Analysis of the Effects of Digital Cities on Foreign Direct Investment Inflows

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Abstract: Continuous promotion of smart city pilot projects is an essential strategy for China to stabilize its foreign direct investment (FDI) environment and form a new development paradigm integrating domestic and international economic circulations. Employing panel data from 226 prefecture-level Chinese cities in the time period of 2004 to 2019, this study applied a multi-period difference-in-differences (DID) method to empirically explore the effects of smart city initiatives on FDI inflows and their underlying mechanisms. Research findings confirmed that smart city projects had significant positive effects on FDI inflows, a result which remains consistent even after solving potential endogeneity concerns and conducting robustness tests. Further analysis revealed that improved business environment, enhanced innovation capacity, and greater economic agglomeration positively moderated the relationships among smart city initiatives and FDI inflows. Heterogeneity analyses indicated that the positive impacts of smart city projects on FDI were more pronounced in larger cities, cities in eastern and central regions, and urban centers. These conclusions provided important insights for the continued advancement of China's urban digitalization efforts and dual enhancement of scale and quality of FDI inflows into cities.

Keywords: Smart Cities; Foreign Capital Inflows; Multi-Period DID; Difference-in-differences

1. Introduction

Since China's accession to WTO, it has consistently unleashed new economic growth drivers across a wide variety of industries. Stable development of its technological, political, economic, and legal environments has laid a strong foundation to attract foreign investment, position China as a leading competitor in the global market for foreign direct investment (FDI). FDI serves as an essential link between domestic and international economic cycles. However, FDI directly stimulates the economic growth of the host country, generally providing advanced technologies to promote local economic development through spillover effects. Specific properties of FDI determine the extent and direction of its impact on the host economy. However, FDI affects industries in the host country, which is largely determined by the interaction of crowding-out and spillover effects. In December 2012, a notice was officially issued China's Ministry of Housing and Urban-Rural Development to launch national smart city pilot projects and provide yearly updates on the new cities selected for digital development. These pilot cities have enhanced the attractiveness of China to FDI. In 2019, the average FDI inflow into the selected pilot cities reached \$806.38 million, compared to only \$407.72 million in non-pilot cities. Various factors, including business environment, economic scale, infrastructure, and labor costs, affect inflows of FDI into cities, all of which have significant impacts on urban FDI levels. FDI contributes to smoother domestic economic circulation through the stimulation of industrial investment, which enhances the industrial chain and boosts consumption. At the same time, it facilitates international economic circulation by helping enterprises integrate into global supply chains, increasing trade, creating investment and trade cycles [1]. Urban digitalization policy has generally expanded the "extensive margin" of FDI but has had limited impacts on "intensive margin" [2]. Smart city pilot projects have positively affected FDI inflows by improving business environment and technology-driven innovation as key mediating factors [3]. These pilot projects have remarkably improved FDI utilization quality in participating cities. Therefore, China should keep advancing urban digitalization initiatives to further optimize the quality of FDI and promote high-quality urban economic growth analyzed Chinese data and his

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findings supported the conclusion that well-developed infrastructure [4, 5], high degree of industrial agglomeration, comprehensive urban facilities, and ample market potential positively influenced FDI inflows. However, it was found that wage costs had less pronounced effects. Overall, FDI inflows demonstrated both agglomeration effects and path dependency.

Previous research works have primarily investigated the driving factors that promoted FDI inflows into cities from the perspectives of economic development level, openness degree to foreign markets, and labor costs. However, relatively few in-depth explorations have been performed of how urban digitalization and smart city pilot projects affected FDI inflows and their underlying mechanisms. Heterogeneous effects of these digital city pilots—stemming from differences in city sizes, locations, and centralities—on both FDI inflow quantity and quality requires further investigation.

2. Analysis of the Effects of Digital Cities on FDI Inflows: Theoretical Framework and Hypotheses

2.1 Development of Research Hypotheses

China, using the advantage of vast domestic market, seeks to attract global resources by promoting a domestic circulation strategy. This strategy aims to strengthen interactions between domestic and international markets to enhance both resource utilization and foreign investment quality. Potential of China's domestic market is a strong driver for FDI inflows and the development of digital cities strengthens this using the following three key mechanisms: "consumption-investment" inducement, information infrastructure empowerment, and magnetic appeal of a favorable business environment. Cities with higher levels of consumption and more favorable business environments present stronger abilities to attract foreign investment [6,7]. Digital city pilot projects, considered as part of China's innovation-driven development framework, are predicted to significantly affect the urbanization and economic development of participating cities. These pilot cities have several advantages including more scientific urban planning, construction of specialized high-tech industrial parks, and supporting infrastructure, all of which generate positive externalities to attract foreign enterprises [8]. In addition, construction of smart cities accelerates digital economy growth by strengthening information infrastructure and boosting information industry, which, in turn, fosters green technological innovation, supports industrial transformation and upgrading, and enhances the efficiency of resource allocation. Smart city pilot policies have even stronger effects on digital economy promotion in cities with lower education and administrative hierarchy levels [9, 10]. When entering new markets, foreign investors face inherent disadvantages caused by information asymmetry, resulting in higher costs in areas such as management, employee selection, and market identification [11] . However, favorable policies regarding smart city pilots mitigate these challenges by attracting key production factors—such as labor and capital—into these cities, resulting in economies of scale. This resource concentration helps foreign enterprises decrease labor search and financing costs. FDI is typically affected by institutional factors, economic conditions, and agglomeration effect [12]. In developing countries, important considerations for the determination of FDI geographical distribution include labor cost, resource intensity, infrastructure quality, and regulatory environment [12]. Well-developed infrastructure, comprehensive urban services, abundant market opportunities, and high industrial agglomeration degree exert positive impacts on FDI inflows, which are further characterized by agglomeration effects and path dependence [5]. Smart city initiatives contribute to urban economic development enhancement by driving industrial upgrading and boosting technological investment. By fostering technological innovation, stimulating market activity, and advancing digital transformation of urban environments, these initiatives remarkably enhance the resilience of city economies [13]. Furthermore, smart city projects promote employment quantity and quality through various mechanisms such as technological innovation compensation, network infrastructure optimization, and human capital accumulation. These employment enhancement effects are especially obvious in large cities with advanced information technology applications and severe labor market distortions [14, 15]. Digital economy development plays a key role in decreasing income inequality by increasing human capital levels and narrowing productivity gaps within cities. In secondary industries, non-tech-intensive sectors, and state-owned enterprises in the eastern regions of China, digital economy has a particularly strong impact on decreasing labor income inequality [16]. In addition, digital city pilot projects focus on human capital elevation by enhancing urban education and cultural levels, thereby improving the overall innovation capacity and potential of the city and providing intellectual support for foreign enterprise entry and investment.

Transportation convenience in digital city pilot projects facilitates the flow of production factors, while open sharing of information and data enhances foreign engagement quality. These factors, along with improvements in overall business environment, increase the willingness of foreign enterprises to invest, playing a key role in FDI inflow promotion. In addition, effective use of technology by the government to concentrate national resources in critical sectors supports future development of these cities [17]. Clear and robust policies for technological innovation are essential for economic development, allowing a country or region to enter a virtuous cycle of "science-driven growth" [18]. With the improvement of the business environment of a city, FDI becomes more attractive aiding the host country to secure foreign investment. Streamlined flow of production factors and faster intelligent approval processes not only improve the business environment, but also enhance FDI inflow. The impacts of digital city pilot projects on attracting FDI are not uniform and can vary depending on city size. Larger cities tend to possess more favorable conditions for such initiatives. For example, they are better equipped to develop smart city management platforms, which use digital twin technologies to generate urban data spaces and obtain widespread interconnectivity. Compared to small- and medium-sized cities, larger cities enjoy from stronger economic foundations, more comprehensive infrastructure, and more advanced information technology capabilities, all of which make faster information resource integration and utilization possible [19]. In addition, large cities have larger population bases and more substantial scientific and technical talent pools, resulting in higher human capital levels. This gives them a profound advantage over smaller cities in attracting FDI inflows. Based on the above analyses, the following four hypotheses were proposed:

H1: Digital city pilot projects enhance the ability of cities to attract FDI inflows.

H2: Digital city pilot projects stimulate FDI inflows by improving business environment, boosting innovation capacity, and fostering economic agglomeration.

H3: Business environment, economic agglomeration, and innovation capacity positively moderate the relationship of digital city construction and FDI inflows.

H4: Positive moderating effects of digital city pilot projects on FDI inflows present heterogeneity depending on the size, geographic location, and urban status of the city.

2.2 Model Construction

This research employed a multi-period difference-in-differences (DID) model to empirically explore the impacts of digital city pilot projects on FDI inflows. First, a group dummy variable, treatedit, was introduced to distinguish between treatment and control groups. If a city was included in the approved smart city pilot project list for three consecutive years by the Ministry of Housing and Urban-Rural Development, it was included in treatment group and group dummy variable set at 1. If a city was not included in any of the three batches of the smart city pilot project list, it was considered as the control group and group dummy variable was set at 0. Second, a policy time dummy variable, periodit, was defined. For cities in treatment group, before becoming a smart city pilot, dummy variable was set at 0 and in the year the city became a pilot, it was set at 1. Cities in the control group remained non-pilot cities ; therefore, policy time dummy variable was always 0. Multi-period DID model was set as follows:

$$FDI_{it} = \alpha_0 + \alpha_1 Treat_{it} \times Period_{it} + \sum \alpha_k Control_{it} + \lambda_i + \eta_t + \varepsilon_{it} \quad (1)$$

where the interaction term $Treat_{it} \times Period_{it}$ was simplified to $Treat_{it}$, giving the following model:

$$FDI_{it} = \alpha_0 + \alpha_1 Treat_{it} + \sum \alpha_k Control_{it} + \lambda_i + \eta_t + \varepsilon_{it} \quad (2)$$

Taking into account the moderating effects of business environment, economic agglomeration, and innovation capacity, the extended model was rearranged as follows:

$$FDI_{it} = \alpha_0 + \alpha_1 Treat_{it} \times M_{it} + \sum \alpha_k Control_{it} + \lambda_i + \eta_t + \varepsilon_{it} \quad (3)$$

where FDI_{it} is dependent variable, indicating the FDI level of city i in year t, $Treat_{it}$ is dummy variable determining whether city i is using a digital city pilot project in year t, M_{it} is moderating variable, $Control_{it}$ is the set of control variables, η_t is city-specific fixed effects, λ_i is time-fixed effects, and ε_{it} is the random error term of the model.

2.3 Variable Description and Data Sources

Based on the panel data collected from 226 prefecture-level cities in China in the time period of 2004 to 2019, this research employed a multi-period method to empirically evaluate the impacts and mechanisms of digital city pilot projects on FDI inflows. Furthermore, endogenous and robustness tests were performed for the verification of the reliability of the obtained results. Treatment group was consisted of 94 smart city pilot prefecture-level cities, while the control group comprised 132 non-pilot cities. Data were sourced from various editions of *China Urban Statistical Yearbook*, National Bureau of Statistics, and provincial and municipal statistical bureaus.

2.3.1 Dependent variable

The dependent variable in the empirical analysis of the impacts of digital city pilot projects on FDI inflows was the FDI itself. Following the method proposed by Lingyun et al. (2021)[20], FDI variable was calculated by the logarithm of the per capita actual FDI used by the prefecture-level city. The values, originally in USD, were converted to RMB based on the average annual exchange rate, with data sourced from *China Urban Statistical Yearbook*. Furthermore, the average FDI enterprise (fdi_1) scale was set as the first FDI quality indicator, obtained by dividing the total amount of actual FDI employed by the number of foreign-invested enterprises in the city, then taking the logarithm [21]. FDI performance index (fdi_2) was employed as the second indicator of FDI inflow quality, calculated using the Eq. (4) and followed by logarithm taking:

$$\text{FDI Performance Index} = \frac{FDIit / FDIt}{GDPit / GDPt} \quad (4)$$

where FDI_{it} is the actual FDI used by city i in year t, FDI_t is the total actual FDI used in China in year t, GDP_{it} is the GDP of city i in year t, and GDP_t is the total GDP of China in year t.

2.3.2 Core independent variable

Digital city pilot project was considered as the core independent variable, which was represented as a dummy variable. If city i was selected as a smart city pilot in year t, the value of dummy variable was set at 1 for that year and subsequent years; otherwise, it was set at 0. Digital city pilot dummy variable ($treat_{it}$) denoted the interaction of group dummy variable ($treated_{it}$) and policy time dummy variable ($period_{it}$).

2.3.3 Moderating variables

The following three moderating variables were selected based on previous mechanism analyses: business environment (rbe), innovation capacity (inno), and economic agglomeration (econa). Marketization index was chosen as a proxy for business environment (rbe), with data sourced from *China Provincial Marketization Index Report* [22]. The number of invention patents was applied as a proxy for innovation capacity (inno) and the relevant data were obtained from the Index of Regional Innovation and Entrepreneurship in China (IRIEC). Urban agglomeration was employed as a proxy for economic agglomeration (econa) and was measured by employment density; i.e., the ratio of the total number of employed people in secondary and tertiary industries to the built-up area [23].

2.3.4 Control variables

Based on existing research on the factors affecting FDI inflows into cities, this research incorporated the following six control variables into the model: economic development level, industrial structure, financial development, fiscal decentralization, urban environmental quality, and transportation infrastructure. Control variables were defined as follows:

a. Economic Development Level: Regions with higher economic development levels tended to attract more FDI. Following the method proposed by Qing et al. (2022)[24], this research used "per capita regional GDP" to measure economic development level, applying a logarithmic transformation to the data.

b. Industrial Structure: Industrial structure was a key factor influencing FDI inflows, where cities with higher proportions of secondary and tertiary industries having higher opportunities to attract FDI. Continuous development of tertiary sector, in particular, provides more comprehensive support services for incoming FDI. According to Guowen (2021)[25], the "proportion of the tertiary industry's added value to GDP" was applied for measuring industrial structure.

c. Financial Development: The financial development of a city offered a favorable financing environment for FDI, with better-developed financial systems providing more advantageous environments. Based on Zhentao and Jinyun (2020)[26], this research used “the ratio of the year-end loan balance of financial institutions to city’s GDP” to measure financial development level.

d. Fiscal Decentralization: Greater fiscal decentralization provided cities with more resources for attracting FDI, thus facilitating its inflow. According to Yuxiu and Xingming (2022)[27], the “ratio of a city’s fiscal budget revenue to budget expenditure” was applied for measuring the level of fiscal decentralization.

e. Urban Environment Quality: Urban environment could affect FDI inflows, especially for high-tech FDI, where investment environment was more sensitive to environmental factors. Based on Ye et al. (2021)[4], this research adopted “industrial sulfur dioxide emission” as a proxy for urban environmental quality, applying a logarithmic transformation.

f. Transportation Infrastructure: Adequate intra-city transportation infrastructure played an essential role in attracting FDI. Based on Shuwei et al. (2022)[28], this research employed “per capita highway mileage” for measuring transportation infrastructure level, with the data logarithmically transformed. The names, definitions, calculation methods, and descriptive statistics of these variables are summarized in Table 1:

Table 1. Descriptive Statistics of These Variables

Variable Category	Variables	Meaning	Calculation Method
Dependent Variable (FDI inflow)	FDI	Foreign Direct Investment	Logarithm of actual per capita FDI (ten thousand yuan)
Dependent Variable (FDI quality)	fdi_1	Average size of FDI enterprises	Logarithm of the ratio of actual FDI utilized to the number of FDI enterprises
	fdi_2	FDI Performance Index	$\ln\frac{FDIit / FDIt}{GDPit / GDPt}$
Group Variable	treated	Group dummy variable	Dummy variable (0,1)
Key Independent Variable	Treat (treated×period)	Smart city pilot project	Dummy variable (0,1)
Moderating Variables	rbe	Business environment	Marketization index (*China Provincial Marketization Index Report*)
	inno	Innovation capacity	Patent score (Index of Regional Innovation and Entrepreneurship in China (IRIEC))
	econa	Economic agglomeration	Employment density (ratio of secondary and tertiary industry employment to built-up area)
Control Variables	lngdp	Economic development level	Logarithm of per capita regional GDP (yuan)
	inst	Industrial structure	Proportion of tertiary industry’s added value to GDP
	fdc	Financial development	Ratio of year-end loan balance to GDP
	fisc	Fiscal decentralization	Ratio of fiscal budget revenue to expenditure
	lnuem	Urban environmental quality	Logarithm of industrial sulfur dioxide emissions (tons)
	lnrd	Transportation infrastructure	Logarithm of per capita highway mileage (kilometers)

3. Urban Digitalization and FDI Inflows: Empirical Results and Estimation Strategy

3.1 Baseline Regression Analysis

The effects of digital urban development pilot projects on FDI inflows were evaluated as the baseline regression results summarized in Table 2. Model 1 shows baseline regression results and core variable was estimated under city-specific fixed impacts while other control variables were controlled. Core variable coefficient was 0.161 and was statistically significant at 1% level, revealing the remarkable promotional effects of smart city pilot projects on FDI inflows. It is worth noting that regression coefficients in Models 1 and 2 were fairly close, indicating that the inclusion of city-specific fixed effects, time fixed effects, and control variables improved regression result reliability and accuracy. Positive and significant regression coefficients of core explanatory variable in both models suggested that under the phased policy of smart city development, pilot cities were more conducive to FDI inflows. Therefore, H1 was supported.

Table 2. Baseline Regression Analysis

Items	Model 1	Model 2
	FDI	FDI
Treat (treated×period)	0.161*** (0.359)	0.166*** (0.037)
Economic Development Level	0.750*** (0.028)	0.443*** (0.063)
Industrial Structure	0.009*** (0.027)	0.004 (0.063)
Financial Development	0.121*** (0.142)	0.147*** (0.027)
Fiscal Decentralization	1.227*** (0.142)	1.269*** (0.145)
Urban Environment Quality	-0.044*** (0.016)	-0.071*** (0.018)
Transportation Infrastructure	0.090** (0.045)	0.170*** (0.058)
Constant	-5.714*** (0.562)	-3.904*** (0.742)
City-specific Fixed Effects	Yes	Yes
Time Fixed Effects	No	Yes
Observations	3557	3557
R^2	0.3697	0.4155

Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

3.2 Parallel Trends Test

In order to ensure the validity of the multi-period DID model developed in this research, a "parallel trends test" had to be performed before evaluating the treatment effects of the policy. This was necessary to confirm that there were no significant differences in FDI levels between treatment and control groups ; therefore, parallel trends assumption was satisfied.

Figure 1 illustrates parallel trends test results, showing 90% confidence intervals for FDI inflows in sample cities. It was seen from the figure that before executing smart city pilot projects, there were no significant differences in FDI inflows between pilot and non-pilot cities. This confirmed the assumption that the application of multi-period DID model was required. However, after executing digital urban development pilot projects, a noticeable divergence was witnessed in the scale of FDI inflows between pilot and non-pilot cities. This indicated the positive promotional effect of digital pilot policy on FDI inflows in urban areas.

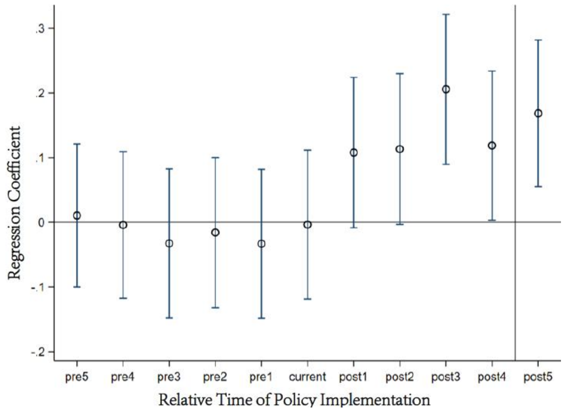

Figure 1. Parallel Trends Test

3.3 Endogeneity Treatment

The factors affecting FDI inflows in urban areas were multifaceted and the endogeneity issue in this research might arise from two primary sources. First, it might be because of omitted variables that correlated with the other variables introduced in the model. Second, there was a possibility of bidirectional causality among independent and dependent variables. To solve the endogeneity problem due to omitted variables, we have previously controlled for city-specific effects, time effects, and other indicators influencing urban FDI inflows. This measure significantly mitigated endogeneity issue due to the omitted variables. However, unobserved and uncontrollable regional variables might still cause estimation errors. We introduced province-year fixed effects in the baseline regression to further improve constraining conditions. From Table 3, it was clear that after controlling for province-year fixed effects, pilot projects for digital urban development continued to enhance FDI inflows into cities, with the coefficient remaining greatly positive, confirming that our conclusion was not affected by omitted variables.

Table 3. Treatment of Endogeneity Issues

Variables	Endogeneity Test			Robustness Test	
	Control Province-Year Effects	Control Variables Lagged One Period	Control Variables Lagged Two Periods	Truncated at 1%	Excluding Special Samples
	FDI	FDI	FDI	FDI	FDI
Treat	0.156^{***}	0.175^{***}	0.192^{***}	0.155^{***}	0.176^{***}
(treated×period)	(0.036)	(0.038)	(0.039)	(0.036)	(0.038)
Control Variables	Yes	Lagged One Period	Lagged Two Periods	Yes	Yes
City-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Province-Year Effects	Yes	No	No	No	No
N	3556	3354	3133	3783	3553
R^2	0.4322	0.3569	0.2845	0.4496	0.4427

Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

FDI inflow into cities contributed to local income level enhancement; however, cities and regions with higher income levels were more likely to serve as pilot sites for digital urban development, potentially resulting in the issues of reverse causality. In this research, we adopted the methodology of Youlin et al. (2021)[19] by lagging all control variables by one and two periods in baseline regression. As presented in Table 3, under the conditions of lagging the control variables by one and two periods, pilot projects for smart cities still demonstrated a strong positive effect on urban FDI inflows, reinforcing the robustness of our primary conclusions.

4. Robustness Test

4.1 Placebo Test

As time progressed, urban development naturally attracted more FDI, potentially causing the effects of smart city pilot projects on urban FDI inflows to seem like random events. A placebo or "fake treatment" test was performed by randomly selecting an equal number of samples as the original treatment group from the entire dataset. Then, policy implementation times were randomly assigned to create a new treatment group where both city samples and policy times were randomized. After the re-estimation of baseline regression model, the coefficients of randomly generated policy times were simulated and plotted in a kernel density distribution after 1000 repetitions of the experiment. Notably, Fig. 2 illustrates that the estimated coefficients mostly centered around zero, revealing a normal distribution. This stark deviation from actual coefficients reinforced the robustness of experimental results.

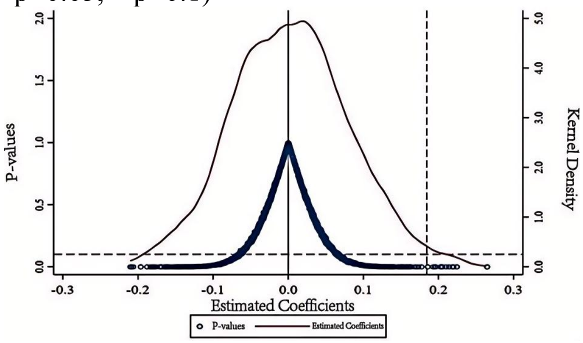

Figure 2. Placebo Test Results

4.2 PSM-DID Estimation

To further decrease the sample selection bias due to non-random factors, such as urban economic levels and scales, and enhance policy identification effectiveness, this research employed a propensity score matching with DID (PSM-DID) approach. Key covariates that may influence both policy assignment and the outcome were selected, including economic development level, industrial structure, financial development, fiscal decentralization, urban environmental quality, and transportation infrastructure. The probability of engaging in smart city pilot projects was estimated based on these covariates using a logit model. Then, a one-to-four nearest neighbor matching method was employed to match the sample cities of the treatment group with those of the control group, giving rise to a paired control group for pilot cities. The results given in Table 4 indicated that differences in all covariates after matching were significantly smaller than those before matching. After matching, all standardized biases for control variables fell below 10%, signifying the condition where no substantial differences remained among the variables, confirming PSM-DID method correctness and efficacy.

Table 4. Hypothesis Test Summary

Variables		Mean (Treatment Group)	Mean (Control Group)	Standardized Bias (%)	**t**	**p**
Economic Development Level	Before Matching	10.276	10.022	31.7	9.66	0.000
	After Matching	10.263	10.261	0.3	0.08	0.939
Industrial Structure	Before Matching	37.909	36.837	12.2	3.74	0.000
	After Matching	37.569	37.709	-1.6	-0.45	0.656
Financial Development	Before Matching	1.296	1.201	15.6	4.89	0.000
	After Matching	1.258	1.253	1.0	0.32	0.752
Fiscal Decentralization	Before Matching	0.507	0.403	50.6	15.50	0.000
	After Matching	0.499	0.504	-2.7	-0.71	0.481
Urban Environment Quality	Before Matching	10.441	10.047	33.1	9.90	0.000
	After Matching	10.423	10.376	4.0	1.18	0.238
Transportation Infrastructure	Before Matching	6.043	5.925	-20.7	-6.27	0.000
	After Matching	6.032	6.050	3.1	0.87	0.383

After matching process, four benchmark regressions were conducted to derive the reuslts presented in Table 4. Regression Model 1 entailed a fixed-effects baseline regression, Model 2 involved regression with samples where weights were not empty, Model 3 employed regression using samples meeting the common support hypothesis and Model 4 integrated frequency-weighted regression considering sample importance. By analyzing the results, the dummy variable "treat" consistently exhibited strong positive effects in all regression models, despite constant control variables. It is worth noting that the regression coefficients of the key variables in Models 2, 3, and 4 displayed minimal deviations from those in Model 1, with the regression coefficients of the control variables aligning with expectations. These observations substantiated the robustness of baseline regression results even after accounting for selection bias concerns.

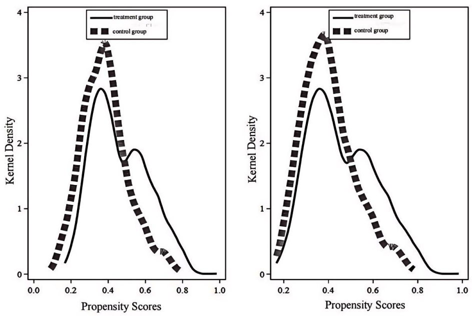

Figure 3. Probability Density Functions of Propensity Scores

Further analysis of propensity score probability density function was conducted to evaluate matching effectiveness between treatment and control groups, as presented in Fig. 3. Both treatment and control groups exhibited some disparities in propensity score values before and after matching. After matching, propensity score values for treatment and control groups became more concentrated, with the probability density distribution of propensity scores becoming closer and the trend lines aligning more closely compared to those before matching. This convergence indicated that there was less disparity in the propensity score values between treatment and control groups after matching, effectively mitigating sample self-selection issues and demonstrating favorable matching effects.

The regression results summarized in Table 5 were obtained using moderation effect analysis model. In Model 1, interactions of dummy variable for smart city pilot projects and business environment significantly influenced the FDI inflows of the city, with coefficient of 0.0160 at 1% statistique significance level, holding control variables constant.

In Model 2, with control variables remaining stable, interactions of smart city pilot project dummy variable and innovation capacity remarkably influenced the FDI inflows of the city, with coefficient of 0.0021 at 1% statistique significance level.

Table 5. PSM-DID Regression Test Results

Variables	**Model 1 FE**	**Model 2 Weight**	**Model 3 On__Support**	**Model 4 Weight__Reg**
Treat (treated×period)	0.184^{***} (5.065)	0.163^{***} (4.275)	0.172^{***} (4.706)	0.169^{***} (5.006)
Constant	-3.495^{***} (-5.012)	-3.936^{***} (-4.308)	-1.955^{**} (-2.570)	-2.111^{***} (-2.875)

Control Variables	Yes	Yes	Yes	Yes
City-specific Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
N	3783	3384	3752	5153

Similarly, in Model 3, while keeping control variables constant, interactions of smart city pilot project dummy variable and economic agglomeration strongly affected the FDI inflows of the city, with coefficient of 0.0014 at 1% statistique significance level.

In conclusion, improving business environment, boosting innovation capacity, and strengthening economic agglomeration positively moderated the promotion effects of smart city pilot projects on FDI inflows, thereby confirming H3.

5. Heterogeneity Analysis

Pilot cities exhibited great disparities in terms of business environment, infrastructure, and market efficiency, which might give rise to heterogeneous effects on attracting FDI inflows. Therefore, we delved into the heterogeneity of the effects on FDI inflows from three perspectives: city size, geographic location, and urban centrality.

Table 6. Heterogeneity Analysis

Items	**Model 1**	**Model 2**	**Model 3**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Large Cities	**Medium-Small Cities**	**Eastern Cities**	**Central Cities**	**Western Cities**	**Central Cities**	**Non-Central Cities**
	FDI	**FDI**	**FDI**	**FDI**	**FDI**	**FDI**	**FDI**
Treat (treated×period)	0.1789^{***} (0.0367)	0.2738 (0.2670)	0.1716^{**} (0.0583)	0.1134^{**} (0.0540)	0.1098 (0.0902)	0.3168^{*} (0.1704)	0.1760^{***} (0.0380)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-specific Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3611	155	1417	1170	612	230	3553
R^2	0.4516	0.4371	0.3482	0.7717	0.4376	0.5378	0.4427

The analysis presented in Table 6 indicated that positive impacts of pilot central cities on FDI inflows were much stronger than those observed in non-central cities. This disparity might stem from more advanced economic development in central cities, with more densely concentrated production factors such as labor and capital. Furthermore, central cities enjoyed superior foundational conditions for digitalization, particularly with more comprehensive information infrastructure. However, non-central cities were relatively deficient in digital resources, such as highly skilled workforce. Hence, central cities possessed stronger foundations for digital development, enhancing positive effects on FDI inflows. Pilot programs in cities across eastern and central regions have significantly facilitated FDI introduction, while the effects in the pilot cities in western region were less pronounced. The already strong digital infrastructure in eastern and central cities has accelerated the informatization, intelligence, and refinement of urban management and services, thereby exerting positive influences on FDI inflows. While digital city pilot project programs promoted FDI inflows in both central and non-central cities, marginal effects in non-central cities were lower. This was because digitalization efforts concentrated more advanced new-generation information technologies, with central cities presenting stronger siphoning effects of digital resources, making them more attractive to FDI. Consequently, H4 was confirmed.

6. Further Analysis

Currently, China has assigned new high-quality economic development goals to meet the requirements of the new era. Evaluation criteria to attract foreign investment have gradually shifted from scale to quality. The quality of FDI inflows referred to the extent to which it improved the supply level and capacity of the host country, comprehensively enhancing its industrial competitiveness. FDI impact on the industries of the host country mainly depended on the combined results of crowding out and spillover effects. FDI inflow quality influenced the degree and direction of its impact on host country's economic growth. High-quality FDI inflows were typically accompanied by advanced technologies, which, through technological spillovers, promoted local economic growth. By sequentially testing the two FDI quality indicators through benchmark regression, we obtained benchmark regression results for the impacts of smart city pilots on FDI inflow quality, as presented in Table 7.

Table 7. The Impact of Digital City Pilot Projects on FDI Inflow Quality

Items	Model 1	Model 2	Model 3	Model 4
	FDI Enterprise Average Size		FDI Performance Index	
Treat (treated×period)	0.2510*** (0.0584)	0.2610*** (0.0602)	0.0729*** (0.0177)	0.0743*** (0.0179)
Constant	3.7380*** (0.0645)	0.0847 (1.1738)	0.4356*** (0.0189)	0.0545 (0.3420)
Control variables	No	Yes	No	Yes
City-specific fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	4003	3723	4066	3783
R^2	0.6345	0.3222	0.2804	0.1743

Models 1 and 3 represented baseline regression models for implementing smart city pilots on the average size of FDI enterprises and FDI performance index without the inclusion of control variables, while Models 2 and 4 presented baseline regression models for the impacts of digital city pilot project policies on the average size of FDI enterprises and FDI performance index after incorporating control variables. The obtained benchmark regression results indicated that, with and without the inclusion of control variables, the implementation of digital city pilot policy srongly and positively affected various FDI quality indicators. This suggested that the implementation of pilot policy notably promoted FDI inflow quality enhancement.

7. Conclusions

This research explored the impacts and mechanisms through which smart city pilots promote FDI inflows, considering both theoretical and empirical aspects. Theoretical analysis reviewed the digital city pilot policy and its role in attracting FDI, evaluating its effects in terms of business environment, innovation capability, and economic agglomeration, and proposed research hypotheses. Empirically, the study employed a multi-period DID model for panel regression to explore the promotion effects of smart city pilots on urban FDI inflows. Control variables, including economic development level, industrial structure, financial development, fiscal decentralization, and transportation infrastructure, were found to significantly and positively affect urban FDI inflows. In addition, higher urban environmental quality correlated with more significant positive effects on FDI inflows. Moderation analyses revealed that improvements in business environment, innovation capability, and economic agglomeration enhanced the positive effects of digital city pilot projects on FDI inflows. Pilots showed significantly positive impacts on FDI inflows in eastern and central regions, but not in the western region. The promotion effect was stronger in large-scale and central cities. In summary, digital city pilot projects improved urban FDI inflow quality. These findings were crucial to guide continued implementation of digital city pilot project policies and boost both the quantity and quality of urban FDI inflows.

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