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Economic Resilience Enhancement of Cities through Digital Infrastructure: A Dual Machine Learning Approach

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Abstract: *This research applies Double Machine Learning (DML) to investigate the impact of infrastructure investment on urban economic resilience in four major Chinese cities from 2018 to 2024. Utilizing indicators such as Internet and mobile phone penetration rates, per capita GDP, educational attainment, and unemployment rates, a comprehensive evaluation model was developed. The DML approach effectively addresses endogeneity issues and biases in traditional econometric methods, providing precise estimations. The study finds a significant positive correlation between infrastructure improvements and urban economic resilience. Infrastructure investment not only enhances economic resilience but also improves a city's adaptability to recover swiftly from economic shocks. The causal effects of infrastructure on economic resilience vary among cities, with Shanghai and Shenzhen showing particularly strong positive impacts, likely due to their economic structures and population densities. This study offers valuable insights into the role of infrastructure in fostering urban economic resilience and provides a scientific basis for urban development planning and resource allocation. It also highlights the need for policymakers to consider regional characteristics when formulating infrastructure investment strategies.*

Keywords: *infrastructure, Urban economic resilience, Dual machine learning, Empirical analysis*

1. Journals reviewed

Urban economic resilience refers to a city's ability to quickly recover and maintain its economic activities and functions in the face of economic shocks such as financial crises, natural disasters, or epidemics. This concept is increasingly crucial in urban planning and policymaking, directly impacting the well-being of urban residents and the long-term competitiveness of cities.

Factors Influencing Resilience: [1]Infrastructure, as the cornerstone of urban operations, significantly impacts economic resilience. Improvements in transportation, communication, education, and healthcare infrastructure facilitate information flow, enhance labor quality, and bolster a city's economic recovery and adaptability.

2. Research background

[2]These challenges pose a threat to the sustainable development of cities, especially when facing external shocks such as natural disasters, economic crises, or public health events, which expose the vulnerability of cities.

The importance of urban economic resilience: Urban economic resilience refers to the ability of a city to quickly recover and maintain its economic activities and functions after experiencing economic shocks. [4]A city with high economic resilience can better cope with various shocks and maintain the stability of its economic and social structure.

The role of infrastructure: [7]The improvement of infrastructure can not only enhance the economic efficiency of cities, promote commercial activities and innovation, but also improve the quality of life of residents, enhance the attractiveness and competitiveness of cities.

Limitations of existing research: [3]The application of dual machine learning methods: In order to overcome these limitations, this study introduces the dual machine learning method (DML). DML

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separates processing effects by constructing predictive models, thereby reducing the impact of endogeneity issues and omitted variable biases. [6]The significance of this study is that by using DML methods, it can not only provide more accurate estimation results, but also reveal the differences in the impact of infrastructure on economic resilience between different cities. This has important implications for urban policy makers as it can help them develop and implement more targeted infrastructure investment strategies to enhance the economic resilience of cities.

3. Descriptive statistics

This study collected key economic and social indicator data from four first tier cities in China (Shanghai, Beijing, Hangzhou, and Shenzhen) between 2018 and 2024 to evaluate the impact of infrastructure on urban economic resilience. The main findings are as follows:

High penetration rate of Internet and mobile communication: Hangzhou has the highest penetration rate of Internet, while Shanghai leads in the penetration rate of mobile communication.

Economic output gap: Beijing has the highest per capita GDP, followed by Shanghai, while Hangzhou and Shenzhen are relatively lower.

Education levels vary: Beijing has the longest average length of education, indicating a strong emphasis on education.

Employment rates vary: Beijing has the lowest unemployment rate, indicating a stable job market, while Hangzhou, Shanghai, and Shenzhen have slightly higher unemployment rates.

These differences in indicators reflect the differences in economic development strategies, population structure, and other aspects among different cities, and may have a significant impact on urban economic resilience.

Comprehensive analysis: by comparing the key indicators of these four cities, we can observe their differences in Internet technology, mobile communication, economic output, education level and employment status. These differences may be related to the economic development strategies, population structure, allocation of educational resources, and industrial structure of each city. In addition, these differences may also have an impact on urban economic resilience, as economic resilience is closely related to the city's economic structure, social capital, and technological innovation. The descriptive statistics in Table 1 clearly display these contents.

Table 1: Descriptive Statistics

City=Shanghai					
Variable	Obs	Mean	Std. dev.	Min	Max
Internet penetration	7	0.731	0.0274773	0.69	0.756
Mobile Phone~People	7	187.26	3.111484	184.76	192
Per capita GDP of 10000~people	7	17.15629	2.002232	14.577	19.879
Average years of education	7	11.59221	0.3147686	11.104	11.875
unemployment rate	7	3.757143	0.5883795	2.7	4.5
City=Beijing					
Variable	Obs	Mean	Std. dev.	Min	Max
Internet penetration	7	0.6626857	0.0308531	0.6221	0.69
Mobile Phone~People	7	183.8714	2.465572	179.8	186.7
Per capita GDP of 10000~people	7	18.00214	2.098283	15.096	20.545
Average years of education	7	12.60478	0.3087238	12.05394	12.964

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unemployment rate	7	2.871429	1.205148	1.3	4.4
City=Hangzhou					
Variable	Obs	Mean	Std. dev.	Min	Max
Internet penetration	7	0.7681143	0.0056708	0.76	0.774
Mobile Phone~People	7	118.1171	6.139114	112.2	127
Per capita GDP of 10000~people	7	9.645	1.090091	8.162	11.028
Average years of education	7	10.84429	0.7644189	9.875	11.754
unemployment rate	7	2.971429	1.317465	1.6	4.8
City=Shenzhen					
Variable	Obs	Mean	Std. dev.	Min	Max
Internet penetration	7	0.7574286	0.0018127	0.756	0.76
Mobile Phone~People	7	118.1171	6.139114	112.2	127
Per capita GDP of 10000~people	7	9.645	1.090091	8.162	11.028
Average years of education	7	11.26014	0.8555779	9.91	11.965
unemployment rate	7	3.242857	1.192836	2.2	4.8

4. Dual machine learning model

4.1 Linear regression model to predict the processing variable (Internet penetration rate)

Internet penetration rate city=β 0+β 1 × year+β 2 × mobile phone penetration rate+β 3 × average years of education+β 4 × unemployment rate+1013city

1) Internet penetration rate Internet penetration rate city is the Internet penetration rate of city city (processing variable)

2) β 0 is the intercept term.

3) β 1, β 2, β 3, and β 4 are coefficients of year, mobile phone penetration rate, average years of education, and unemployment rate.

4) ϵ city is the error term.

4.2 Linear regression model for predicting the outcome variable (per capita GDP)

Per capita GDP=α 0+α 1 x year+α 2 x mobile phone penetration rate+α 3 x average years of education+α 4 x unemployment rate+μ city

1) Per capita GDP is the per capita GDP of a city (outcome variable).

2) α 0 is the intercept term

3) α 1, α 2, α 3, and α 4 are coefficients of year, mobile phone penetration rate, average years of education

4.3 Residual regression model for estimating causal effects

Residual outcome, city=γ0+γ1×residualtreated,city+ζcity

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1) Residual outcome, city is the residual of per capita GDP, which is the difference between the actual per capita GDP and the predicted value

2) Residual treated, city is the residual of the Internet penetration rate, that is, the difference between the actual Internet penetration rate and the predicted value.

3) γ0 is the intercept term.

4) γ1 is the estimated coefficient of causal effects, which is the average causal impact of the processed variable on the outcome variable.

5) ζcity is the error term

In dual machine learning, through the above steps, we can obtain causal effect estimates γ 1 specific to each city. The following Table 2 shows the estimated causal effects for each city.

Table 2: Output the causal effect estimation results for each city

	(1)Residual-Shanghai	(2)Residual-Beijing	(3)Residual-Hangzhou	(4)Residual-Shenzhen
Residual-Shanghai	-48.94 (25.31)			–
Residual-Beijing		18.36 (10.35)	-81.20 (36.46)	
(3)Residual-Hangzhou				
(4)Residual-Shenzhen				412.1 (243.2)
_cons	- 0.000000146 (0.0604)	- 0.000000275 (0.0989)	- 0.000000475 (0.0381)	- 0.000000861 (0.0378)
N	7	_7	7	_7
_				

Standard errors in parentheses
*p<0.05,**p<0.01, ** p<0.001

5. Summary

This study uses the DML method to analyze the relationship between digital infrastructure and economic resilience in China's four first tier cities (Beijing, Shanghai, Hangzhou and Shenzhen) from 2018 to 2024, and uses indicators such as the Internet, mobile phone penetration, per capita GDP, years of education and unemployment rate to build a model. Research has found that:

[5]Inter city differences: Infrastructure investment in Shanghai and Shenzhen has a significant positive impact on economic resilience, reflecting their economic structure, population density, and policy advantages.

Policy support: The research results provide data support for policy-making, emphasizing the need to develop infrastructure investment strategies based on urban characteristics.

Research significance:

New perspective: providing new insights into the impact of infrastructure on economic resilience.

Precision improvement: DML method enhances the accuracy of results.

Policy inspiration: To assist policy makers in accurately planning infrastructure projects.

Limitations and Future Directions:

Sample limitations: Need to expand to more cities to improve universality.

[8]In depth research: Explore the comprehensive impact of multiple factors such as environment, population migration, and policy changes on urban economic resilience.

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