, and V. Ghosal, 2020, Firm-Level Human Capital and Innovation: Evidence from China. *China Economic Review* 59, pp.101388.

[29] Wantchekon, L., M. Klašnja, and N. Novta, 2015, Education and Human Capital Externalities: Evidence from Colonial Benin. *The Quarterly Journal of Economics* 130(2), pp.703-757.

[30] Zanello, G., X. Fu, P. Mohnen, and M. Ventresca, 2016, The Creation and Diffusion of Innovation in Developing Countries: A Systematic Literature Review. *Journal of Economic Surveys* 30(5), pp.884-912.

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