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SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2025, 22(2), 1053.
https://doi.org/10.62617/mcb1053

Article

Research on the mechanism of promoting precise poverty alleviation through educational informatization based on biomechanical mechanism

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CITATION

Jiang H, Yin G. Research on the mechanism of promoting precise poverty alleviation through educational informatization based on biomechanical mechanism. Molecular & Cellular Biomechanics. 2025; 22(2): 1053. https://doi.org/10.62617/mcb1053

ARTICLE INFO

Received: 9 December 2024
Accepted: 15 December 2024
Available online: 21 January 2025

Abstract: Drawing on the theory of biomechanics, this study explores the mechanism of promoting precision poverty alleviation through education informatization. Precision poverty alleviation is at the core of China's poverty reduction strategy, addressing the root causes of poverty through targeted interventions. Under this framework, education informatization has become a key tool for bridging systemic inequalities by enhancing the quality and equity of education through information technology. From basic digital construction to the deep integration of big data, cloud computing and artificial intelligence, education informatization has made remarkable progress. Analogous to how biomechanical systems optimize force transmission and movement efficiency, it showcases great potential for the optimal distribution of educational resources, enhancing access to education in impoverished regions, and fueling long-term socio-economic progress. However, its role in rural and underdeveloped areas still faces many challenges. Viewing education informatization as a dynamic "biomechanical structure" and borrowing concepts like structural adaptation, load optimization, and connectivity from biomechanics, we posit that big data technology, acting as a "biomechanical signal", can precisely pinpoint needy students and allocate educational resources adeptly, much like how forces are coordinated in a mechanical system. Based on the fuzzy breakpoint regression model and fixed-effects analysis of CFPS (China Family Panel Studies) data, the study finds that education informatization significantly improves the subjective well-being, health care, and employment outcomes of rural families. This study highlights the innovative role of education informatization in enhancing resilience, equity, and resource efficiency through the synergy of technological evolution and policy adaptation, providing a new perspective on precision poverty alleviation.

Keywords: educational informatization; biomechanics; precision poverty alleviation; digital ecosystems

1. Introduction

In nature, biological systems adapt to complex environments through evolution, thereby maintaining the survival and reproduction of populations. The core of this process lies in the transmission of genes and the optimized allocation of resources, ensuring efficient energy flow and balance in the ecosystem [1–3]. The education system and biological system share similarities to some extent—both are complex networks that rely on information transmission and optimized resource allocation to achieve system goals. When education is used as the core tool for targeted poverty alleviation, this analogy is particularly prominent [4–6].

Educational informatization can be seen as a dynamic 'educational ecosystem', whose development and optimization process is similar to the evolutionary mechanism in biological systems. Big data technology plays a key role in it, similar to the "genetic material" in biology, promoting the precise dissemination of information and the intelligent allocation of resources. Just as biological evolution needs to cope with environmental pressures and resource scarcity, educational informatization also needs to address the major challenge of social inequality through the synergy of technology and policies [7–9].

The construction of a data system for poor students has many positive implications. Firstly, it can ensure that education authorities at all levels monitor and pay attention to the learning and living conditions of poor students in a timely manner, and improve the level of their work. Secondly, it can provide the possibility of keeping long-term data on poor students, and at the same time provide theoretical and data support for poverty alleviation through in-depth analysis of the data. Thirdly, the implementation of a big data system can successfully raise the bar for poverty alleviation efforts by facilitating oversight and accountability of all societal sectors and encouraging openness and transparency in the process [10].

As education progresses, teachers are in a fundamental position. Therefore, in the process of promoting the informatization and modernization of education for poverty alleviation, we should not only take students as our service targets, but also provide high-quality information resources for teachers. Firstly, it is necessary to enhance the ability of teachers to use information technology, in order to establish a framework for the eventual advancement of education's digitization for the purpose of reducing poverty. Secondly, we should also collect and analyze data for teachers, and use the Internet as a basis to launch targeted training for teachers in order to improve their teaching ability [11].

At the same time, big data analysis has also brought many challenges to the work of poverty alleviation: massive data make data analysis time-consuming and energy-consuming, and it is difficult to provide timely scientific references for decision makers of poverty alleviation; multi-dimensional data of poverty alleviation behavior lead to "dimensional disaster" in data mining, and the validity and credibility of the analysis conclusions are reduced; there is a contradiction between traditional statistical analysis methods on the basis of a priori assumption and big data analysis thinking emphasizing the prediction of the future, which requires further coordination. There is a contradiction between the traditional statistical analysis based on a priori assumptions and the big data analysis thinking that emphasizes the prediction of the future, which needs to be further coordinated, resulting in a great deal of changes to the way poverty alleviation is approached, organized, and conceptualized [12].

2. Empirical model, data sources and variable selection

2.1. Breakpoint regression model

In the modeling process, this paper takes into account the fact that in the practice of poverty alleviation in rural China, local governments follow the principle of "consultation by village representatives on the basis of income assessment" when accurately identifying poor households, i.e., through the democratic consultation of villagers' representatives, poor households are accurately identified on the basis of the income poverty line, and comprehensively identified by considering welfare factors in addition to the income poverty line. Welfare factors other than the income poverty line are also taken into account for comprehensive identification. Specifically, this paper considers the welfare factor of "two no worries, three guarantees" for comprehensive identification. In fact, due to the introduction of villagers' democratic evaluation, the identification of poor households may result in households with income higher than the poverty line being incorrectly identified as poor households and thus enjoying the precise poverty alleviation policy; at the same time, it may also be affected by external factors such as ineffective or unfair implementation by the grassroots government, which results in some households with income lower than the poverty line not being identified as poor households [13]. In view of the above problems, this paper adopts the fuzzy breakpoint regression (FuzzyRD) method to identify whether a household is poor or not through the poverty line criterion. In addition, the estimation method in this paper draws on the model setup of Brollo et al. and uses two-stage least squares (2SLS), which is equivalent to instrumental variable (IV) estimation [14]. Specifically, the estimation of FuzzyRD can be achieved by either the non-instrumental-variable instrumental-variable (IV) method or the parametric 2SLS method, which are equivalent to both estimation methods. The specific model setup is as follows:

$$D_i = \delta + \lambda T_i + g(z_i) + \varphi X_{it} + \mu_{it} \tag{1}$$

$$Y_{it} = \alpha + \beta \widehat{D}_i + f(z_i) + \gamma X_{it} + \varepsilon_{it} \tag{2}$$

where Y_{it} is the outcome variable of interest in this paper (residents' subjective well-being) and β is the pro-poor policy effect to be estimated in this paper. One-stage and two-stage regression expressions are found in Equations (1) and (2), respectively. z_i denotes household per capita income, which is standardized as the driving variable, specifically the difference between the household per capita income and the breakpoint (the poverty line criterion). $g(z_i)$ and $f(z_i)$ are polynomial functions of z_i. $T_i = 1$ (per capita income below the poverty line criterion) denotes the per capita income criterion based on which the identified Precision Poverty Alleviation Eligibility (Identification Rule), i.e., individuals under the income poverty line criterion are eligible to participate, but it does not indicate that they have actually been aimed as poor households. Conversely, $T_i = 0$ (per capita income above the poverty line criterion). $\widehat{D}_i$ is the treatment status variable, $\widehat{D}_i = 1$is the poor households targeted by precision poverty alleviation, which means that the farmers who enjoy the precision poverty alleviation policy enter the treatment group, otherwise they enter the control group. In the FuzzyRD analysis, T_i is the instrumental variable for the treatment status $\widehat{D}_i$. X_{it} is the control variable, and μ_{it} and ε_{it} are both residual terms.

Due to the special causal inference approach of the FuzzyRD method, whether or not control variables are added to the model does not have a substantial impact on the results, however, when the control variables violate the exogeneity assumption or when the control variables have a linear effect on the driver variables, adding control variables may instead lead to biased or inconsistent estimation results [15]. In this paper, the above factors are taken into account when choosing control variables and further justified in the robustness section. In the empirical estimation, the FuzzyRD regression parameters are sensitive to the selection of bandwidth, and the estimation results of different bandwidths may differ [16]. In order to ensure the stability of the empirical results, this paper not only adopts multiple bandwidths and multiple $f(z_i)$ form settings, in order to reduce bias brought on by the bandwidth issue or the differing slopes of the regression lines on either side of the breakpoints, it also adds an interaction term between the driving factors and the treatment state [17].

2.2. Fixed effects model

As rural households are affected by the precise poverty alleviation policy differently due to the differences in income level, demographic structure, health status, geographic environment, traditional culture and other factors [18]. Furthermore, the identifying unit of households is the basis for precise poverty reduction; nevertheless, the number of impoverished households varies among regions, resulting in disparities in the execution of policies aimed at reducing poverty [19]. In order to analyze the heterogeneous effects of the precision poverty alleviation policy on the subjective well-being of different households (poor and non-poor), this paper further relies on a fixed-effects regression model, in which an interaction term between the implementation strength of the precision poverty alleviation policy (depthct) and the influencing factors X_{it} is introduced, to analyze the heterogeneity and spillover effects in terms of factor endowment, health status, and non-farm employment of different households. The specific model settings are as follows:

$$Y_{it} = \beta_0 + \beta_1 depth_{ct} + \beta_2 X_{it} + \beta_3 depth_{ct} \cdot X_{it} + \alpha_k Z_{ikt} + \lambda_i + \pi_t + \mu_{it} \tag{3}$$

In Equation (3), Y_{it} is the outcome variable (residents' subjective well-being), and the coefficient of the interaction term β_3 is the center of attention in this paper, reflecting whether the relevant factor X_{it} has a heterogeneous effect on the subjective well-being of households with different factor endowments through the precision poverty alleviation policy. If $\beta_3 > 0$, it means that as the influencing factor X_{it} increases, the subjective well-being of residents increases as a result of the poverty alleviation policy. In short, if there is an interaction effect between the influencing factor X_{it} and the policy of poverty alleviation, then the policy of poverty alleviation will have an effect on the subjective well-being of households through X_{it}. In addition, Z_{ikt} is an individual-level, household-level, and area-level control variable that controls as much as possible for relevant heterogeneity factors that do not vary over time. λ_i is an individual fixed effect, π_t is a time fixed effect, and μ_{it} is a residual term. To prevent the effects of serial correlation or heteroskedasticity problems, standard errors are clustered to the individual level when estimating the coefficients in this paper.

2.3. Data sources

This paper mainly adopts the 2022 CFPS data. the CFPS data includes information on education, healthcare, occupation, household size, income, consumption and life satisfaction [20]. Since the precise poverty alleviation policy mainly targets rural households, this paper selects the sample of rural households (about 53.6% of the total sample) from the CFPS data. All family members in the sample are survey respondents, and the CFPS sample covers 25 provinces, municipalities and autonomous regions in China. The process of data cleaning and processing revealed that: first, the data on residents' subjective well-being were missing in the 2015 sample; second, there were more missing values and outliers in the individual well-being indicators in the 2017 sample, and only 448 valid samples were left after elimination, and the 2017 sample was also excluded in consideration of the issue of sample validity. Therefore, this paper chooses the data from 2022, 2015 and 2018, and the interval between these three surveys is exactly four years, tracking and matching the families participating in all three surveys, and obtaining a balanced set of tracking samples with data before and after the implementation of the policy, thus ensuring the validity and stability of the sample. In addition, due to differences in individual ratings of happiness indicators between 2022 and 2022, in 2022, a range of 1 to 5 is used for subjective happiness, where 1 indicates very poor and 5 indicates very good. In contrast, in the 2015–2020 sample, scores for subjective well-being use a range of 0 to 10, where 0 indicates the lowest and 10 the highest. Due to the difference in statistical caliber and the fact that 2013 is the baseline data at the beginning of the CFPS survey, this paper takes the 2013 data as a separate subsample for the robustness test of the regression analysis results.

2.4. Variable selection and statistical description

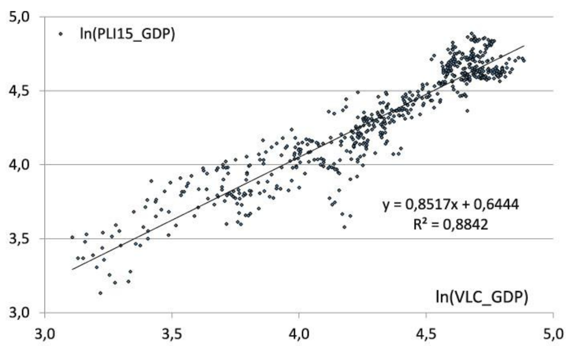
This paper's research is primarily split into two sections: an examination of policy heterogeneity and spillover effects, and an evaluation of the effectiveness of specific policies aimed at reducing poverty. In order to analyze the policy heterogeneity and spillover effects, the main influencing factors selected in this paper are considered from the following aspects: first, the strength of the assistance in different regions is directly related to the subjective well-being of the residents in the region.

Through variable selection and descriptive statistics, all nominal variables are excluded from the impact of the price index, deflated to 2010. It is known through statistics (variable descriptions and descriptive statistics are limited to space and are left for the record) that, firstly, residents' subjective well-being is statistically on an upward trend, and in 2017, compared with 2013, residents' subjective well-being has increased by nearly 3.7 percentage points. Second, the implementation of precise poverty alleviation policies in rural areas has increased by nearly 8.8% compared to 2013. In 2013, precise poverty alleviation was fully implemented in rural areas, directly targeting poor households, in accordance with the 2022 per capita poverty standard of 2300 yuan per year, combined with the “two no worries, three guarantees” determination of the standard of subsistence and the two rounds of “precise poverty alleviation review” measures implemented in 2014 and 2015. Meanwhile, in conjunction with the “two no worries, three guarantees” standard of subsistence and the two rounds of “precise poverty alleviation look-back” measures implemented in 2014 and 2015, the scale of poverty identification has been greatly increased in the latter stages of precise poverty alleviation, from the previous “scale control” to the “inclusion of the fullest possible inclusion and support of the fullest possible support”, which has led to an increase in the strength of the assistance and measures provided to impoverished families. Therefore, while the policy of precise poverty alleviation has expanded the scale of poverty benefits for low-income groups, the implementation of precise poverty alleviation has also been strengthened in the short term. Third, compared with 2013, the proportion of non-farm employment in the village increased and health care expenditure slowed down in 2017, while at the same time, government transfers to the poor increased significantly, with per capita access to government transfers increasing by about 452 yuan. In addition, as can be seen from the values of sample statistics that do not change over time, such as the distribution of different regions, the samples selected in this paper do not show obvious sample aggregation characteristics.

3. Analysis of empirical results

3.1. FuzzyRD estimation results

The validity of FuzzyRD is tested by examining the relationship between the driving variable and the result variable, which is the subjective well-being of the inhabitants, as shown in **Figure 1**. With clear jumps on the left and right sides of the institutional breakpoint of the specific poverty alleviation criterion (2300 yuan/year, 2010 prices), **Figure 1**’s results demonstrate that the outcome variable exhibits clear disparities at the breakpoints. In the later portion, the regression analysis of the breakpoint is performed using the segmented linear and polynomial regression forms since the trend of change on both sides of the breakpoint exhibits a nonlinear tendency.



Notes: PL15_GDP: the price level of GDP; VLC_GDP: per capita GDP measured at PPP (both relative to the EU15).
Sources: Eurostat, PPP-database.

Figure 1. Relationship between per capita income and outcome variables (2022).

Note: The driver variables were standardized. The outcome variable is the subjective well-being of the population, and the optimal bandwidth of subjective well-being is ±820 (calculated by the CCT method adopted for the optimal bandwidth).

Table 1 estimates the effect of institutional breakpoints specified by the poverty standardization line on whether or not a household is targeted as precisely poor, i.e., the one-stage estimation results under FuzzyRD identification. In this paper, we take the estimation results under three different bandwidths and optimal bandwidth forms, and also consider the interaction term between the treatment state and the driver variable to minimize the bias caused by the different slopes of the regression lines on both sides of the breakpoint. In **Table 2**, Equations (1)–(2) are the narrower bandwidths, thus controlling the nonlinear trend of per capita income in a lower-order form; Equation (3) is the larger bandwidth, which increases the sample size while controlling the higher-order function; and Equation (4) is the optimal bandwidth of residents' subjective well-being as a reference for the robustness of the estimation results with the manually set bandwidths. In addition, the *F*-test values in **Table 2** are used to determine whether income poverty line eligibility is a valid instrumental variable for precision poverty alleviation policies. The *F*-statistics of the instrumental variables largely exceed the 10% level error tolerance threshold, implying that the instrumental variables used in this paper have a high probability of passing the weak instrumental variable test.

Table 1. Impact of poverty alleviation criteria line provisions on whether or not a household is targeted for poverty (2013).

Variant	**Dependent variable: precise identification of poor household eligibility (1 = yes, 0 = no)**			
	±300	**±500**	**±1000**	**Optimal broadband**
	(1)	**(2)**	**(3)**	**(4)**
Per capita income ≤2300	0.068***(0.026)	0.064**(0.021)	0.086***(0.015)	0.033**(0.014)
$f(z)$segmented linear function	Yes	Yes	Yes	Yes
$f(z)$: polynomial function	Yes	Yes	Yes	Yes
F-test	156.2	277.3	480.5	392.2
R^2	0.477	0.507	0.464	0.465
Sample size	730	1134	2323	1905

Note: Robust standard errors in parentheses, *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. where the optimal bandwidth of subjective well-being was calculated by taking the CCT method. All of the above models include polynomial terms, which are mainly used to detect special equation forms where the income breakpoints do not depend on the driving variables alone, and the polynomial terms include quadratic and cubic terms, respectively, and the quadratic form results are reported above.

Table 2. Impact of precise poverty alleviation policies on residents' subjective well-being (FuzzyRD estimation).

Variant	**2013**	**2017**	**Full sample**
	(1)	**(2)**	**(3)**
Policy effect	0.451*(0.245)	0.611**(0.265)	0.648**(0.257)
$f(z)$: segmented linear function	Yes	Yes	Yes
$f(z)$: polynomial function	Yes	Yes	Yes
Sample size	1071	1134	2323

The results in **Table 1** show that the different bandwidths are set to vary somewhat in the first-stage regressions, but maintain overall robustness, that the impact of the poverty alleviation standard line provision on whether or not a household is targeted as a precise poor household is relatively significant, and that the probability of a household with an annual per capita income of less than 2300 yuan being supported by precise poverty alleviation policies is higher, with statistically significant results, and that the qualification for poverty identification is therefore a good proxy for actually being identified as a poor household.

The outputs of the two-stage estimation are given in **Table 2**. The results show that the precise poverty alleviation program significantly improves the subjective well-being of the residents and that the estimation results are robust to different bandwidth conditions. The particular poverty alleviation approach considerably raises inhabitants' subjective well-being by 45% to 65%, according to additional analysis. This estimation result is consistent with the expectation that the specific poverty alleviation policy is more sophisticated and specialized than China's previous poverty alleviation practices. Through specific assistance measures like income subsidies, expenditure reductions and exemptions, protection for medical and educational needs, and industrial assistance, the poor groups receive more tangible policy dividends in the process of escaping poverty. They also have a greater awareness of the national policies on agricultural benefits and people's livelihoods, which generally improves the subjective well-being of the residents.

3.2. Robustness tests

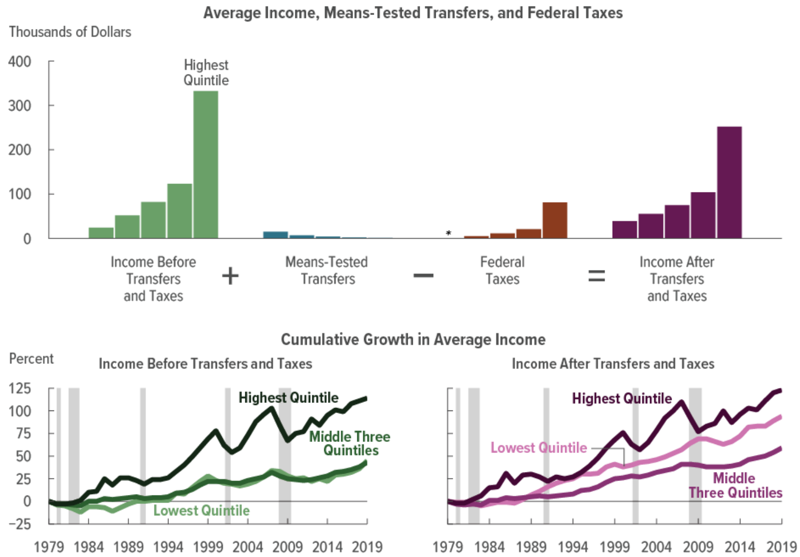


Figure 2. Per capita household income at critical value of $2300 (2010 Prices) mccrary test (2022).

Note: McCrary test for the driver variable at the $2300/year (2010 prices) breakpoint. Since per capita income of $5000 and above samples are unlikely to be the identification of precise poverty alleviation, only the results of the samples with per capita income of $5000 and below are considered in the above figure, and the McCrary test that extends the range of that per capita income to a wider range of incomes is basically consistent with the results. Moreover, the results are basically the same when the test is conducted on the 2017 data.

This paper chooses to perform the McCrary test on the distribution of the per capita income variable near the breakpoints in order to test whether the samples near the breakpoints have self-manipulated the level of per capita income to change the status of poverty identification or eligibility. It is evident from **Figure 2** that there is no discernible difference between the density functions on either side of the breakpoints (the density distribution interval on the vertical axis is very small), and that the confidence intervals of the density function estimates on both sides of the breakpoints generally overlap and are relatively smooth. Therefore, it is reasonable to assume that there is no sample manipulation of the driving variables near the breakpoints, and the FuzzyRD method is feasible and effective.

The continuity test of the control variables is displayed in **Table 3**. The continuity of the control variables is also necessary for the FuzzyRD method of identification to be valid; that is, the treatment variables must not affect any of the predefined factors that resulted in the household being targeted as a "poor household," failing which the FuzzyRD identification is invalidated. In accordance with the FuzzyRD methodology's hypothesis, the results in **Table 3** demonstrate that all of the control variables are insignificant, meaning that the treatment variables have no effect on the pertinent characteristic factors that existed prior to the household being classified as poor. Additionally, the results indirectly rule out the influence of other policies or factors that might have affected the residents' subjective well-being, guaranteeing the robustness of the policy effects.

Table 3. Control variable continuity test (FuzzyRD estimation).

Implicit variable	**2013**	**2017**	**Full sample**
	(1)	**(2)**	**(3)**
Gender	0.808(0.590)	0.144(0.430)	0.011(0.222)
Age	6.516(14.922)	4.033(10.466)	2.670(4.695)
Years of education	0.216(2.455)	−1.014(2.009)	0.114(1.396)
Health status	0.825(0.589)	0.066(0.440)	1.577*(0.919)
Number of children	−0.738(0.589)	−0.021(0.567)	0.575(0.477)
Marital status	0.268(0.173)	0.200(0.140)	0.191(0.162)
Population size	−1.311(2.646)	−0.533(1.717)	−0.277(0.898)
Regional	−0.488(0.655)	0.439(0.551)	−0.440(0.353)
$f(z)$: segmented linear function	Yes	Yes	Yes
$f(z)$: polynomial function	Yes	Yes	Yes
Sample size	730	1134	2323

In addition, the paper further implements a placebo test and adopts three manual bandwidth setting methods to compare with the optimal bandwidth estimation (**Table 4**). In particular, this paper uses the "precise poverty alleviation policy" forward to 2010 as a spurious policy shock to analyze whether the spurious policy shock also affects residents' subjective well-being. The regression results are not expected to be significant because the policy of precise poverty alleviation was not implemented in

2010, and only the original poverty alleviation model at the county level was maintained, so households were not able to obtain the benefits of the policy of precise poverty alleviation. **Table 4**'s regression results demonstrate that the placebo policy effect of advancing the policy to 2010 is not statistically significant when utilizing either the manually set bandwidth or the optimal bandwidth adopted. This suggests that the spurious precision poverty alleviation policy is not having any policy effect, eliminating the possibility that other policies or factors could have an impact on the household's subjective well-being, and reaffirming that the precision poverty alleviation policy has no effect on the subjective well-being of the poor.

Table 4. "Placebo" test estimation results (FuzzyRD estimation).

Variant	**$\pm$300**	**$\pm$500**	**$\pm$1000**	**Optimal broadband**
	(1)	**(2)**	**(3)**	**(4)**
Policy effect	0.019(0.032)	0.046(0.063)	0.322(0.290)	0.217(0.177)
$f(z)$: segmented linear function	Yes	Yes	Yes	Yes
$f(z)$: polynomial function	Yes	Yes	Yes	Yes
Sample size	1005	1600	2928	1446

Note: The above results are estimated on a 2010 sample, with the Precision Poverty Reduction Policy carried forward to 2010 as a "placebo" shock to the timing of policy implementation.

4. Conclusion

This study highlights the critical role that informatization technology plays in improving the effectiveness of educational resource allocation and advancing educational fairness by examining the mechanism of interaction between educational informatization and precision poverty alleviation. In addition to improving the disparity between urban and rural educational resources, educational informatization based on big data technology and the Internet platform offers a potent tool for precisely identifying impoverished groups and optimizing the allocation of educational resources. The empirical study's findings demonstrate that the specific poverty alleviation program significantly improves rural households' subjective well-being, particularly when it comes to non-farm work and medical expenses. The study also notes that obstacles like a lack of technical assistance and data integration issues still exist in the process of encouraging the use of informatization for reducing poverty in education, and that these issues require immediate attention through technological innovation and policy support.

All things considered, this study demonstrates that the use of digital technology in precision poverty alleviation not only increases the effectiveness of poverty alleviation but also establishes a strong basis for the achievement of educational equity and social inclusion. Strengthening the technological support system for education informatization, encouraging the development of informatization infrastructure in remote locations, and guaranteeing the sustainability and accessibility of digital educational resources should be the main goals of future research and policy development.

Author contributions: Conceptualization, HJ and GY; methodology, HJ; software, HJ; validation, GY; formal analysis, HJ; investigation, GY; resources, GY; data curation, HJ; writing—original draft preparation, HJ; writing—review and editing, GY; visualization, HJ; supervision, GY; project administration, GY; funding acquisition, GY. All authors have read and agreed to the published version of the manuscript.

Funding: 2023 Natural Science Foundation of Hunan Province: Departmental Joint Fund, Research on the Mechanism of Education Informatization Promoting Precise Poverty Alleviation from the Perspective of Digital Divide, 2023JJ60250.

Ethical approval: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

References

1. Liu Y, Fan Y, Wang Y, et al. City innovation ability and internet infrastructure development: Evidence from the “Broadband China” policy. Bulletin of Economic Research. 2023; 76(1): 121-146. doi: 10.1111/boer.12421
2. Xu J, Zhang A, Chen Q. Internet Development, Population Aging and Urban-rural Income Gap: An Empirical Analysis Based on Provinces in China. Advances in Management and Applied Economics; 2024.
3. Altay A, Mirici İH. Efl Instructors’ Implementations of 21st Century Skills in Their Classes. International Journal for Housing Science and Its Applications. 2024; 45(2): 37-46.
4. Wu Y. Exploration of the Integration and Application of the Modern New Chinese Style Interior Design. International Journal for Housing Science and Its Applications. 2024; 45(2): 28-36.
5. Xiang Y, Lyu Y, Wang D. Effects of Digital Economy on Factor Market Distortion in China: A Spatial Econometric Approach. Journal of Advanced Computational Intelligence and Intelligent Informatics. 2024; 28(4): 909-919. doi: 10.20965/jaciii.2024.p0909
6. Njanike K, Mpofu RT. Factors Influencing Financial Inclusion for Social Inclusion in Selected African Countries. Insight on Africa. 2023; 16(1): 93-112. doi: 10.1177/09750878231194558
7. Tariq H, Amer MM, Ali K. Unveiling the Efficacy: Examining the Influence of Public Surveillance Cameras on Crime Rates. Journal of Excellence in Social Sciences. 2024; 3(2): 33-46. doi: 10.69565/jess.v2024i3.185
8. Kumar S, K. KP, Aithal PS. Tech-Business Analytics in Primary Industry Sector. International Journal of Case Studies in Business, IT, and Education; 2023.
9. Wang J, Wang K, Ding X. The threshold effect of tourism economy development on the relationship between FDI and SIDS’ inclusive growth. Current Issues in Tourism. 2022; 26(24): 4001-4017. doi: 10.1080/13683500.2022.2154198
10. Xia R, Wei D, Jiang H, et al. Study on the coupling coordination development of China’s multidimensional digital economy and industrial carbon emission efficiency. Environmental Science and Pollution Research. 2023; 30(53): 114201-114221. doi: 10.1007/s11356-023-29862-2
11. Krishnan S. Digitalisation of Indian smart cities: post-Covid-19 approaches to data, recognition and health monitoring. Cambridge Journal of Regions, Economy and Society. 2023; 16(2): 349-359. doi: 10.1093/cjres/rsad010
12. Yu K, Shi Y, Feng J. The influence of robot applications on rural labor transfer. Humanities and Social Sciences Communications. 2024; 11(1). doi: 10.1057/s41599-024-03333-6
13. Wang J, Xu Y. Factors influencing the transition of China’s economic growth momentum. National Accounting Review. 2024; 6(2): 220-244. doi: 10.3934/nar.2024010
14. Wang Y, Bai Y, Quan T, et al. Influence and effect of industrial agglomeration on urban green total factor productivity—On the regulatory role of innovation agglomeration and institutional distance. Economic Analysis and Policy. 2023; 78: 1158-1173. doi: 10.1016/j.eap.2023.04.024
15. Shahid MN, Fatima E, Gul H, Ali M. The Nexus between, Trade Openness, Foreign Remittances, Public Awareness, Energy Consumption, Economic Growth, and CO2 Emissions in Industrialized and Emerging Digital Economies. Business Review of Digital Revolution. 2024; 4(1): 12-25.

16. Fang F, Luo D, Huang Y, et al. How does regional GDP manipulation affect livelihood investment? Humanities and Social Sciences Communications. 2024; 11(1). doi: 10.1057/s41599-024-03735-6
17. Gao ZB, Qiu W, et al. On Vertex Euclidean Deficiency of One-Point Union and One-Edge Union of Complete Graphs. Journal of Combinatorial Mathematics and Combinatorial Computing. 2024; 121(1): 107-112. doi: 10.61091/jcmcc121-11
18. Lee CC, Du L, Wang C song. Carbon blessing or carbon curse? The role of fiscal policy. Economic Analysis and Policy. 2024; 83: 1097-1114. doi: 10.1016/j.eap.2024.08.012
19. Ribeiro VM. Role of next generation access networks on COVID-19 propagation: Empirical assessment with a dynamic multinomial discrete choice model framework. Journal of Digital Economy. 2023; 2: 97-118. doi: 10.1016/j.jdec.2023.06.002
20. Zhou Y, Li Y, Zhang L, et al. Spatial–temporal characteristics of geological disaster resilience in poverty and disaster-prone areas in China: a case study of Ganzi Prefecture. Environmental Science and Pollution Research. 2023; 30(35): 83401-83420. doi: 10.1007/s11356-023-28049-z