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Article

Digital infrastructure and cognitive ability of children

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Abstract: Digital technologies have become an integral part of most children's lives, significantly influencing their development. This study takes the Broadband China Pilot Policy as a quasi-experiment, using the data from China Family Panel Studies (CFPS) to analyze the effects of digital infrastructure on children's cognitive ability. The extended two-way fixed effects estimator was employed to conduct the Staggered Difference-in-Differences estimation. The findings indicate that the average treatment effect of treatment group of "Broadband China" is significantly positive on children's cognitive ability. Additionally, heterogeneities of gender and urban-rural were found: (1) The Broadband China policy had a significant positive impact on boys only; (2) The policy had a greater and more significant impact on the word test scores results of urban children; (3) The policy had a negative impact on the math test scores of urban children, while showing a positive impact on the math test scores of rural children. Finally, the paper makes the following recommendations: (1) Digital infrastructure development should be emphasized; (2) More emphasis should be placed on rural areas when building digital infrastructure; (3) Gender differences should be considered when formulating policies to help girls benefit from digital technologies.

Keywords: digital infrastructure; children; cognitive ability; extended two-way fixed effects estimator

1. Introduction

In this digital era, the influence of digital technology is pervasive. Digital technology has significantly enhanced the speed and efficiency of information transmission, changed the ways in which people learn and interact, and profoundly affected of daily life. Researches have shown the significant influences of digital technologies on economy [1], society [2], health [3] and education [4,5]. This impact is not only reflected in adults. As children born in the digital era, the effects of digital technology on them may be even more substantial than we realize.

Children's development not only influences their future living standards but also shapes the trajectory of social development, as they will become future participants in the labor market and builders of society. Childhood is a critical stage in individual development and plays a vital role in the formation of individual skills. The skills acquired during this period significantly impact their level of human capital in adulthood. Cognitive ability is at the core of children's development. It influences their problem-solving skills, adaptability to their environment, and, to some extent, determines their future career performance.

Cognitive ability, as the ability of an individual to acquire, process, store and apply information, is an important research topic of common concern to many disciplines. In economics, cognitive ability is an important topic in the study of skill formation and human capital. It affects individual decision-making, risk preferences and market behavior, and thus affects resource allocation efficiency and economic growth. In biological research, cognitive ability is an extremely important part. The study of cognitive ability runs through all levels of biology, from molecular mechanisms to behavioral manifestations, from individual development to species evolution. Psychology regards cognitive ability as the key to understanding human behavior and explores its impact on psychological processes such as learning, memory, language, and emotions. In addition, cognitive ability is also closely related to fields such as education, sociology, and artificial intelligence. Research on it can help to better understand human behavior, promote social development, and promote scientific and technological progress.

It is crucial to study the impact of digital technology on children's cognitive abilities. With the widespread availability of the Internet and electronic devices, children have quick access to vast amounts of information. Understanding how digital technologies affect children's development will not only benefit parents and educators in guiding children to make better use of these technologies. It can also provide a basis for policy makers to help them formulate more effective education policies and digital development strategies. In conclusion, the question of how digital technologies affect children's development deserves more attention, and cognitive ability, as a key in children's development, should be researched in a targeted way.

Although some existing studies have explored the impact of digital technology on children's development, the role of digital infrastructure, as the important support for digital technologies, has been neglected. This study uses the "Broadband China" pilot policy as a quasi-experiment to explore the impact of digital infrastructure on children's cognitive abilities, which is of significance in expanding the scope of research in this area. Methodologically, this paper adopts the Extended Two-Way Fixed Effects (Extended TWFE) model and applies the Staggered Difference-in-Differences (Staggered DID) method, in which the samples of the not-yet-treated and never-treated samples are used as the control group, further expanding the scope of research in this area. samples as the control group, further expanding the application of the Extended TWFE method, which is methodologically useful for subsequent studies. Based on the China Family Panel Studies (CFPS) data, this paper estimates the baseline model and conducts parallel trend tests, placebo tests, robustness check, and analyses of gender and urban-rural heterogeneity.

The estimation results in this paper show that the "Broadband China" pilot policy has a significant positive impact on children's cognitive ability. Heterogeneity analysis further reveals the following results: (1) this significant positive effect is only valid for male children; (2) the "Broadband China" policy has a more significant effect on word test scores of urban children; (3) the "Broadband China" policy has a positive effect on rural children's math test scores for rural children, while it has a negative effect on urban children.

2. Literature review

In recent years, there has been extensive research into the impact of digital technology—particularly the use of the Internet and Information and Communication

Technology (ICT) on several aspects of children's cognitive and academic development. Banerjee et al. found that remedial education and computer-assisted learning programs significantly improved the performance of the students in mathematics [6]. Using data from PISA (Programme for International Student Assessment) 2009, Biagi and Loi found that broadband Internet had different levels of impact upon students' vocabulary and mathematics scores. While frequent use of the computer for curricular-related activities was associated with a decline in scores, a wider range of computer activities was related to improvement in these scores [7]. Zhang and Liu analyzed data from the PISA from 2000 to 2012 to evaluate how the use of ICT affects students' performance in mathematics and science. Results indicated that, in the short term, ICT had a positive impact on students' performance both in mathematics and vocabulary. For the long term, though, it showed that the more frequency ICT was used, the lower the performances were both in mathematics and science [8]. These results suggest that the effects of digital technology on students' academic performance are very complicated, depending upon how and under what conditions the technology is used.

Besides, some studies found that the national level of ICT development affects students' academic attainment significantly. Skryabin et al. from international datasets such as the Trends in International Mathematics and Science Study (TIMSS) and Progress in International Reading Literacy Study (PIRLS), developed by IEA, showed that the higher a country's ICT development, the better the students' achievements in reading, mathematics, and science [9]. Similarly, Hu et al. established that increased national resources for ICT were associated with higher math and reading scores. These thus show the crucial role that ICT resources play within education systems and, therefore, suggest a need to have investment at a national level in ways that will help improve children's academic performance [10].

However, the impacts of digital technologies are not similar everywhere. For instance, Meng et al. found that a positive relationship among Chinese students between interest in ICT and academic achievement was not evidenced by German students; this would indicate that the influence of digital technology on cognitive capabilities is dissimilar and might be culturally and educationally biased [11].

Limited research into the impact of digital technology on the cognitive development of children has been conducted in China, with inconsistent results from the limited studies conducted so far. Some studies find that Internet access improves cognitive ability. Cao et al. conducted an instrumental variable quantile regression analysis based on the data from CEPS 2013–2015. They found that Internet access had a greater positive effect on urban adolescents than on rural adolescents, which to some extent widened the cognitive ability gap between urban and rural adolescents. They noted that increasing Internet penetration in rural areas may help to promote the cognitive ability development of rural adolescents and reduce the cognitive ability gap between urban and rural adolescents [12]. Another study by Lei et al. used the same data from CEPS to determine if home access to the Internet had a positive effect on the cognitive ability of junior high school students. They determined that about 57% of the gap in cognitive competencies comes from whether the students access the Internet or not [13]. Li verified the enhancement effect of the Internet on cognitive ability through Propensity Score Matching (PSM) and Difference-in-Differences (DID) methods. He found that the cognitive ability of primary school students who were exposed to the Internet increased by 4.6%, while those who were not exposed to the Internet showed almost no improvement in cognitive ability [14].

However, other studies have highlighted the negative effects of the internet on various aspects of cognitive development. Chen and Gu examined the impact of educational informatization on students' performance in science, reading, and mathematics under different conditions, utilizing PISA 2015 data from major cities in China. Their findings revealed that technology use significantly enhanced the academic achievement of rural students but had detrimental effects on urban students. Additionally, prolonged internet usage, particularly when exceeding four hours, was found to exhibit a notable negative correlation with academic performance [15]. Similarly, Lin and Hu analyzed data from the PISA 2012 computer-based mathematics test and discovered that teachers' utilization of ICT in the classroom contributed to improved student performance on the test. In contrast, while students' independent use of ICT also enhanced their scores on the computer-based mathematics test, it adversely affected their mathematical literacy [16]. Tian et al. utilized data from the 2016 Academic Quality Monitoring in Jiangsu Province, which provided evidence that the type of classroom, particularly multimedia classrooms, enhances student achievement. In contrast, the overall ICT infrastructure does not seem to have a significant impact on academic performance [17].

In summary, there is no consensus in the existing literature regarding whether digital technology contributes to children's cognitive abilities. Its specific impact largely depends on how the technology is utilized, the frequency of its use, and the cultural context. Most studies indicate that moderate use of digital technology positively affects cognitive development. However, some research highlights that excessive or inappropriate use may have negative effects, particularly in various cultural contexts where the effects are more complex. Overall, the impact of digital technologies on children's development is multidimensional, governed and moderated by multiple factors. Furthermore, the current literature has not thoroughly examined the impact of digital infrastructure on children's cognitive abilities. Most studies focus primarily on the application of technology itself, overlooking the significance of infrastructure construction and popularization in children's cognitive ability development. In fact, the construction and enhancement of digital infrastructure may indirectly promote the development of children's cognitive ability by optimizing the learning environment, increasing educational resources, and broadening the access to information. Therefore, it is of great value and practical significance to explore in depth the impact of infrastructure on children's development.

This paper exploits a quasi-experiment with the "Broadband China" pilot policy to identify the effect of digital infrastructure on children's cognitive ability and provides evidence for understanding the role of infrastructure in children's development. In particular, the results of this study are also very meaningful for other developing countries in formulating relevant policies.

3. Broadband China policy

The "Broadband China" policy aims to enhance the construction of broadband infrastructure across the country. Three batches of "Broadband China" demonstration cities (or city clusters) were announced in 2014, 2015, and 2016, respectively. The primary objectives of the "Broadband China" policy include expanding broadband network access, increasing network speeds, reducing tariffs, fostering technological innovation, and facilitating economic transformation. The implementation of the "Broadband China" policy includes accelerating the construction of optical fiber and 4G/5G base station infrastructure, especially in rural and remote areas; focusing on promoting the optimization and technological upgrading of broadband networks, improving service quality and level, and optimizing broadband networks, improving independent capabilities and improving the industrial chain through technology research and development, industrialization, smart terminal development and platform construction. The "Broadband China" policy has the potential to enhance children's cognitive abilities by accelerating the development of network infrastructure, expanding their sources of information, and improving the quality of education as well as the family learning environment.

The implementation time of the "Broadband China" policy in different regions is different, which provides experimental conditions for setting the treatment group and the control group using the double difference method. In addition, as an important national strategy, the "Broadband China" policy has strong policy independence and is less affected by other policies, which is conducive to more accurate identification of the treatment effect. Therefore, it can be considered reasonable to use the double difference method to estimate the "Broadband China" policy as a quasi-experiment. In addition, the article uses the event study method to conduct a rigorous test of the parallel trend conditions, and also conducts a placebo test to further ensure the robustness of the estimation results.

4. Data and variables

4.1. Data source

The individual and household data used in this paper come from the China Family Panel Studies (CFPS) 2010, 2014 and 2018. As a national and comprehensive micro-tracking survey, CFPS adopts a multi-stage systematic probability proportional to size sampling (PPS) methodology, which improves the efficiency and precision of sampling and ensures the national representativeness of the sample. In addition, CFPS covers rich data at the regional, household, and individual levels, providing solid data support for the research in this paper. In addition, the data for city-level control variables in this paper come from the China Urban Statistical Yearbook. The data on the "Broadband China" pilot policy are obtained from the official website of the State Council of the People's Republic of China.

4.2. Variables setting

4.2.1. Independent variable

The independent variable of this study is the implementation of the "Broadband China" policy, that is, the policy shock. As mentioned above, the "Broadband China" policy was implemented three times. If the city where the child lives was selected as a pilot city in any policy year, the variable *treat* is 1, otherwise it is 0. The variable time is a dummy variable that signifies the implementation of the "Broadband China" policy, if the policy has been implemented, set it to 1, otherwise set it to 0.

4.2.2. Dependent variables

Cognitive ability

CFPS tests cognitive ability in individuals 10 years of age and older, with answers collected through a self-administered interview questionnaire. In order to measure cognitive ability more comprehensively, CFPS uses two methods to measure cognitive ability: word and math tests; memory and number sequence tests. Word and math tests examine the educational achievements of respondents and represent crystallized intelligence; memory and number sequence tests examine the potential abilities of individuals and reflect fluid intelligence. These two measurement methods are used alternately, that is, the same measurement method is used in the questionnaire every 4 years. CFPS 2010, 2014 and 2018 use word and math tests, and CFPS 2012, 2016 and 2020 use memory and number sequence tests. Due to Covid-19, the proportion of face-to-face interviews in CFPS 2020 is relatively low, resulting in a large amount of missing cognitive ability data. Therefore, this study chose to analyze the data of CFPS 2010, 2014 and 2018, focusing on word and math tests as cognitive assessment tools.

The theoretical basis of the CFPS math and word test is the design of the Guttman Scale. In these tests, the interviewer presents the respondent with 24 math questions (34 Chinese characters in word test) ranging from easy to difficult. The test will cease if the respondent answers three consecutive questions incorrectly or answers the last question correctly. The score of a respondent will be determined by the most difficult question they answered correctly. Additionally, the test will begin at different starting points based on the respondent's educational level.

In the original CFPS data, the values of the math test and word test ranged from 0 to 24 and 0 to 34, respectively. Since the same questionnaire was used for different ages, the test results are comparable across ages. Furthermore, to estimate the comparability of the coefficients, I standardized the values of these two tests using the Min-max normalization method and mapped the value range to the interval [0,10].

4.2.3. Control variables

Based on the literature and available data, this study proposes to control for variables at the individual, household, school and city levels. Individual level: hukou (non-agricultural = 1, agricultural = 0), urban (urban = 1, rural = 0), age, educational stage (grade 1–2 in primary school = 1, grade 3–4 in primary school = 2, grade 5–6 in primary school = 3, junior high school = 4, senior high school = 5), whether the child is raised by his or her grandparents (yes = 1, no = 0). Household level: the highest years of education of parents, household income per capita (taking the logarithm in regression). School level: whether the child is in a key school or private school (yes = 1, no = 0), whether the child is in a key class (yes = 1, no = 0). City level: Gross domestic product (GDP) of city (unit: 10 billion Chinese yuan). Additionally, parents' cognitive abilities were controlled.

Table 1 summarizes the key variables used in this study. The mean scores of word and math test scores are 7.098 and 5.177, respectively, and the variance of math test score is slightly higher. According to the description of variable treat, 12.9% of the sample exposed to the policy. In addition, it is worth noting that while 39.3% of children live in towns, only 15% have non-agricultural household registration.

Table 1. Descriptive statistics.

	Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Dependent variables	wordtest	7.098	1.753	0	10
	mathtest	5.177	1.869	0	10
Independent variable	treat	0.129	0.336	0	1
Individual level	hukou	0.15	0.357	0	1
	urban	0.393	0.489	0	1
	age	13.183	2.012	10	17
	edustage	3.493	0.905	1	5
	grand	0.089	0.285	0	1
Household level	peduy	8.781	3.634	0	18
	lnfinc	8.373	1.87	0	10.434
School level	kschool	0.311	0.463	0	1
	kclass	0.148	0.356	0	1
City level	GDP	18.061	19.996	1.284	203.632
Abilities of parents	m_wordtest	5.17	3.135	0	10
	m_mathtest	3.643	2.391	0	10
	f_wordtest	5.954	2.626	0	10
	f_mathtest	4.399	2.13	0	10
N		789	789	789	789

5. Empirical strategy

5.1. Staggered DID and Extended TWFE

Staggered DID was used to estimate the impact of "Broadband China" policy on children's cognitive ability in this paper. Different with classic 2 × 2 DID approach, staggered DID allows for multiple treatment periods for different observations. Staggered DID greatly increases the flexibility of the DID estimation model, expands the scope of use of DID, makes it more consistent with most policy implementation processes in the real world, and helps to obtain more accurate estimation results. However, it should be noted that due to the time asynchrony of treatment, Staggered DID usually requires more complex model settings to control interference factors from time and other levels to ensure accurate estimation results.

As the workhorse for classic DID estimations, traditional TWFE estimators have been found to have several shortcomings in accurately estimating treatment effects across multiple treatment periods. For example, when the treatment effect varies over time, TWFE may assign negative weights to some estimated effect parameters, which may lead to estimation bias (de Chaisemartin and D'Haultfoeuille; Callaway and Sant'Anna) [18,19].

The Extended TWFE approach, proposed by Wooldridge [20] and Wooldridge [21], includes not only treatment × time interaction, but also interactions between covariates and cohort dummies, time dummies and cohort × time dummies in the treated periods. By adding these interaction terms, Extended TWFE can more accurately identify the heterogeneous treatment effects of different individuals across various time periods. This approach helps to mitigate estimation bias and enhances the robustness of the results.

5.2. Benchmark model

The benchmark model used in this paper is modified based on the estimating equations of Wooldridge and Wooldridge. He estimated average treatment effect of treatment group (ATT) by using samples that were never treated as the control group. However, in this paper, both individuals who have never been treated and those who have not yet been treated are included in the control group. The advantage of this approach is that it can enhance the accuracy of estimation results, particularly when the sample size is limited. According to the equations of Wooldridge and Wooldridge, this paper defines q as the time when the "Broadband China" policy was first implemented, and T as the last year of the sample analyzed, $g \in \{q, \dots, T\}$; $t \in \{g, \dots, T\}$. Consequently, in the benchmark model of this paper, the range of time in the double summation term is $t \geq g$. The benchmark model can be written as Equation (1):

$$\begin{aligned} Y_{i,t} = \alpha + \sum_{g=q}^{T} \sum_{t \geq g}^{T} \tau_{g,t}\left(treat_{g(i)} \cdot time_t\right) + \sum_{g=q}^{T} \beta_g treat_{g(i)} + \varphi \mathrm{X_i} + \sum_{g=q}^{T} \xi_g\left(treat_{g(i)} \cdot \mathrm{X}_i\right) \\ + \sum_{t \geq g}^{T} \gamma_t time_t + \sum_{t \geq g}^{T} \pi_t (time_t \cdot \mathrm{X}_i) + \sum_{g=q}^{T} \sum_{t \geq g}^{T} \rho_{g,t}\left(treat_{g(i)} \cdot time_t \cdot \dot{\mathrm{X}}_{i,g}\right) + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where $Y_{i,t}$ represents the cognitive ability of child *i* at time *t*. Variables $treat_{g(i)}$ and $time_t$ have been described in 4.2.1. X_i is the set of control variables. $\dot{\mathrm{X}}_{i,g} \equiv \mathrm{X}_i - E(\mathrm{X}_i | treat_{g(i)} = 1)$. In actual estimation, the mean of the subsamples was utilized, indicating that $\dot{\mathrm{X}}_{i,g} = \mathrm{X}_i - \overline{\mathrm{X}}_g$. $\tau_{g,t}$ is the coefficient of average treatment effect of "Broadband China" policy at time *t* (ATT (*g*, *t*)). α is constant term. $\beta_g, \varphi, \xi_g, \gamma_t, \pi_t, \rho_{g,t}$ are the coefficients of each term. However, these coefficients do not hold direct economic significance. Instead, they are primarily employed to eliminate confounding factors that may influence treatment effects and to reduce estimation bias, thereby facilitating a more accurate identification of the treatment effect. $\varepsilon_{i,t}$ is residual term.

5.3. Empirical results

Table 2 shows the results of benchmark model. The positive effects of "Broadband China" policy on cognitive ability were found. According to the coefficients, the implementation of "Broadband China" policy has significantly improved children's word and math test scores, with the effect on math being slightly greater.

Table 2. Effects of "Broadband China" policy on children's cognitive ability.

		(1)	**(2)**
Cognitive ability	Wordtest	0.665* (0.285)	
	Mathtest		0.688* (0.352)
Controls	Individual	YES	YES
	Household	YES	YES
	School	YES	YES
	City	YES	YES
	Parent's abilities	YES	YES
Adj. R^2		0.656	0.743
N		789	789

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered by city are in parentheses.

6. Parallel trends and placebo tests

6.1. Parallel trends test

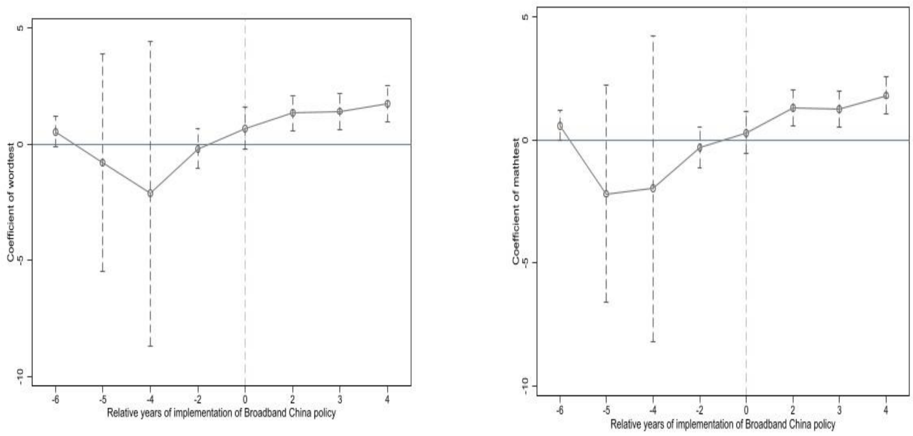
A critical assumption that must be fulfilled in DID estimation is the parallel trends assumption. It assumes that, in the absence of treatment, the dependent variables of the treatment group and the control group would have followed a similar path over time. If the parallel trends assumption is violated, the estimated results may reflect not only the impact of the policy intervention but also be influenced by other confounding factors that introduce bias into the estimation. Therefore, whether the parallel trend assumption is established is an important criterion for judging the reliability of the DID estimation model.

I use event study to test the parallel trends assumption. Subtract the year of policy implementation from the current year of the sample, resulting in the following values: −6, −5, −4, −2, −1, 0, 2, 3, 4. Remove the period before the policy takes effect, as this serves as the baseline period to prevent multicollinearity. Equation (2) is the event study model.

$$\begin{aligned}\mathrm{Y}_{i,t} = \beta_0 + \beta_1 Before6_{i,t} + \beta_2 Before5_{i,t} + \beta_3 Before4_{i,t} + \beta_4 Before2_{i,t} + \beta_5 Current_{i,t} + \beta_6 After2_{i,t} \\ + \beta_7 After3_{i,t} + \beta_8 After4_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}\end{aligned} \tag{2}$$

where the time dummy variables are the observation values in the first *n* years, the current year and the next *n* years when each city implements the "Broadband China" policy. The dummy variables for non-pilot cities are all 0. μ_i and λ_t are city and year fixed effects respectively. The other variables or coefficients are the same as in Equation (1).

Figure 1 shows that the coefficients before the policy are not significant. It means that before the policy, there was no significant difference in the cognitive abilities of children in the treatment group and the control group, that is, the "Broadband China" policy satisfies the parallel trend assumption.



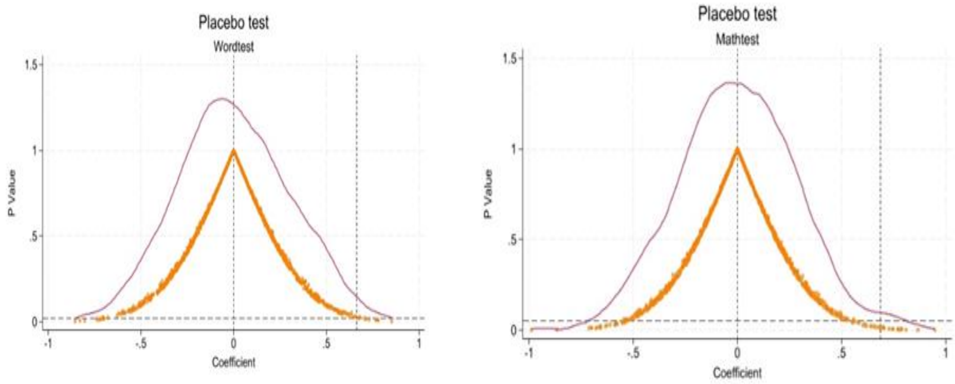
(a) **(b)**

Figure 1. Parallel trends tests, **(a)** parallel trends test of wordtest; **(b)** parallel trends test of mathtest.

6.2. Placebo test

The placebo test is conducted to ensure that other factors do not interfere with the estimated result in a study. Placebo test can help confirm that the model's causal inference is valid and robust. To further verify the robustness of the results, I conducted a placebo test on the baseline estimation results. I first grouped the data by city, and then randomly selected a year within each city group to serve as the treatment year. I re-estimated the baseline model using this new data and obtained new estimated coefficients. This process was repeated 1000 times, and the probability distribution of the results was plotted, as shown in **Figure 2**.

Figure 2 shows the results of the placebo tests alongside the benchmark regression results for comparison. The estimated coefficients from the placebo tests are centered around 0 and closely resemble a normal distribution. In contrast, the estimated results of the benchmark regression, shown in the lower right corner of the coordinate axes in the figures, differ significantly from those of the placebo tests. Additionally, most of the estimated results from the placebo tests are not statistically significant. In summary, the results of the placebo tests indicate that the results of the benchmark regression are unlikely to have occurred by chance, thereby further confirming the robustness of these results.



(a) **(b)**

Figure 2. Placebo tests. The X-axis represents the estimated value of the coefficient $\beta_{g,t}$ in Equation (1). The curve is the kernel density distribution, and the dots are the p values. The intersection of the two dashed lines is the result of the baseline regression, **(a)** placebo test of wordtest; **(b)** placebo test test of mathtest.

7. Robustness check based on regional broadband development levels

While the benchmark regression has used the Extended TWFE method, controlling for a sufficient number of control variables and interaction terms to obtain robust estimate results. However, in order to further validate the positive impact of digital infrastructure on cognitive ability, I conducted the robustness test. In this section, I replaced the independent variables and utilized the level of regional broadband development as a proxy variable for digital infrastructure. Specifically, I used the number of Internet broadband access users (in millions of households) to represent the level of regional broadband development, and the source of data is the China Urban Statistical Yearbook for each year. I employed TWFE method to estimate the effect of digital infrastructure on children's cognitive ability again. The specific estimation model used is Equation (3):

$$\mathrm{Y}_{i,t} = \beta_0 + \beta_1 BD\_LEVEL_{i,t} + \beta_2 \mathrm{X_i} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{3}$$

Where $BD\_LEVEL_{i,t}$ represents the level of regional broadband development. The other variables or coefficients are the same as in Equations (1) or (2).

Table 3 shows the estimate results of Equation (3). It is clear that the results of the robustness regression are the same as those of the baseline regression, and that digital infrastructure has a significant and positive effect on the results of both mathtest and wordtest. This suggests that it is still possible to verify that digital infrastructure has a positive impact on children's cognitive development even when the measure of digital infrastructure, as well as the estimation method, is replaced. This further validates the robustness of the main results of this paper.

Table 3. Effects of level of regional broadband development on children's cognitive ability.

		(1)	(2)
Cognitive ability	Wordtest	0.648*	
		(0.372)	
	Mathtest		0.851*
			(0.461)
Controls	Individual	YES	YES
	Household	YES	YES
	School	YES	YES
	City	YES	YES
	Parent's abilities	YES	YES
Adj. R^2		0.539	0.622
N		1042	1042

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered by city are in parentheses.

8. Heterogeneity analysis based on gender and urban-rural classification

In order to further explore the impact of the "Broadband China" policy on children's cognitive abilities, I conducted a heterogeneity analysis based on gender and urban-rural classification. The results of the analysis are presented in **Table 4**.

Table 4. Results of heterogeneity analysis.

		Gender				**Urban/rural**			
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
		Male	**Female**	**Male**	**Female**	**Urban**	**Rural**	**Urban**	**Rural**
Cognitive ability	Wordtest	1.034**	−0.027			1.887***	0.996*		
		(0.348)	(0.888)			(0.196)	(0.511)		
	Mathtest			0.846*	0.924			−2.241**	2.488**
				(0.440)	(0.615)			(0.683)	(0.940)
Controls	Individual	YES	YES	YES	YES	YES	YES	YES	YES
	Household	YES	YES	YES	YES	YES	YES	YES	YES
	School	YES	YES	YES	YES	YES	YES	YES	YES
	City	YES	YES	YES	YES	YES	YES	YES	YES
	Parent's abilities	YES	YES	YES	YES	YES	YES	YES	YES
Adj. *R*2		0.683	0.720	0.728	0.798	0.938	0.691	0.759	0.642
N		439	374	439	374	309	478	309	478

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered by city are in parentheses.

According to the results presented in **Table 4**, we can find that although the baseline estimation results above have shown that the average effect of the "Broadband China" policy on children's cognitive ability is positive and significant, there are significant differences between genders and between urban and rural areas. Specifically, there are the following points can be observed: (1) The “Broadband China” policy only has a significant positive impact on boys’ cognitive ability, and the impact on girls is not statistically significant, whether it is wordtest or mathtest; (2) The “Broadband China” policy has a positive impact on the wordtest scores of children in both urban and rural areas, but the positive impact on urban children is greater and more significant; (3) The “Broadband China” policy has a negative impact on the mathtest scores of urban children, but a positive impact on the math test scores of rural children.

9. Conclusion

Using the “Broadband China” pilot policy as a quasi-experiment, this study further explores the application of the Extended TWFE method in staggered DID and finds that digital infrastructure positively influences children’s cognitive abilities. This may be because the “Broadband China” policy can increase the scope and speed of children’s access to information, enhance their learning environment, and consequently improve their learning efficiency. These factors can provide diverse stimulation to children's brains, potentially promoting the growth of neurons and strengthening the connections between them. Ultimately, these factors contribute to the development of children’s cognitive abilities. In addition, this paper conducted a heterogeneity analysis from the perspectives of gender and urban and rural areas. The results showed that the impact of “Broadband China” policy on children’s cognitive ability varies between genders, urban and rural areas, and disciplines.

These results explore the impact of digital technology on children’s cognitive abilities from the perspective of digital infrastructure, provide evidence for research on the impact on child development. Furthermore, these findings have important policy implications. First, the results show that expanding digital infrastructure can significantly improve children’s cognitive abilities, especially in rural areas. Therefore, not only should digital infrastructure be vigorously promoted, but the focus should be on strengthening digital infrastructure in rural areas in order to alleviate urban-rural inequalities. Secondly, as the positive impact of digital technologies may vary by gender, the gender impact should be taken into account in policymaking to help girls benefit from digital technologies.

Although this paper found that digital infrastructure may have a positive impact on children’s cognitive abilities, the impact of digital technology on children is complex and may also bring other negative effects. Therefore, in future research, both positive and negative aspects can be considered to discuss the impact of digital technology more comprehensively.

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