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# THE LEADING EFFECT OF DEVELOPING COUNTRIES' CAPITAL CITIES IN INNOVATION: EVIDENCE FROM CHINESE PROVINCIAL CAPITALS

Peng HU[1], Yemin DING[2], Lee CHIN[3,4]✉, Paik Xuan POH[3], Shuying YU[2]

[1] *School of Mathematics and Finance, Chuzhou University, China*
[2] *College of Business, Yancheng Teachers University, Yancheng, Jiangsu, China*
[3] *School of Business and Economics, Universiti Putra Malaysia, Serdang, Malaysia*
[4] *Department of Econometrics, Tashkent State University of Economics, Tashkent, Uzbekistan*

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**Abstract.** Motivated by the limited research on the role of capital cities in driving innovation within developing countries, this study used China as a sample to examine the relationship between Provincial Capitals' Priority Development (PCPD) and Provincial Innovation Capacity (PIC). The findings revealed that PCPD significantly enhances PIC. Quantile regression further demonstrated the varying impact of PCPD at different stages of PIC. A lag effect was also identified, as evidenced by regressing lagged PCPD variables on PIC. Additionally, by incorporating interaction terms in the regression, we verified the positive moderating effects of industrial isomorphism, fiscal support for innovation, and higher education resources on the PCPD–PIC link. Finally, heterogeneity analysis indicated that PCPD initially benefits innovation primarily in provincial capitals; however, over time, its positive impact gradually extends to non-provincial capital cities. These findings offer insights for policymakers in developing countries seeking to foster innovation through the strategic prioritization of capital cities.

**Keywords:** capital cities, innovation, industrial isomorphism, China, developing countries.

**JEL Classification:** R11, O33, C23.

✉Corresponding author. E-mail: *leechin@upm.edu.my*

## 1. Introduction

Many developing countries worldwide prioritize the development of capital cities (Abubakar & Doan, 2017; Syaban & Appiah-Opoku, 2023), due to the crucial role that a highly developed key city can play in fostering regional development. This perspective is widely supported by scholars. For example, Perroux's (1950) growth pole theory asserts that balanced regional development is a mere idealization; rather, regional economic growth is usually achieved by gradual diffusion from a growth center to surrounding areas. Friedmann's (1966) core and periphery theory supports Perroux's (1950) position, suggesting that a spatial system consists of a core area and a periphery area. The core area has a high ability for innovation and transformation, and being attached to the core area, peripheral areas' development level is almost entirely determined by the core area. More scientifically, Krugman (1991) proposed a core-periphery pattern, which depicts the dynamic equilibrium process of industrial spatial structure evolution under the influence of agglomeration and dispersion. Krugman (1991) specifically found that industries not only undergo a dynamic process of agglomeration towards the core region, but also a dynamic process of diffusion towards the periphery region. Without exception, the above theories emphasize the prominent role of core cities in regional development.

Although prioritizing the development of capital cities could lead to a crowding-out effect on non-capital cities, resulting in a shortage of production factors in non-capital cities and thus exacerbating development imbalances (Shi et al., 2020), it is important to acknowledge that this approach can also yield positive outcomes. Specifically, prioritizing capital cities can promote their expansion through resource agglomeration, creating economies of scale. This helps reduce unit production costs and improve production efficiency. Additionally, the growth of capital cities can enhance their influence, thereby driving the development of non-capital cities (Niu & Wang, 2022). In a word, prioritizing capital cities' development could produce both positive and negative outcomes. Especially in comparison to developed countries, developing countries often experience more pronounced issues of uneven development (Kaplinsky & Kraemer-Mbula, 2022). As such, researchers should not place blind faith in the theories mentioned in the previous paragraph, uncritically supporting the prioritization of capital cities in developing countries. Instead, it is essential to investigate the actual impacts of prioritizing capital cities' development to avoid further exacerbating regional disparities in these nations.

So far, we have only found very few empirical studies on this topic (Al-Jebouri et al., 2020; Sridhar, 2023). Specifically, Al-Jebouri et al. (2020) examined data from 16 countries between 1970 and 2014 and found that prioritizing the development of large cities has a positive impact on regional economic growth. Furthermore, Al-Jebouri et al. (2020) used an empirical model including the squared term of the core explanatory variable to reject the existence of a non-linear relationship between them. In contrast to Al-Jebouri et al. (2020), who focused on economic growth, Sridhar (2023) investigated the impact of urban expansion on public health, confirming that the expansion of large cities facilitates the spread of epidemics. A review of the existing literature reveals limited scholarly attention to this field, with the existing empirical studies focusing primarily on economic growth and public health. In other words, although theories such as growth pole theory and core and periphery theory emphasize the diffusion of innovation from core to peripheral regions, there is, to our knowledge, no empirical investigation into the innovation effects of prioritizing the development of capital cities. Endogenous growth theory posits that technological innovation is the core driving force for sustained and stable economic growth, which has been widely substantiated by empirical studies (Ding et al., 2023a). As such, in the context of global economic stagnation, empirically examining its innovation effect holds significant practical relevance.

This study selected China as the research sample. First, Chinese governments at all levels have been restructuring their economic development, guiding production factors to further concentrate in provincial capitals to support their prioritized development (Zhou & Shen, 2024). This aligns with the focus of this paper on examining the innovation effect of prioritizing capital cities' development. Furthermore, as the largest developing country around the world, China's development model holds significant reference value for other developing countries. As such, this study empirically investigated the leading role of Chinese provincial capitals in provincial innovation activities, aiming to provide insights into urban development models for China and other developing countries.

To comprehensively investigate the impact of Provincial Capitals' Priority Development (hereafter referred to as "PCPD") on Provincial Innovation Capacity (hereafter referred to as "PIC"), this paper conducted a series of empirical tests using data from 27 China's provincial-level regions from 2006 to 2020. We first constructed a fixed effect model for benchmark estimation, and the results indicate that PCPD can significantly promote PIC. Subsequently, various robustness checks were conducted, including placebo test, replacing the proxies of variables, and employing different estimation methods, all of these checks consistently supporting the positive effect of PCPD on PIC. Considering the potential bias in OLS estimation due to its sensitivity to outliers, quantile regression was employed to further estimate the relationship between PCPD and PIC. The estimation results indicate that, on the one hand, PCPD exhibits a significant positive effect on PIC at all quantiles; On the other hand, as PIC increases, the promoting intensity of PCPD on PIC shows a trend of initially rising and then declining. Additionally, motivated by the fact that the diffusion of new technologies takes time, the core explanatory variable was lagged from 1 to 9 periods, and separately estimated with PIC to explore the time lag effect of PCPD on PIC. The results show that, over time, the positive impact of PCPD on PIC goes through a process from weak to strong and then to weak. We utilized three fixed effect models containing interaction terms to examine and confirm the moderating effects of industrial isomorphism, government innovation support, and higher education resources on the impact of PCPD on PIC. Furthermore, this study also performed heterogeneity analysis by disaggregating innovation from the perspective of city's identity. The findings indicate that, initially, PCPD primarily focuses on promoting innovation in provincial capitals; however, as time progresses, its beneficial impact will also encompass both provincial capitals and non-provincial capital cities.

The marginal contributions of this paper are as follows. First, unlike previous studies that primarily focus on economic growth (Al-Jebouri et al., 2020) and public health (Sridhar, 2023), this study is the first to empirically examine the impact of PCPD on PIC, thereby expanding the scope of research in this field. Second, this study critically applies regional development theories, including growth pole theory (Perroux, 1950), core and periphery theory (Friedmann, 1966), and the core-periphery pattern (Krugman, 1991), enriching their applicability. Third, we introduce innovations in research methods and framework by employing quantile regression, lagged effect models, and moderation effect analysis to systematically examine the heterogeneous impact of PCPD on PIC across different stages, temporal dynamics, and regional characteristics. Combined with the empirical design that decomposes provincial innovation capacity into that of capital and non-capital cities, these efforts provide a more detailed understanding of the development priorities between provincial capitals and non-capital cities in China. Lastly, this paper provides new empirical evidence in support of prioritizing capital cities' development in China and other developing countries.

The remaining sections of this paper are arranged as follows. The Section 2 develops the research hypotheses. The data and methodology used in this study are introduced in the Section 3, while the empirical results are reported and discussed in the Section 4. The Section 5 summarizes the study's conclusions and proposes corresponding policy implications.

## 2. Literature review and hypothesis development

According to Zhou and Shen (2024), prioritizing support for the development of provincial capitals enables various innovation factors to agglomerate in these capitals. This study argues that agglomeration of resources enhances these capitals' innovation capacity in three aspects. Firstly, the agglomeration of innovative talents in these capitals can promote knowledge exchange and collaboration, thereby promoting innovation (Fritsch & Wyrwich, 2021). Secondly, collaborative innovation among similar enterprises agglomerating in these capitals, characterized by the sharing of benefits and risks, reduces the enterprises' R&D costs and disperses their R&D risks, thereby stimulating innovation activities (Liu et al., 2020b). Lastly, the agglomeration of innovation factors produces the scale effect, which decreases innovation costs and improves innovation efficiency (Battaggion & Tedeschi, 2021)[1].

Subsequently, the enhancement of innovation capacity in these capitals via prioritizing their development creates a potential innovation gap between capital and non-capital cities in the province. This is conducive to generating positive externality, which drives the improvement of innovation capacity in non-provincial capital cities (Gao & Yuan, 2022). Non-provincial capital cities achieve this by studying, assimilating, and re-innovating new technologies from provincial capitals. Indeed, Ding et al. (2023a) concurred that some newer innovation outputs are modifications of existing ones. In short, higher innovation output in provincial capitals provides more opportunities for imitation and secondary innovation in non-provincial capital cities, allowing the latter to enhance their innovation capacity.

Based on the above analysis, we posit that prioritizing provincial capitals' development not only directly enhances innovation capacity in these capitals, but also drives the innovation capacity of non-provincial capital cities through the externality effect. Accordingly, Hypothesis 1 is proposed.

**H1:** *PCPD can increase PIC.*

Industrial isomorphism could impact the relationship between PCPD and PIC in two aspects. First, when capital and non-capital cities in a province have a similar industrial structure, enterprises in these cities are more likely to find partners in their industries for collaborative innovation. Compared to independent work, collaborative work can improve innovation efficiency through resource sharing, specialized division of labor, and risk diversification (Sánchez-González & Herrera, 2015). Similar industrial structures in a province also mean that new technologies from the provincial capital can be more easily understood and absorbed by non-provincial capital cities, as related industries find it easier to learn and apply common technologies and experiences. In short, when the industrial structure within a province has an isomorphic pattern, the positive externality of technology from the provincial capital towards non-provincial capital cities is stronger, which then reinforces the positive effect of PCPD on PIC. Based on the above analysis, Hypothesis 2 is proposed.

**H2:** *Industrial isomorphism has a positive moderating effect on the relationship between PCPD and PIC.*

[1] Scale effect is a phenomenon in the production process where unit costs decrease as a result of the expansion of production scale.

The externality effect through which prioritizing provincial capitals' development improves the innovation capacity of non-provincial capital cities is mainly realized by these cities' learning and secondary innovation of new technologies from the capitals. Such learning and re-innovation not only require substantial investments of time and resources, but also expose cities to the risk of innovation failure (Castellion & Markham, 2013). In this sense, fiscal support for innovation, provided by the governments of non-provincial capital cities, can reduce learning costs and diffuse innovation risks. This encourages enterprises in the non-capital cities to learn and re-innovate new technologies from the capital, thus strengthening the externality effect of technology. Based on the above analysis, Hypothesis 3 is proposed.

**H3:** *Fiscal support for innovation in non-provincial capital cities has a positive moderating effect on the relationship between PCPD and PIC.*

Higher education resources in non-provincial capital cities could influence the relationship between PCPD and PIC in three ways. Firstly, higher education institutions actively engage in R&D, which serves as a primary arena for innovation activities (Berbegal-Mirabent et al., 2015). Therefore, non-provincial capital cities with abundant higher education resources are more likely to absorb new knowledge from provincial capitals and engage in secondary innovation, thereby enhancing their innovation output. Secondly, well-endowed higher education institutions in non-provincial capital cities nurture a significant number of skilled professionals for local areas. These professionals typically possess superior learning abilities and a stronger sense of innovation compared to those without higher education. Consequently, they contribute to amplifying the externality effect of technology from provincial capitals to non-provincial capital cities, thus fostering innovation development in the latter. Lastly, it should be noted that innovation adoption is typically limited in the early stage (Kucharavy & De Guio, 2011), implying that new technologies from provincial capitals could not be immediately assimilated by non-provincial capital cities. However, higher education institutions in non-provincial capital cities can facilitate the dissemination of new technologies among local enterprises through industry-university-research collaboration, which helps enterprises to absorb new technologies more quickly and carry out exploitative innovation towards these new technologies (Xiao et al., 2023). Based on the aforementioned analysis, Hypothesis 4 is proposed.

**H4:** *Higher education resources in non-provincial capital cities have a positive moderating effect on the relationship between PCPD and PIC.*

## 3. Data and methodology

### 3.1. Data

The main objective of this study was to explore the impact of PCPD on PIC in China. Accordingly, PIC (*PIC*) was the dependent variable in the model. According to Pradhan et al. (2016), patents can, to some extent, reflect the level of regional innovation. Although both the number of patent applications (Wen et al., 2021; Ding et al., 2023a) and that of patent authorizations (Guo & Zhong, 2022; Liu et al., 2020a) have been used to measure a region's innovation capacity, compared to the latter, the former can measure innovation output more promptly (Jalles, 2010). As such, this study used the number of annual patent applications at the provincial level as the proxy variable for *PIC*.

The main variable of interest in this study was PCPD (*PCPD*). We used provincial capital primacy in economy as the proxy variable of *PCPD*, as the most direct manifestation of prioritizing provincial capitals through resource reallocation from non-provincial capital cities is an increase in the economic primacy of provincial capitals. To calculate provincial capital primacy in economy, we referred to Jefferson (1939) and used the GDP of the capital in a province divided by the GDP of the city with the highest GDP among all other cities in the province (excluding the provincial capital).

Additionally, several indicators that could affect PIC, such as per capita GDP (Wen et al., 2021), fiscal expenditure on education (Bianchi & Giorcelli, 2020), percentage of tertiary industry's output of GDP (Ding et al., 2023a), total volume of export-import (Ali & Li, 2021), and permanent population (Dong et al., 2016), were included in the research framework as control variables[2]. The data for these variables can be acquired from the CEInet statistics database, China's real estate information network, the China National Intellectual Property Administration, the statistical yearbooks of provinces, and the statistical yearbooks of cities.

Based on data availability, we selected 27 provincial-level regions in China as the research sample, which are presented in Appendix List A. Furthermore, since the Chinese central government identified the period from 2006 to 2020 as a strategic window for building an innovative country (Li et al., 2020), this study selects this timeframe as the sample period. Accordingly, the dataset used in this study was panel data of 27 provincial-level regions in China from 2006 to 2020. Table 1 shows the descriptive statistics for the variables mentioned above, which notably, all have positive values. Importantly, the standard deviations of these variables are small, indicating that the distribution of the data used in this empirical study is relatively concentrated. Additionally, the mean value of *PCPD* being greater than two suggests that the economic levels of most provincial capitals in China are in leading positions within their respective provinces.

**Table 1.** Descriptive statistics of full sample

| Category | Variable Name | Measurement | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| Dependent variable | PIC | Piece | 9.92 | 1.81 | 4.49 | 13.78 |
| Independent variable | PCPD | Ratio | 2.09 | 1.29 | 0.55 | 6.69 |
| Control variables | GDP | RMB | 10.41 | 0.56 | 8.72 | 11.71 |
| | FEE | $10^8$ RMB | 6.14 | 0.92 | 3.33 | 8.16 |
| | TIO | Ratio | 0.45 | 0.06 | 0.30 | 0.60 |
| | TVE | $10^4$ US dollars | 14.76 | 1.71 | 10.34 | 18.51 |
| | PP | $10^4$ people | 8.18 | 0.88 | 5.65 | 9.44 |

*Notes*: All variables except for *PCPD* were log-transformed for their mean, standard deviation, minimum, and maximum values. *PIC* = PIC; *PCPD* = Provincial capital primacy in economy; *GDP* = Per capita GDP; *FEE* = Fiscal expenditure on education; *TIO* = The percentage of tertiary industry's output of GDP; *TVE* = Total volume of export-import; *PP* = Permanent population.

[2] These five variables were abbreviated as *GDP*, *FEE*, *TIO*, *TVE* and *PP*, respectively.

To further ensure the reliability of the estimations, multicollinearity was examined, with the results reported in Table A1 of the Appendix. The VIF values for all variables were found to be below 5.0, suggesting that multicollinearity is not a concern in this analysis. As such, the regression estimates can be considered robust with respect to multicollinearity.

## 3.2. Methodology

### *3.2.1. Benchmark estimation and robustness checks*

To verify the impact of PCPD on PIC as per Hypothesis 1, we conducted a series of empirical estimations. For the benchmark regression, a fixed effect model was established as in Eq. (1), where $Z$ represents the control variables involved in this study, $\mu_i$ and $\nu_t$ are province and year fixed effects, respectively, $\alpha_0$, $\alpha_1$ and $\beta$ are the coefficients for estimation, and $\varepsilon_{it}$ is the error term. To alleviate the heteroscedasticity problem, all the variables involved in this study except *PCPD* were logarithmically treated.

$$Ln(PIC_{it}) = \alpha_0 + \alpha_1 PCPD_{it} + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}. \quad (1)$$

To test whether the benchmark regression results are robust, we also performed a series of robustness checks, the first being a placebo test. According to Ding et al. (2023b), due to limitations in the research design, the *PCPD-PIC* link shown in the benchmark estimation results may only be a placebo effect. To rule out this possibility, referring to Cornaggia and Li (2019), a placebo test was conducted. Specifically, we first extracted all the *PCPD* data and then randomly reallocated these data to each sample. Next, we re-estimated Eq. (1). If the *PCPD-PIC* relationship indicated by the benchmark estimation is a placebo, *PCPD* in the placebo test should obtain a significant coefficient with the same sign as the one from the benchmark estimation.

The second robustness check involved replacing the proxy of *PCPD*. According to Yang et al. (2021), Nighttime Light Intensity (NLI) can, to some extent, reflect the level of economic development of a city. As such, as a robustness check, we replaced the proxy for *PCPD* from the GDP ratio[3] to the NLI ratio[4] and then re-estimated Eq. (1). The data on NLI was derived from two satellites, namely DMSP-OLS and VIIRS. The time span of the data from the DMSP-OLS is 1992 to 2013, while that of the VIIRS is from 2012 to date. Unfortunately, due to the non-inclusiveness between the DMSP-OLS and VIIRS data (Zheng et al., 2019), the two types of NLI data cannot be directly integrated. Accordingly, to obtain NLI data for the period from 2006 to 2020, we referred to Zheng et al. (2019) and took the annual data of the fourth version provided by the DMSP-OLS along with the annual data of the second version provided by the VIIRS as original data to fuse the two data sets.

The third robustness check was dynamic GMM estimation. Although a fixed effect model can provide reliable static estimation results, it may produce biased estimates by ignoring the potential endogeneity caused by dynamic panel deviation (Wen et al., 2021). Following Arellano and Bond (1991), as shown in Eq. (2), we added the lag term of the dependent

[3] The detailed definition of this indicator can be found in Section 3.1.

[4] The NLI ratio refers to the ratio of the NLI of the capital in a province to the NLI of the city with the strongest NLI among all other cities in the province (excluding the provincial capital).

variable as an instrumental variable into Eq. (1), then used system GMM to dynamically estimate the impact of PCPD on PIC. In Eq. (2), $PIC_{i,t-1}$ is the lag term of $PIC_{it}$, and the meaning of other variables is the same as in Eq. (1).

$$Ln(PIC_{it}) = \alpha_0 + \alpha_1 Ln(PIC_{i,t-1}) + \alpha_2 PCPD_{it} + \beta Z_{it} + \varepsilon_{it}. \tag{2}$$

### 3.2.2. Quantile regression

On the one hand, the impact of PCPD on PIC could vary depending on the different stages of a province's innovation capability. On the other hand, due to OLS regression's sensitivity to outliers, outliers could lead to biased estimates in OLS regression, a drawback that can be effectively alleviated by quantile regression (Syed et al., 2022). Therefore, we also conducted quantile regression at five quantiles (0.10, 0.25, 0.50, 0.75, and 0.90) to explore the different impacts of PCPD on PIC at various stages of a province's innovation capability.

### 3.2.3. Time lag effect

Motivated by the innovation diffusion theory (Kucharavy & De Guio, 2011), we believe that PCPD has a time lag effect on PIC. To verify this, we lagged the independent variable called *PCPD* for periods 1, 3, 5, 7 and 9 and regressed it with the dependent variable, in line with Wen et al. (2022). In other words, we estimated Eqs. (3)–(7), where $PCPD_{i,t-1}$, $PCPD_{i,t-3}$, $PCPD_{i,t-5}$, $PCPD_{i,t-7}$, $PCPD_{i,t-9}$ represent *PCPD*'s lagged periods of 1, 3, 5, 7, and 9, respectively. Other variables in these five equations have the same meanings as in Eq. (1).

$$Ln(PIC_{it}) = \alpha_0 + \alpha_1 PCPD_{i,t-1} + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \tag{3}$$

$$Ln(PIC_{it}) = \alpha_0 + \alpha_1 PCPD_{i,t-3} + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \tag{4}$$

$$Ln(PIC_{it}) = \alpha_0 + \alpha_1 PCPD_{i,t-5} + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \tag{5}$$

$$Ln(PIC_{it}) = \alpha_0 + \alpha_1 PCPD_{i,t-7} + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \tag{6}$$

$$Ln(PIC_{it}) = \alpha_0 + \alpha_1 PCPD_{i,t-9} + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}. \tag{7}$$

### 3.2.4. Moderating effects

To verify the moderating effects of industrial isomorphism, government innovation support, and higher education resources on PCPD and PIC relationship as in Hypotheses 2 to 4, referring to Ding et al. (2023b), we constructed three models containing the interaction terms of the moderating variables with the core explanatory variable. These are shown in Eqs. (8)–(10).

$$Ln(PIC_{it}) = \alpha_0 + \alpha_1 PCPD_{it} + \alpha_2 II_{it} + \alpha_3 (PCPD_{it} * II_{it}) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \tag{8}$$

$$Ln(PIC_{it}) = \alpha_0 + \alpha_1 PCPD_{it} + \alpha_2 FSI_{it} + \alpha_3 (PCPD_{it} * FSI_{it}) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \tag{9}$$

$$Ln(PIC_{it}) = \alpha_0 + \alpha_1 PCPD_{it} + \alpha_2 HER_{it} + \alpha_3 (PCPD_{it} * HER_{it}) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}. \tag{10}$$

In Eq. (8), *II* means industrial isomorphism, which is used to measure the similarity in industrial structure between capital and non-capital cities in a province. Following Kang and Liu (2020), Eq. (11) was used calculate *II*, where $x_{ck}$ represents the proportion of industry k's output to total output in the capital of a province and $x_{nk}$ represents the proportion of industry k's output to total output in the non-capital cities of a province. *II* fluctuates from zero to one, whereby the larger its value, the more similar the industrial structure between the capital and non-capital cities in a province.

$$II = \frac{\sum_{k=1}^{n} x_{ck} x_{nk}}{\sqrt{\sum_{k=1}^{n} x_{ck}^2 \sum_{k=1}^{n} x_{nk}^2}}. \tag{11}$$

In Eq. (9), *FSI* means fiscal support for innovation in non-capital cities, which is expressed by the fiscal expenditure on science and technology in those cities. In Eq. (10), *HER* refers to the higher education resources of non-capital cities, which is measured by the number of university teachers in those cities. Other variables in Eqs. (8)–(10) carry the same meanings as in Eq. (1). The data for *FSI* and *HER* and the data required to calculate *II* were obtained from the CEInet statistics database, China's real estate information network, and the statistical yearbooks of cities.

# 4. Empirical findings and discussion

## 4.1. Benchmark estimation and robustness checks

The estimation results of the benchmark regression are presented in Column I of Table 2. The results show a significant and positive coefficient for *PCPD*, confirming its role in promoting PIC and supporting Hypothesis 1. This finding emphasizes the leading role of provincial capitals in innovation and the effectiveness of prioritizing their development, reminding Chinese central and provincial governments to accord significance to the leadership position of provincial capitals when formulating policies and allocating resources. Supporting this, Shi et al. (2020) argued that Chinese authorities should avoid excessively suppressing the development of provincial capitals under the pretense of promoting balanced regional development.

As for the control variables, first, the statistically significant positive coefficient of *GDP* confirms the positive impact of a high economic level on PIC, as a good economy not only provides direct funding for innovation activities but also creates a favorable social atmosphere for innovation activities (Wen et al., 2021). Second, *FEE* obtained a statistically significant positive coefficient, indicating a positive role of education input in innovation. Supporting this, Bianchi and Giorcelli (2020) indicated that education investment can promote innovation output by cultivating more innovative talents. Third, consistent with Ding et al. (2023a), *TIO* obtained a statistically significant positive coefficient, indicating that the tertiary industry cluster can stimulate innovation activities by providing professional services for innovation, such as financial, legal, and advisory services during the patent application process. Fourth, consistent with Yu and Cai (2021), *PP* obtained a statistically significant positive coefficient, implying that innovation growth can stem from an increase in the population (Dong et al., 2016). Overall, among these control variables, *FEE* has the weakest promoting effect on PIC, which could be related to the time lag effect of education investment on innovation (Zhang & Li, 2023).

The results of the robustness checks are reported in Columns II to IV of Table 2. Column II reports the results of the placebo test, wherein the coefficient obtained by *PCPD* is not statistically significant. This indicates that the positive effect of PCPD on PIC as per the benchmark estimation is not a placebo effect, and is reliable. Moreover, after replacing the proxy variable of *PCPD* from the GDP ratio to the NLI ratio (Column III) and changing the fixed effect estimation method to system GMM estimation (Column IV), the coefficients obtained by *PCPD* are both statistically significant and consistent with the benchmark estimation results, again proving the robustness of the benchmark estimation.

**Table 2.** The impact of PCPD on PIC (Fixed effect model, Placebo test, Proxy replacement and System GMM)

| | Fixed effect | Placebo test | Proxy replacement | System GMM |
|---|---|---|---|---|
| | I | II | III | IV |
| PCPD | 0.895*** | 0.048 | 0.314*** | 0.154** |
| | (3.17) | (0.36) | (2.83) | (2.30) |
| GDP | 1.970*** | 1.977*** | 1.850*** | 0.546*** |
| | (11.30) | (11.29) | (10.56) | (4.69) |
| FEE | 0.245* | 0.240* | 0.265** | 0.085* |
| | (1.83) | (1.79) | (2.02) | (1.70) |
| TIO | 2.084*** | 2.082*** | 2.396*** | -0.965* |
| | (5.16) | (5.16) | (5.77) | (-1.86) |
| TVE | –0.190 | –0.192 | –0.108* | 0.003 |
| | (–0.75) | (–0.84) | (–1.91) | (0.16) |
| PP | 0.943** | 0.949** | 0.632 | 0.157* |
| | (2.24) | (2.25) | (1.48) | (1.86) |
| Constant | –2.839*** | –2.841*** | –2.453*** | –5.317*** |
| | (–4.26) | (–4.27) | (–3.60) | (–2.92) |
| Lagged dep. var | | | | 0.755*** |
| | | | | (10.93) |
| R-squared | 0.921 | 0.914 | 0.925 | |
| Observations | 405 | 405 | 405 | 378 |
| province FE | YES | YES | YES | |
| year FE | YES | YES | YES | |
| Sargan test | | | | 0.291 |
| AR (1) | | | | 0.000 |
| AR (2) | | | | 0.598 |

*Note*: t-statistics are in parenthesis; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

## 4.2. Quantile regression

To empirically test the differential impact of PCPD on PIC at multiple stages, a quantile regression was implemented. Based on the results in Table 3, *PCPD* obtained statistically significant positive coefficients at all five quantiles. It can be inferred that regardless of the stage of PIC, PCPD significantly promotes PIC. Furthermore, it can be observed that with the increase of quantile, the *PCPD* coefficients first increase and then decrease, implying that with the improvement of PIC, the positive effect of PCPD on PIC first shows an upward trend before moving downward. This phenomenon is justified. In provinces with relatively weak innovation capacity, the capitals themselves may face the challenge of low innovation, which impedes the externality effect of technology from provincial capitals to non-provincial capital cities. Although PCPD can improve the innovation capacity of these provinces' capitals through the agglomeration of innovation factors, the limited technology spillover is manifested as a weak positive effect of PCPD on PIC. With the improvement of provincial capitals' innovation capacity (also reflected as higher PIC), the technology externality effect of provincial capitals towards non-provincial capital cities gradually increases, strengthening the promotion effect of PCPD on PIC. However, when PIC is enhanced to a certain extent, a marginal diminishing effect could emerge, which then causes a decline in PCPD's positive influence. These findings reflect the diverse impact of PCPD on PIC at different stages of innovation capability.

**Table 3.** The Impact of PCPD on PIC (quantile regression)

| | QR_10 | QR_25 | QR_50 | QR_75 | QR_90 |
|---|---|---|---|---|---|
| | I | II | III | IV | V |
| PCPD | 0.793** | 1.929** | 0.834*** | 0.789** | 0.734** |
| | (2.34) | (2.47) | (4.47) | (2.44) | (2.41) |
| GDP | 1.569*** | 1.859*** | 1.889*** | 1.973*** | 1.725*** |
| | (5.35) | (15.28) | (10.30) | (9.82) | (8.80) |
| FEE | 0.160 | 0.125 | 0.114 | 0.233 | 0.202** |
| | (0.69) | (1.30) | (0.78) | (1.46) | (2.58) |
| TIO | 3.337*** | 1.967*** | 1.902*** | 0.693 | 1.638** |
| | (2.88) | (4.09) | (2.62) | (0.87) | (2.11) |
| TVE | 0.068 | 0.011 | 0.008 | –0.046 | –0.005 |
| | (0.84) | (0.34) | (0.15) | (–0.82) | (–0.09) |
| PP | 1.559*** | 1.427*** | 1.394*** | 1.301*** | 1.007*** |
| | (3.37) | (3.02) | (3.10) | (3.74) | (3.14) |
| Observations | 405 | 405 | 405 | 405 | 405 |
| province FE | YES | YES | YES | YES | YES |
| year FE | YES | YES | YES | YES | YES |

*Note*: t-statistics are in parenthesis; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

## 4.3. Time lag effect

To examine the time lag effect of PCPD on PIC, we empirically estimated Eqs. (3)–(7), the results of which are shown in Columns I to V of Table 4, respectively. It is evident that PCPD has a long-term effect on improving PIC. In addition, the impact of PCPD experiences a trend of initial growth and subsequent decline, which actually makes sense. As mentioned earlier, an important reason for PCPD's beneficial impact on PIC is the technology externality effect from provincial capitals towards non-provincial capital cities. According to Kucharavy and De Guio

(2011), the diffusion of new technologies goes through three stages, namely the initial stage, rapid growth stage, and saturation stage. In the initial stage, due to information asymmetry and the uncertainty of new technologies, the adoption rate of new technologies is low. Once a new technology gains enough positive word-of-mouth from early adopters, its adoption rate sharply increases, entering the rapid growth stage. When diffusion enters the saturation stage, however, the diffusion speed of new technologies decreases again due to the limited number of potential users in the market. Corresponding to these three stages of technology diffusion, the technology externality effect from provincial capitals towards non-provincial capital cities is also expected to undergo the process of being weak, strong, and then weak again. Accordingly, the promotional effect of PCPD on PIC tends to be time-lagged and follow this process as well. This finding suggests that China's provincial governments should practice more patience when advancing the development model of prioritizing provincial capitals[5].

**Table 4.** The time lag effect of PCPD on PIC

| | Lag1 | Lag3 | Lag5 | Lag7 | Lag9 |
|---|---|---|---|---|---|
| | I | II | III | IV | V |
| PCPD | 0.936*** | 1.489*** | 1.998*** | 0.966** | 0.595 |
| | (3.26) | (3.82) | (3.97) | (2.44) | (1.41) |
| GDP | 1.517*** | 1.868*** | 2.196*** | 1.850*** | 1.270*** |
| | (10.87) | (8.83) | (6.14) | (4.79) | (4.17) |
| FEE | 0.299** | 0.611*** | 0.894*** | 0.982*** | 1.613*** |
| | (2.09) | (3.56) | (3.81) | (3.09) | (3.66) |
| TIO | 1.768*** | 0.942** | 0.972 | 1.411* | 1.856* |
| | (4.15) | (2.04) | (1.63) | (1.76) | (1.93) |
| TVE | –0.184 | –0.229*** | –0.164*** | –0.030 | –0.230 |
| | (–1.51) | (–4.40) | (–2.61) | (–0.50) | (–0.59) |
| PP | 0.894** | 1.161*** | 1.731*** | 1.700*** | 0.852 |
| | (2.38) | (3.19) | (3.94) | (2.68) | (0.69) |
| Constant | –2.951*** | –2.991*** | –3.706*** | –5.631** | 12.869 |
| | (–4.19) | (–3.73) | (–3.36) | (–2.53) | (0.75) |
| R-squared | 0.923 | 0.908 | 0.850 | 0.798 | 0.728 |
| Observations | 378 | 324 | 270 | 216 | 162 |
| province FE | YES | YES | YES | YES | YES |
| year FE | YES | YES | YES | YES | YES |

*Note*: t-statistics are in parenthesis; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

[5] The regression results for lags 2, 4, 6, 8, and 10 omitted in the paper do not change the finding covered in this section. If readers are interested, they can request these results from the corresponding author.

### 4.4. Moderating effects

The estimation results of moderating effects using Eqs. (8)–(10) are reported in Table 5. First, according to Column I, the interaction term of *PCPD* and *II* obtained a significant positive coefficient at the 1% level, confirming the positive moderating effect of industrial isomorphism on the *PCPD-PIC* link. Therefore, Hypothesis 2 is supported. The moderating effect of industrial isomorphism is consistent with the theory of industrial agglomeration, which posits

**Table 5.** The moderating effects of industrial isomorphism, government innovation support, and higher education resources

| | Industrial isomorphism | Fiscal support in innovation | Higher education resources |
|---|---|---|---|
| | I | II | III |
| PCPD | –0.728 | 0.274 | 0.935** |
| | (–1.27) | (0.91) | (2.47) |
| II | –0.678*** | | |
| | (–3.29) | | |
| PCPD*II | 0.892*** | | |
| | (2.97) | | |
| FSI | | –2.409*** | |
| | | (–4.71) | |
| PCPD*FSI | | 0.183*** | |
| | | (2.90) | |
| HER | | | –0.189*** |
| | | | (–3.61) |
| PCPD*HER | | | 0.001*** |
| | | | (4.51) |
| GDP | 1.326*** | 1.043*** | 1.491*** |
| | (11.62) | (8.63) | (11.52) |
| FEE | –0.098 | –0.386 | 0.091 |
| | (–0.61) | (–0.61) | (1.16) |
| TIO | 2.320*** | 1.319*** | 2.380*** |
| | (4.94) | (3.05) | (5.81) |
| TVE | –0.028 | –0.031 | –0.036 |
| | (–0.84) | (–0.49) | (–0.92) |
| PP | 1.105*** | 1.410*** | 0.919*** |
| | (3.29) | (3.12) | (2.61) |
| Constant | 9.629 | 2.583** | –1.983*** |
| | (0.91) | (2.28) | (–4.17) |
| R-squared | 0.926 | 0.932 | 0.937 |
| Observations | 405 | 405 | 405 |
| province FE | YES | YES | YES |
| year FE | YES | YES | YES |

*Note*: t-statistics are in parenthesis; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

that enterprises in the same industry are more likely to share knowledge and technology, thereby promoting the dissemination and innovation of technology (Yang et al., 2022). Second, Column II reports that the interaction term of *PCPD* and *FSI* obtained a statistically significant positive coefficient, indicating that with more fiscal support for innovation in non-provincial capital cities, the promotional effect of PCPD on PIC is stronger, verifying Hypothesis 3. Lastly, as shown in Column III, the interaction term of *PCPD* and *HER* also obtained a statistically significant positive coefficient, albeit a very small one (0.001). While we can validate the positive moderating effect of higher education resources in non-provincial capital cities as proposed in Hypothesis 4, we acknowledge that this moderating effect is rather weak. This finding may reflect limitations faced by universities in non-provincial capital cities in terms of innovation awareness and ability. Specifically, compared with universities in provincial capitals that usually secure more government funding and advanced research facilities, those in non-provincial capital cities often face constraints in allocating resources, which restricts their ability to amplify the positive impact of PCPD on PIC. Additionally, the relatively weaker appeal of non-provincial capital cities in terms of career development opportunities and living conditions makes it harder for their universities to retain top-tier researchers and attract innovative teams, further limiting the strength of the moderating effect.

## 4.5. Heterogeneity analysis: provincial capitals versus non-provincial capital cities

Motivated by the fact that the development model of prioritizing provincial capitals aims to transfer innovation resources from non-provincial capital cities to provincial capitals, we believe that the impact of PCPD on the innovation capacities of provincial capitals and non-provincial capital cities is different. To verify this, we subdivided the dependent variable PIC into the innovation capacity of provincial capitals (*PCIC*) and that of non-provincial capital cities (*NCCIC*), and then proceeded to regress them with the independent variables separately using Eqs. (12)–(13). We respectively use the annual number of patent applications in provincial capitals and that in non-provincial capital cities to measure *PCIC* and *NCCIC*[6], the data of which can be obtained from the China National Intellectual Property Administration and the statistical yearbooks of cities. Furthermore, as confirmed earlier, PCPD exhibits a lag effect on innovation, which reminds us that the impact of PCPD on *PCIC* and *NCCIC* could also have a time lag effect. As such, we employed the method described in Section 3.2.3 to verify this.

$$Ln(PCIC_{it}) = \alpha_0 + \alpha_1 PCPD_{it} + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}, \tag{12}$$

$$Ln(NCCIC_{it}) = \alpha_0 + \alpha_1 PCPD_{it} + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}. \tag{13}$$

The estimation results of Eqs. (12)–(13) are presented in Columns I and VII of Table 6, respectively. It can be found that *PCPD* in Column I obtained a statistically significant positive coefficient, while *PCPD* in Column VII obtained a statistically insignificant coefficient. This indicates that PCPD can significantly promote provincial capitals' innovation capacity, while

[6] Taking Jiangsu Province as an example, we use the annual number of patent applications in Nanjing (the provincial capital of Jiangsu) to measure *PCIC* of this province, and that in all other cities (excluding Nanjing) to measure *NCCIC* of this province.

has no significant influence on the innovation capacity of non-provincial capital cities. In other words, in the initial stage, PCPD mainly plays a positive role for provincial capitals, because this development model relocates innovative factors from non-provincial capital cities to provincial capitals. As for non-provincial capital cities, although their original innovation factors have been transferred out, it does not significantly weaken their innovation capacity. This could be due to the relatively lower innovation efficiency of non-provincial capital cities (Fan et al., 2020), meaning these cities cannot effectively translate innovation factors into innovation output. Accordingly, the deprivation of some innovation factors does not significantly impact the innovation output of these cities. The estimation results of the time lag effect of PCPD on *PCIC* and *NCCIC* are presented in Columns II to VI, as well as Columns VIII to XII of Table 6. The results indicate that over time, the positive impact of PCPD on the innovation capacity of both categories of cities experienced an initial increase followed by a decrease, with the strongest positive effect observed in the fifth year, which is consistent with the finding in Section 4.3. Furthermore, it can be observed that PCPD begins to positively impact the innovation capacity of non-provincial capital cities after three years[7]. This suggests that PCPD is beneficial not only for provincial capitals but also has the potential to facilitate the innovation activities of non-provincial capital cities in the long term, which further provides evidence for the rationale behind the development model of prioritizing provincial capitals.

**Table 6.** The impact of PCPD on the innovation capacity of provincial capitals and non-provincial capital cities

| | Provincial capitals | | | | | | Non-provincial capital cities | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | PCPD | PCPD$_{-1}$ | PCPD$_{-3}$ | PCPD$_{-5}$ | PCPD$_{-7}$ | PCPD$_{-9}$ | PCPD | PCPD$_{-1}$ | PCPD$_{-3}$ | PCPD$_{-5}$ | PCPD$_{-7}$ | PCPD$_{-9}$ |
| | I | II | III | IV | V | VI | VII | VIII | IX | X | XI | XII |
| PCPD | 2.306*** | 2.503*** | 2.754*** | 3.214*** | 1.487 | –1.642 | –0.668 | 0.658 | 0.013*** | 0.184*** | 0.091*** | –0.791 |
| | (3.12) | (2.96) | (2.72) | (3.52) | (0.86) | (–0.76) | (–0.91) | (0.81) | (3.36) | (3.39) | (2.72) | (–0.57) |
| GDP | 1.108*** | 0.942*** | 0.655* | 1.115*** | –0.456 | –0.153 | 2.060*** | 2.197*** | 2.068*** | 0.996*** | 1.666*** | 1.508** |
| | (4.62) | (3.44) | (1.85) | (3.95) | (–0.62) | (–0.16) | (8.63) | (8.33) | (6.59) | (3.13) | (3.21) | (2.53) |
| FEE | 0.635*** | 0.787*** | 1.051*** | 0.909*** | 2.248*** | 3.971*** | 0.163 | 0.165 | 0.493** | 1.091*** | 0.834 | –0.249 |
| | (3.59) | (3.92) | (3.89) | (3.73) | (2.65) | (2.83) | (0.93) | (0.85) | (2.06) | (3.97) | (1.39) | (–0.28) |
| TIO | 2.767*** | 2.793*** | 2.059*** | 4.026*** | –0.238 | –3.117 | 1.538*** | 1.061* | –0.133 | –0.441 | 1.324 | 5.585*** |
| | (4.95) | (4.48) | (2.67) | (5.88) | (–0.11) | (–0.97) | (2.77) | (1.77) | (–0.20) | (–0.57) | (0.84) | (2.70) |
| TVE | –0.045 | –0.056 | –0.010 | 0.043 | –0.069 | –0.365 | –0.143* | –0.139* | –0.206** | –0.122 | –0.263 | –0.240 |
| | (–0.60) | (–0.68) | (–0.10) | (0.53) | (–0.29) | (–1.11) | (–1.92) | (–1.74) | (–2.43) | (–1.34) | (–1.55) | (–1.14) |
| PP | 0.539*** | 0.393*** | 0.379*** | 0.361*** | 1.255 | 4.437 | 1.075*** | 1.063*** | 0.877** | 1.346** | 1.453*** | 0.267 |
| | (2.92) | (3.59) | (3.43) | (3.54) | (0.42) | (1.02) | (2.85) | (2.66) | (2.13) | (2.32) | (2.68) | (0.10) |
| Constant | –2.806*** | –2.732** | –3.153** | –5.287*** | –1.787 | 2.103 | –3.085*** | –3.232*** | –3.419*** | –4.817*** | 3.492 | 9.309 |
| | (–3.01) | (–2.59) | (–2.29) | (–3.95) | (–0.42) | (0.04) | (–3.32) | (–3.18) | (–2.80) | (–3.20) | (0.12) | (0.24) |
| R-squared | 0.864 | 0.849 | 0.768 | 0.875 | 0.245 | 0.208 | 0.870 | 0.869 | 0.837 | 0.739 | 0.567 | 0.451 |
| Observations | 378 | 351 | 297 | 243 | 189 | 135 | 378 | 351 | 297 | 243 | 189 | 135 |
| province FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

*Note*: t-statistics are in parenthesis; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

[7] The regression results for lags 2, 4, 6, 8, and 10 omitted in the paper do not change the finding covered in this section. If readers are interested, they can request these results from the corresponding author.

# 5. Conclusions

## 5.1. Summary of findings and policy implications

This study concludes the following findings based on the estimations on the panel data of 27 China's provincial-level regions from 2006 to 2020. (1) PCPD has a significant positive impact on PIC. (2) As PIC improves, the promoting intensity of PCPD on PIC first increases, then decreases. (3) The positive effect of PCPD on PIC exhibits a lag effect. (4) Industrial isomorphism, fiscal support in innovation, and higher education resources have positive moderating effects on the *PCPD-PIC* relationship. (5) Initially, PCPD primarily benefits innovation in provincial capitals, but over time, its positive impact extends to non-provincial capital cities.

The findings of this study provide alternative references for developing countries in promoting innovation, corresponding to the above five conclusions. (1) Governments should increase targeted support for capital cities to promote innovation. This includes expanding investment in research and development, improving infrastructure, and implementing talent recruitment and retention policies. By strengthening the innovation capacity of capital cities, governments can create regional hubs that generate spillover effects benefiting surrounding areas. (2) Governments should adopt a phased approach. In the early stages, efforts could focus on enhancing the innovation capacity of capitals by leveraging their agglomeration effects, such as talent concentration and infrastructure advantages. As regional innovation capacity reaches higher levels, governments need to shift their focus to sustaining innovation through diversified regional development policies that support broader inter-city collaboration and knowledge diffusion. (3) Policy evaluations should account for the time-lagged effects of innovation diffusion. Since the benefits of prioritizing capital cities could take several years to emerge in non-capital regions, governments should avoid frequent policy shifts based on short-term performance. Instead, they should develop medium- to long-term plans with stable financial and administrative backing to maintain continuity and policy credibility. (4) Industrial coordination across cities should be actively promoted. Governments could encourage industrial clusters in capital and non-capital cities to engage in collaborative R&D and supply chain integration. Establishing regional innovation alliances and cross-city industry platforms can enhance knowledge sharing, reduce duplication of effort, and improve overall innovation efficiency. The innovation environment in non-capital cities should be strengthened through targeted measures. This includes increasing fiscal support for local innovation projects, improving the quality of higher education institutions, and encouraging partnerships between universities and industries. (5) The diffusion of innovation from capital to non-capital cities should be encouraged and gradually developed. Specifically, governments could encourage the transfer and joint utilization of technological achievements, fund collaborative innovation projects across cities, and promote talent mobility through professional exchange and secondment programs. These measures can help extend innovation benefits beyond capital cities and contribute to more balanced regional development.

## 5.2. Limitations and suggestions for future research

While utmost effort was invested in the precise execution of this empirical study, there remain some limitations that currently elude resolution; however, they serve to delineate avenues for future research. First, considering the interdependence among regional developments, spatial econometric models could also be applicable to this study. As such, researchers could expand this study by employing spatial econometric methods. Additionally, while this study has examined the moderating effects of industrial isomorphism, fiscal support for innovation, and higher education resources on the *PCPD-PIC* relationship, other moderating variables could exist. Further research could attempt to discover the unexplored moderators.

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## Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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# APPENDIX

## A. The province list

Anhui, Fujian, Gansu, Guangdong, Guangxi, Guizhou, Hainan, Hebei, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Jiangxi, Jilin, Liaoning, Neimenggu, Ningxia, Qinghai, Shaanxi, Shandong, Shanxi, Sichuan, Xinjiang, Xizang, Yunnan, Zhejiang.

**Table A1.** Multicollinearity test

| Variable name | VIF | 1/VIF |
|---|---|---|
| FEE | 3.65 | 0.274263 |
| PP | 3.26 | 0.306678 |
| TVE | 3.17 | 0.315615 |
| GDP | 2.63 | 0.379881 |
| TIO | 1.45 | 0.68768 |
| PCPD | 1.21 | 0.824319 |
| Mean VIF | 2.56 | |