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The Impact of AI Development on Urban Residents' Consumption Potential: Evidence from a Quasi-Natural Experiment in China's Next-Generation AI Innovative Development Pilot Zones

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Abstract: This study investigates the impact of artificial intelligence (AI) development on the consumption potential of urban residents. A quantitative indicator system is constructed across three dimensions: consumption capacity, consumption expenditure, and the consumption environment. Taking the phased establishment of AI Innovative Development Pilot Zones since 2019 as a quasi-natural experiment, the study utilizes panel data from 290 Chinese cities spanning 2015 to 2022. A multi-period difference-in-differences approach, combined with fixed effects models, is employed for empirical analysis. The results reveal that AI development has a significant and sustained stimulating effect on urban residents' consumption potential. This study broadens the existing research on the economic effects of AI. It also provides empirical support for efforts to stimulate domestic demand, improve and expand consumption quality, and foster a new development paradigm driven by consumption.

Keywords: Artificial Intelligence (AI); AI Innovative Development Pilot Zones; Urban Residents' Consumption Potential

1. Introduction

In recent years, artificial intelligence (AI) has achieved transformative breakthroughs, demonstrating its potential in fostering new quality productive forces, enhancing economic efficiency, and optimizing resource allocation. Its profound socioeconomic impacts across industries have become increasingly evident. Concurrently, as one of the three key drivers of economic growth, consumption has assumed heightened strategic importance in China's economic development. Unleashing household consumption potential has emerged as a critical measure for tapping domestic demand and revitalizing economic vitality. However, the turbulence of the international situation has substantially eroded income expectations and dampened consumer confidence, rendering the exploration of new technological solutions to activate consumption potential an urgent priority for achieving high-quality economic development.

AI expands the boundaries of consumption potential through multidimensional pathways: (1) Digitalized services and intelligent products diversify consumption options while elevating quality standards; (2) Reconstruct more flexible consumption scenarios to enhance experience; (3) Production process optimization reduces costs of goods and services, thereby strengthening households' real purchasing ability; (4) AI-driven personalized recommendation systems and intelligent customer services elevate shopping efficiency and satisfaction, catalyzing latent consumption willingness.

Based on the panel data of 290 cities in China from 2015 to 2022, this study constructs a quantitative index system to systematically measure the consumption potential of urban residents. Leveraging the quasi-natural experiment created by the implementation of Artificial Intelligence Innovative Development Pilot Zones, we empirically evaluate AI's effects on residents' consumption potential. On the one hand, this study provides robust empirical evidence for tracking the evolutionary trend of China's consumption potential in recent years, while simultaneously enriching methods for quantifying consumption potential. On the other hand, this research expands the analytical perspective of AI's economic effects by empirically verifying the positive role of the next generation of

National AI Innovative Development Pilot Zones policy in promoting residents' consumption. These findings offer both empirical substantiation and actionable policy insights for leveraging technological advancement to unlock consumption potential and amplify domestic demand.

2. Literature Review

2.1 Consumption Potential and Its Measurement

Consumption potential reflects the developmental capacity and scale dynamics of consumer markets within specific temporal-spatial frameworks. Existing research has employed multidimensional approaches to quantify consumption potential. Early studies predominantly adopted single indicator frameworks, including per capita consumption expenditure, average propensity to consume, consumption rate and savings balances [1-2]. Comparative analytical approaches also adopt a single indicator, Cheng & Yin estimated migrant populations' latent consumption potential through expenditure elasticity differentials [3].

Scholarly has gradually realized that consumption potential shaped by cultural backgrounds, demographic transitions, income dynamics, and behavioral inertia [4]. Therefore, comprehensive measurement methods have emerged. Liu & Lou measured the leisure consumption potential of urban residents in Shanghai based on three aspects (leisure consumption capacity, expenditure, and environment) [5]. Long & Zhang designed a current surplus consumption index system covering current consumption capacity, expenditure, and constraint factors [6]. Contemporary scholars have progressively refined these frameworks. Tang constructed an index system composed of three primary indicators (consumption capacity, expenditure, and environmental enablers) [7]. Zhou & Shao further supplemented this system with the dimensions of consumption expectation and consumption quality [8]. Cui integrated behavioral willingness metrics while Zhang & Song proposed that consumption foundation should be incorporated into the index system as a vital factor to support consumption demand and stimulate consumption potential [9-10].

2.2 Artificial Intelligence and Urban Residents' Consumption Potential

In the study of artificial intelligence (AI) promoting residents' consumption, the academic has mainly explored several aspects, such as optimizing the consumption structure, improving the consumption environment, and narrowing consumption disparities.

In terms of optimizing the consumption structure, Lin et al. pointed out that AI technology promotes the optimization of the consumption structure, thereby promoting residents' consumption growth and assisting overall economic development [11]. Wan et al. conducted path analysis from both supply and demand sides based on provincial panel data from 2012 to 2020 and found that AI innovation has a significant positive impact on residents' consumption, especially in the aspect of enjoyment-oriented consumption [12]. Micro-level empirical evidence from Shi also shows that the improvement of industrial intelligence level helps to increase the expenditure of urban residents on development-oriented and enjoyment-oriented consumption [13].

In terms of improving the consumption environment and enhancing the consumption experience, Wu et al. found that AI recommendation systems can provide personalized product recommendations based on consumer preferences, thereby significantly improving the purchase conversion rate [14]. In terms of promoting consumption equity and narrowing the consumption gap, Zhang & Wei pointed out that digital technologies, while promoting consumption growth, have also reduced consumption inequality among residents to a certain extent [15]. Wang & Hu analyzed the data from the China Family Panel Studies (CFPS) and pointed out that AI helps to increase residents' consumption expenditure and plays an indirect role through optimizing the industrial structure, improving digital access and increasing income [16]. Jin used provincial panel data from 2007 to 2020 to empirically find that AI development has significantly narrowed the consumption gap between urban and rural residents [17].

Regarding the relationship between AI and residents' consumption potential, Yang et al. constructed an evaluation index system of AI development index and residents' consumption potential based on panel data of 30 provinces

in China from 2011 to 2022, pointing out that AI has effectively released residents' consumption potential by narrowing the digital divide [18]. However, this study has not yet been refined to the city-level analysis.

Overall, although the relevant studies have initially revealed the multidimensional impact of AI on residents' consumption, the current literature lacks systematic research on the more forward-looking and policy-oriented indicator of consumption potential. Empirical quantitative analysis and mechanistic discussions at the urban level are still relatively weak. This is where this paper seeks to break through: by introducing AI policy pilots as exogenous shock variables and combining them with urban-level panel data, it aims to identify the real impact of AI development on residents' consumption potential, thereby providing theoretical support and empirical evidence for stimulating domestic demand and promoting high-quality development of China's economy.

3. Research Design

3.1 Theoretical Analysis

Since the promulgation of the *Next-Generation Artificial Intelligence Development Plan* in 2017, AI has progressively ascended as a pivotal national strategic priority. The 2019 *Guidelines for Establishing Next Generation of National AI Innovative Development Pilot Zones* marked the initiation of localized AI policy experimentation to accelerate technology implementation. In February 2019, China inaugurated its inaugural AI Innovation and Development Pilot Zone in Beijing, with the primary objectives of constructing an AI innovation ecosystem and accelerating industrial integration. Subsequently, regions such as Shanghai and Tianjin also set up AI Innovative Development Pilot Zones. By February 2024, 18 regions across China had established pilot zones, committed to creating a favorable ecosystem for AI innovation and development.

Building upon the preceding analysis, we posit that AI development may influence residents' consumption potential in complex ways. From the consumption capacity perspective, AI boosts production efficiency and cuts costs, lowering goods' real prices and raising consumers' purchasing power. It also upgrades consumption structures, giving consumers more choices. Regarding consumption ecosystems, AI creates convenient and efficient consumption scenarios, enhancing consumer experience.

After the comprehensive review of prior studies on consumption potential, we propose that AI development positively promotes residents' consumption potential.

3.2 Model Design

To verify the research hypothesis, we adopt a multi-period difference-in-differences (MDID) model, which controls for both individual and time effects. This model is employed to examine whether the pilot AI innovation and development zones influence the consumption potential of urban residents. The specific model is formalized as:

$$Consumption_{i,t} = \alpha_0 + \alpha_1 post \times treat + \alpha_c X_{i,t} + \gamma_i + \eta_t + \varepsilon_{i,t} \quad (1)$$

In this model i is defined as the individual cities, t is defined as the year. The core explanatory variable is post × treat (referred to as did later), an interaction term of dummy variables representing the control and treatment groups of the AI Innovative Development Pilot Zones. $Consumption_{i,t}$ (referred to as y latter) is the dependent variable, measuring the consumption potential of city i in year t. $X_{i,t}$ is the set of control variables; γ_i and η_t represent individual and time-specific fixed effects, and $\varepsilon_{i,t}$ is the residual term. α_1 is the key coefficient of interest, reflecting the impact of AI innovation on urban resident consumption potential in pilot cities relative to non-pilot cities. A positive coefficient is expected.

3.3 Variable Selection

3.3.1 Dependent variable

Scholars have yet to reach a consensus on measuring consumption potential. Based on theoretical analysis, this paper argues that consumption potential should be considered from both demand and supply perspectives. Consequently, we adopt the multidimensional indicator construction method proposed by Huang & Dou [19]. Specific indicators are listed in Table 1. Under the demand perspective, the hierarchical standards consist of monetary payment ability, consumption cognitive ability, consumption expenditure, and economic environment. Under the supply

perspective, the focus is on the consumption environment. Overall, there are 11 secondary indicators under these hierarchical standards.

Given the significant dimensional and magnitude differences among the indicators, including both positive and negative ones, dimensionless processing is essential for ensuring the scientific and rational evaluation results. We use the range standardization method for dimensionless transformation of the evaluation indicators. Subsequently, the entropy method is applied to the 11 secondary indicators to calculate the comprehensive index of residents' consumption potential (y), with specific weights presented in Column (6) of Table 1.

This paper examines the exogenous impact of the three-batch pilot zones for the next-generation AI Innovation and Development experiments launched between 2019 and 2021. It selects city-level panel data from 2015 to 2022 in China as the research sample.

The composite index of urban residents' consumption potential across Chinese cities from 2015 to 2022 ranged between 0.24 and 0.59, with both the median and arithmetic mean stabilizing at 0.33, indicating a generally subdued level of aggregate consumption potential. By calculating the annualized consumption potential indices, the top seven cities ranked as Beijing, Shenzhen, Zhuhai, Shanghai, Guangzhou, Dongguan, and Suzhou. This result is relatively consistent with the statistical data of the regional economy. Notably, according to 2024 statistical yearbooks, six of these cities (excluding Guangzhou) ranked within China's top 20 in per capita GDP, demonstrating a correlation between high per capita GDP and latent consumption capacity.

Figure 1 shows the average composite consumption potential scores of urban residents across all cities, incorporating the top four cities by annual mean consumption potential into the trend analysis. The line graph demonstrates a significant upward trajectory in urban residents' consumption potential, with an approximate increase of 17.5%. Figure 2 illustrates the trends in the composite consumption potential index for China as a whole and its three major economic regions: the east, central, and west. The index has risen in all regions, signaling a gradual increase in residents' consumption potential. The eastern region consistently shows the highest average index value, surpassing the national average, while the other regions remain below the national level. This clearly shows that there are noticeable differences in residents' consumption potential across different regions.

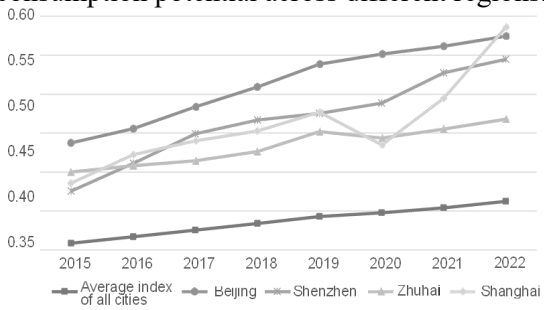

Figure 1. Trends in the Annual Composite Coefficients of Residents' Consumption Potential (2015-2022)

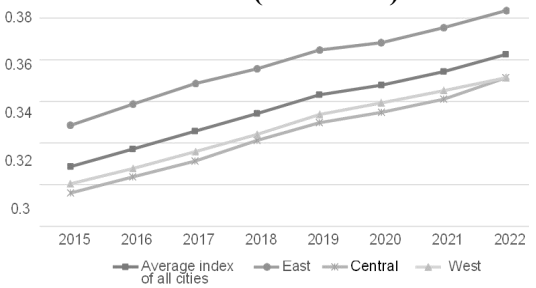

Figure 2. Regional Differences in Residents' Consumption Potential (2015-2022)

3.3.2 Independent variable

We use the pilot program of Next Generation of National AI Innovative Development Pilot Zones as an exogenous shock to evaluate its effect on residents' consumption potential. The Ministry of Science and Technology of the People's Republic of China designated three batches of pilot cities between 2019 and 2021. Following the approach of Ouyang et al., cities approved near the end of the year were assigned to the next year [20].

For the core explanatory variable (did = post × treat), post is set as follows: for the first-batch cities (Beijing & Shanghai) approved before September 2019, post is 1 from 2019; for the second-batch cities approved before September 2020, post is 1 from 2020; for cities approved before September 2021, post is 1 from 2021; and for those approved after September 2021 (e.g. Zhengzhou & Shenyang & Harbin), post is 1 from 2022. Otherwise, post is 0. Treat is 1 for the 18 pilot cities and 0 otherwise.

3.3.3 Control variable

Based on prior studies, the control variables include urbanization rate (x1), government intervention (x2), the degree of openness of

China (x3), urban unemployment rate (x4), and the logarithm of regional GDP (x5).

3.4 Data Sources and Processing

This paper constructs a panel dataset covering 290 prefecture-level cities in China from 2015 to 2022. Data sources include the EPS database, *China Statistical Yearbook*, local city statistical yearbooks, *China Environment Statistical Yearbook* and China Industrial and Commercial Enterprise Data.

Table 1. Indicator Construction of Urban Residents' Consumption Potential

Standard	Primary Indicator	Secondary Indicator	Measurement Method	Attribute	Weight
Monetary Payment Ability	Income	Per capita disposable income of urban residents	-	Positive	0.091116
	Capacity Constraint	Housing Price to Income Ratio	Average sales price of commercial housing * Per capita living area of urban residents / Per capita disposable income of urban residents	Negative	0.091975
Consumption Cognitive Ability	Educational Level	Expenditure on education	Educational expenditure / Local general public budget expenditure	Positive	0.091827
Consumption Expenditure	Consumption Level	Per capita consumption expenditure of urban residents	-	Positive	0.091591
	Consumption Structure	Per capita fiscal expenditure on health and medical care	-	Positive	0.090644
		Per capita expenditure on social security and employment	-	Positive	0.090599
		Engel's Coefficient	Proportion of food in residents' consumption	Negative	0.091896
Macroeconomic Environment	Economic Environment	Industrial Structure	-	Positive	0.09184
	Infrastructure Environment	Per capita paved road area in cities	-	Positive	0.091404
Consumption Environment	Consumption Supply Environment	Number of Patent Applications	-	Positive	0.08518
	Urban Natural Environment	Greening Coverage Rate	-	Positive	0.091929

For the dependent variable, linear interpolation fills minor missing data in some secondary indicators. After sample collection and matching, cities with significant data loss, like Shigatse, Qamdo and Nyingchi, are excluded, leaving 290 cities. All continuous variables were winsorized at the 1% significance level to mitigate outlier effects, resulting in a final balanced panel of 2,320 observations.

3.5 Descriptive Statistics

The descriptive statistics of the key variables are presented in Table 2. The average household consumption potential is 0.33, indicating a generally low level. The mean of did is 0.0198, showing that approximately 1.98% of the sample size was a pilot in the Artificial Intelligence Innovative Development Pilot Zones from 2015 to 2022.

Table 2. Descriptive Statistics of the Main Variables

VarName	Obs	Mean	SD	Min	Median	Max
Residents' Consumption Potential	2320	0.3367	0.038	0.24	0.33	0.59
did	2320	0.0198	0.139	0.00	0.00	1.00
Urbanization rate	2320	0.5929	0.140	0.31	0.57	0.95
Government intervention	2320	0.2105	0.103	0.08	0.18	0.59
Degree of openness	2320	0.0156	0.017	0.00	0.01	0.09
Urban unemployment rate	2320	2.9677	0.798	1.04	3.01	4.94
Regional GDP (ln)	2320	7.5346	0.929	5.64	7.44	10.13

4. Results and Discussion

4.1 Benchmark Regression

4.1.1 Parallel trend test

The core assumption of using the difference-in-differences method to evaluate policy impacts is that, in the absence of policy shocks, the treatment and control groups would follow the same trend before the policy implementation. To ensure the reliability of the results, this paper conducts a parallel trend test. To avoid potential bias from extreme data and to better visualize the policy impact, the sample observation period is set from four years before to three years after the policy implementation, with the first year before the policy as the base period. Figure 3 shows the results that we pass the parallel trend test. The policy had a significant and sustained promoting effect in the first to third year after implementation.

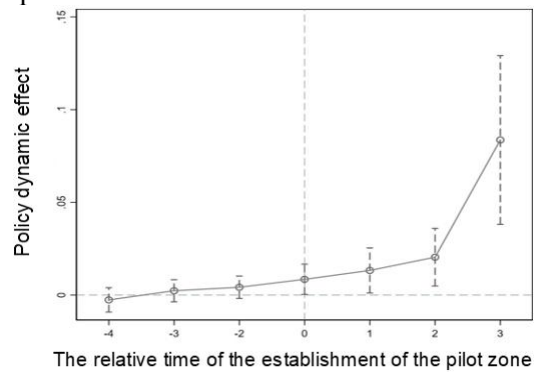

Figure 3. Parallel Trend Test Results

4.1.2 Benchmark regression results

Table 3 presents the impact of policy pilots on urban residents' consumption potential. Column (1) shows a basic regression without controls or fixed effects, revealing a significant positive relationship at the 1% level. Column (2) adds city-fixed and time-fixed effects. Column (3) includes control variables, indicates that AI positively affects household consumption potential at the 1% significance level, with a coefficient of 0.014.

The benchmark regression shows that the Next Generation of National AI Innovative Development Pilot Zones have a statistically significant positive impact on urban residents' consumption potential. After controlling for time trends, city fixed effects and other covariates, the policy is associated with an average increase of 0.014 units in consumption potential.

Table 3. Benchmark Regression Results

	(1)	(2)	(3)
VAR	y	y	y
did	0.0466***	0.0143***	0.0142***
	(0.0038)	(0.0055)	(0.0054)
x1			0.0073
			(0.0131)
x2			-0.0340***
			(0.0125)
x3			-0.0588
			(0.0481)
x4			-0.0024**
			(0.0009)
x5			-0.0027
			(0.0042)
Constant	0.336***	0.336***	0.367***
	(0.0017)	(0.0001)	(0.0347)
Year FE	N	Y	Y
City FE	N	Y	Y
Obs	2,320	2,320	2,320
Number of id	290	290	290

4.2 Robustness Checks and Endogeneity Test

4.2.1 Subsample analysis

The consumption potential of urban residents may be influenced by municipalities with unique resource allocations. To eliminate potential biases from these special-treatment cities, we exclude Beijing, Shanghai, Tianjin and Chongqing, and then re-conducts the regression analysis. As shown in column (1) of Table 4, AI development remains positively correlated with urban residents' consumption potential at the 1% significance level.

4.2.2 Different clustering levels

In the previous analysis, fixed-effects clustering was done at the city level. To enhance the reliability of the results, the paper conducts robustness checks by clustering at the provincial level. As shown in column (2) of Table 4, the dependent and independent variables remain positively correlated at the 5% significance level. Notably, the coefficient for provincial-level clustering is larger than that for city-level.

4.2.3 Alternative dependent variable

The analysis is repeated using urban residents' savings rate as the dependent variable. Under the income invariance assumption, elevated savings rates inherently suppress consumption expenditure. Defined as:

$$\text{Savings Rate} = \frac{\text{Disposable Income} - \text{Consumption Expenditure}}{\text{Disposable Income}} \quad (2)$$

A negative correlation between AI and savings would support the study's hypothesis. Column (3) shows a significant negative correlation at the 5% level.

4.2.4 Alternative explanatory variable

The core explanatory variable is switched to the number of AI firms. Column (4) indicates this variable positively affects the dependent variable at the 1% significance level, with a coefficient similar to the benchmark regression.

4.2.5 Instrumental variable method

To address potential endogeneity, the one-period-lagged explanatory variable is used as an instrumental variable. The Hausman test yields a p-value of 0, leading to the rejection of the null hypothesis at the 1% level. This indicates no significant difference between the IV and OLS results, which both converge to the true parameter value. Column (5) confirms the instrumental variable meets the necessary assumptions.

4.2.6 Controlling for other policy interferences

The four batches establishment of AI Innovation Application Pilot Zones by the Ministry of Industry and Information Technology (MIIT) since 2019 is accounted for in the regression model [20]. In order to accurately evaluate the policy effect, this paper incorporates the pilot zone policy into the regression model as a control variable for processing. Results show these zones do not affect the conclusions.

Table 4. Robustness Test Results

	(1)	(2)	(3)	(4)	(5)	(6)
VAR	Delete municipalities	Cluster at the provincial level	Savings rate	AI enterprises	Instrumental variables	Include control variables
did	0.0093***	0.0192**	-0.0400**	0.0103***	0.0425***	0.0143***
	(0.0021)	(0.0079)	(0.0156)	(0.0006)	(0.0148)	(0.0054)
IV					0.9221***	
					(0.0185)	
Innovation Pilot Zone						-0.0019
						(0.0161)
Controls	Y	Y	Y	Y	Y	Y
Constant	0.300***	0.254***	1.366***	0.256***	0.2154***	0.367***
	(0.0195)	(0.0408)	(0.490)	(0.0078)	(0.0127)	(0.0347)
Year FE	Y	Y	Y	Y	Y	Y
City FE	Y	N	Y	Y	Y	Y
Province FE	N	Y	N	N	N	N
Obs	2,288	2,320	2,320	2,312	2,030	2,320
Number of id	286	290	290	289	290	290

4.3 Placebo Test

Results might be influenced by omitted variables and random factors. To evaluate the impact of these factors, this paper conducts a placebo test. It randomly selects provinces and cities for the Next Generation of National AI Innovative Development Pilot Zones and sets random start times for these pilots. By rerunning the regression analysis and examining the probability distribution of the regression coefficients, the study assesses the robustness of its conclusions. To enhance the placebo test's effectiveness, the process is repeated 500 times, and the distribution of the estimated coefficients is plotted.

Figure 4 shows the distribution of the estimated coefficients from the placebo test. The coefficients are normally distributed around 0, with the highest placebo coefficient (0.004) being smaller than the benchmark regression coefficient (0.0142). This confirms the benchmark regression results are reliable and that residents' consumption potential is not significantly affected by other factors beyond AI development.

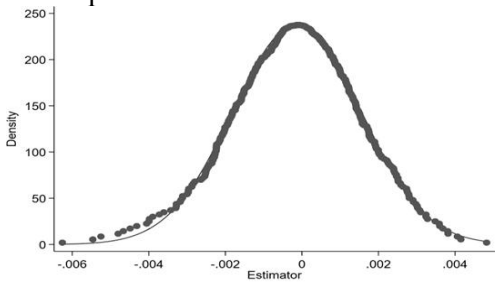

Figure 4. Placebo Test Results

4.4 Heterogeneity Test

To check for regional heterogeneity in AI's

impact on urban residents' consumption potential, the paper tests samples of 101 eastern cities, 100 central cities, and 89 western cities. As per column (1) of Table 5, the impact in the eastern region is significant and larger than the benchmark coefficient. But for the central and western regions (columns (2) & (3)), the effects on consumption potential are insignificant.

The significant impact of AI on consumption potential in the eastern region, may stem from its higher economic development, better infrastructure, and advanced digitalization, which facilitate AI application. In contrast, the central and western regions lag in these aspects, leading to less pronounced effects. The eastern region's higher internet and smart device usage, coupled with mature E-commerce, allows AI to drive consumption upgrades more effectively. Meanwhile, the central and western regions have relatively underdeveloped economies and lower demand for digital services, limiting AI's role in boosting consumption potential.

Table 5. Heterogeneity Test Results

	(1)	(2)	(3)
VAR	Eastern	Central	Western
did	0.0221***	-0.0003	0.0045
	(0.0026)	(0.0042)	(0.0039)
x1	-0.0111	0.0358***	0.0105
	(0.0100)	(0.0121)	(0.0129)
x2	-0.0128	-0.0160	-0.0621***
	(0.0188)	(0.0136)	(0.0121)
x3	-0.0857**	-0.0243	-0.127**
	(0.0426)	(0.0415)	(0.0571)
x4	-0.0041***	-0.0018**	-0.0006
	(0.0009)	(0.0008)	(0.0009)
x5	0.00386	-0.0058*	0.0056
	(0.0041)	(0.0033)	(0.0037)
Constant	0.459***	0.342***	0.295***
	(0.0446)	(0.0318)	(0.0321)
Year FE	Y	Y	Y
City FE	Y	Y	Y
Obs	808	800	712
Number of id	101	100	89

5. Conclusions and Recommendations

This study establishes that AI development effectively and sustainably boosts urban residents' consumption potential. Empirical results show that, compared to non-pilot cities, the implementation of pilot policies enhances consumption potential by 0.014 units. Furthermore, heterogeneity analysis reveals a more pronounced effect in eastern regions. This likely reflects both the regional distribution of pilot zones and differences in baseline consumption potential across regions.

To build on these findings, governments should boost investment in the AI industry, expand AI pilot policies to more non-pilot cities, especially small and medium sized cities with digital and industrial foundations. As well as stimulating new consumption models and potential, enterprises are encouraged to accelerate the R&D and application of AI in consumer-facing scenarios such as retail, healthcare, cultural tourism, and education.

Given the regional differences in AI's impact on residents' consumption potential, policymakers should focus on balanced regional development. For central and western regions, this means stronger policy support and digital infrastructure development to narrow the digital divide. Local governments should also cultivate AI-related industries and emerging professions to boost employment and income, thereby strengthening residents' consumption capacity and intent.

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