Digitalization and the Urban-Rural Education Gap: Evidence from China's Rural Distance Compulsory Education Project

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Abstract: *Public investment in the information and telecommunications technology (ICT) for rural basic education is crucial for promoting the sharing of high-quality educational resources urban and rural areas and advancing educational equity. Utilizing data from the 2015 China 1% Population Sample Survey, this study evaluates the impact of the "Pilot Project for Modern Distance Education in Rural Primary and Secondary Schools" on educational equity. We analyze these effects through two lenses: the urban-rural education gap and inter-generational educational mobility within rural areas. Our findings reveal a dual effect: while a 100-yuan increase in per-student funding from the project narrows the urban-rural attainment gap by approximately 12.80%, it simultaneously diminishes relative inter-generational mobility within rural communities. Specifically, the correlation between the educational rank-orders of parents and their children increases by roughly 9.52%, suggesting a strengthening of educational persistence. To explore the mechanisms behind these divergent results, we conduct an analysis based on theoretical models of public education investment and human capital accumulation. The analysis demonstrates that although the project promotes overall human capital formation in rural areas, individuals from advantaged family backgrounds benefit disproportionately. This skewed distribution of benefits stems primarily from uneven improvements in educational quality resulting from the project's implementation strategies. Heterogeneity analysis further indicates that females and children from wealthier households experience greater gains, while local fiscal preferences and managerial incentives influence the extent to which policy effects are realized. We conclude that while advancing rural distance education remains vital, policy focus should prioritize equitable fund allocation and the establishment of robust oversight mechanisms to ensure that educational informatics investments realize their potential for inclusive growth.*

Keywords: *Rural distance compulsory education; Urban-rural education gap; Inter-generational educational mobility; Public investment in education*

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1. Introduction

The quality of education an individual receives in early life profoundly shapes their lifelong development; consequently, educational equity plays a pivotal role in advancing overall social justice. As society evolves, the focus of educational equity has shifted from a mere "access to schooling" toward the "quality of education received" (Yang et al., 2021). Notably, this transition is underscored in recent national policy agendas: the Report to the 19th National Congress of the Communist Party of China (CPC) pledged to "strive to ensure that every child enjoys fair access to good education," a commitment reaffirmed by the 20th CPC National Congress, which emphasized achieving equity through a high-quality education system and "accelerating the high-quality, balanced development and urban-rural integration of compulsory education." Despite sustained increases in national investment, imbalances in educational quality—particularly in basic education—remain acute. As such, a substantial resource gap persists between urban and rural areas. Furthermore, disadvantaged families remain at a competitive disadvantage when vying for scarce, high-quality resources, leading to a visible ossification of inter-generational educational transmission (Lv et al., 2020; Zhang et al., 2020). Consequently, increasing attention from scholars and policymakers is being paid to issues of educational equity, particularly the equitable distribution of resources and the persistent correlation between an individual's socioeconomic background and their educational outcomes.

This study evaluates rural educational equity through two primary lenses: the urban-rural education gap and inter-generational educational mobility. While the former captures regional inequality between urban and rural sectors, the latter denotes the ease with which rural individuals can surpass their parents' educational attainment through individual effort. Historically, rural China has been economically disadvantaged by the urban-rural dual economy, a developmental model that prioritized urban growth. As a result, the accumulation of human capital through education has become the primary conduit for rural households to achieve upward social mobility. However, a systemic scarcity of high-quality basic education resources has increasingly blocked this avenue. This is evidenced by a widening urban-rural attainment gap (Yang et al., 2021) and a declining trend in overall inter-generational mobility (Fan et al., 2021; Hu, 2022). In the current stage of "high-quality development," narrowing disparities and revitalizing mobility have become imperative policy objectives to ensure that rural children enjoy equitable opportunities from the earliest stages of their development.

To address the deficit in rural education quality, the Chinese government has explored leveraging Information and Communication Technology (ICT) to bridge the urban-rural divide by sharing premier pedagogical resources. A landmark initiative in this effort was the "Pilot Project for Modern Distance Education in Rural Primary and Secondary Schools" (the "Rural Distance Education Project", RDEP), which the Ministry of Education mandated in 2003, to be implemented starting in the autumn semester of the following year. Importantly, this project established three distinct configurations—CD-based teaching stations, satellite-linked reception sites, and specialized computer classrooms—to transmit high-quality content to rural compulsory education schools. Beyond infrastructure, this initiative integrated the development of digital courseware, pedagogical research, and teacher training, with the explicit aim of facilitating the sharing of

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high-quality urban-rural educational resources and enhancing the caliber of rural teaching staff. Unlike traditional classroom instruction, the RDEP overcomes geographical barriers at a relatively low marginal cost, delivering high-quality educational resources directly to project schools. This approach provided crucial support to alleviate chronic shortages and capacity constraints among teaching staff in rural areas.

The RDEP was implemented in phases over the 2004-2007 period, eventually spanning 2,444 county-level administrative regions[1]. While the initial budget was set at 10 billion yuan, total expenditure reached 11.1 billion yuan. The fiscal architecture of this program utilized a top-down, tiered governance structure: the central government first allocated earmarked transfer quotas to provincial governments. This subsequently identified project sites and schools and coordinated matching-fund commitments from provincial and sub-provincial budgets. A defining feature of the initiative was its regionally differentiated cost-sharing mechanism. Under this framework, the central government assumed the primary fiscal burden in western regions, contributing two-thirds of the total investment; played a supplementary role in central regions by covering one-third of the costs; and delegated financial responsibility to local governments in the east, where central support was reserved for designated impoverished areas. Ultimately, this large-scale investment benefited over 100 million students and achieved universal coverage across rural primary and secondary schools within the project's scope.

Evaluating the policy effects of an initiative on this scale is essential for informing the future trajectory of ICT-driven educational reform. Existing evidence remains sparse; notably, Bianchi et al. (2022) utilized 2014 China Family Panel Studies (CFPS) data to demonstrate that the project significantly enhanced beneficiaries' long-term human capital, labor market outcomes, and digital literacy. Expanding on these findings, the present study adopts an educational equity lens to address the following questions. First, has the RDEP narrowed the urban-rural education gap and rectified the structural imbalances within rural basic education? Second, how has the project reshaped inter-generational educational mobility within rural communities? Third, what are the underlying causal mechanisms driving these effects? Finally, what implementation shortcomings persist, and how might they be optimized? Therefore, answering these questions facilitates a more comprehensive assessment of the project's policy impact and provides empirical benchmarks for refining digitalization policies amidst the global trend of digital transformation.

The contributions of this study are threefold. First, in terms of perspective, it simultaneously examines the effects of targeted, distance-compulsory education investment on educational equity between urban and rural areas and within rural communities. Notably, this dual focus provides a comprehensive appraisal of the project's balancing effects and expands the research frontier regarding the beneficiaries of rural distance education policies. Second, methodologically, by treating the RDEP as an exogenous policy shock, the study identifies its causal effects on the urban-rural education gap and inter-generational mobility. Thus, it employs rigorous rank-order

[1] Initial implementation in 2004 covered 678 counties, followed by successive expansion to 893, 493, and 380 counties from 2005 to 2007, spanning 12 western provinces (autonomous regions and municipalities), six central provinces, as well as Shandong, Hebei, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan, and the Xinjiang Production and Construction Corps.

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correlation metrics to capture both the relative and absolute dimensions of mobility, thereby offering a more precise evaluation of policy impacts and elucidating the underlying causal mechanisms. Third, from a theoretical standpoint, the study contributes to the literature on public education investment by challenging the prevailing consensus that increases in public spending necessarily bolster inter-generational mobility. Based on theoretical modeling and empirical evidence, this study demonstrates that public education investment promotes mobility if and only if the distribution of incremental benefits is progressive, effectively favoring disadvantaged groups.

2. Literature Review and Theoretical Framework

2.1 Literature Review

The urban-rural education gap in China is rooted in a historical urban-bias in resource allocation and the dual economic structure that emerged under this policy orientation. This prolonged institutional dichotomy has generated entrenched disparities between urban and rural sectors in terms of economic endowments, cultural capital accumulation, educational systems, and pedagogical norms (Lv and Liu, 2010). Importantly, public education policy intervention is an indispensable instrument for arresting the path-dependent widening of these disparities. However, the efficacy of such interventions hinges on whether the benefits disproportionately accrue to rural individuals. Existing studies illustrate this conditionality: while the abolition of tuition and fees for compulsory education primarily alleviated the liquidity constraints faced by rural households, thereby fostering human capital accumulation and narrowing the urban-rural attainment gap (Lin, 2021), the expansion of higher education was largely captured by urban individuals from advantaged backgrounds, inadvertently exacerbating the gap (Li, 2010; Luo and Liu, 2018). While the RDEP theoretically insulated its beneficiaries from urban competition by targeting rural areas exclusively, whether this public investment has indeed boosted overall rural human capital and narrowed the urban-rural gap remains an open question, requiring rigorous empirical investigation.

Inter-generational educational mobility measures the degree to which educational attainment is transmitted from parents to children, with weaker correlations indicating greater mobility and greater educational equity. Compared with alternative indicators—such as inter-generational income or occupational mobility—educational measures offer distinct empirical advantages. Specifically, educational attainment is more readily and accurately observed, attenuating the life-cycle bias inherent in income data (Haider and Solon, 2006; Fan et al., 2021) as well as attenuation bias arising from measurement error (Solon, 1992; Wang et al., 2019). Furthermore, as most individuals in China complete formal schooling early in life, educational mobility provides a particularly effective lens for assessing equality of opportunity during formative years (Fletcher and Han, 2019; Lv et al., 2020). Current literature typically bifurcates mobility into relative and absolute measures, which are conceptually distinct yet highly complementary (Torche, 2021; Wang and Shao, 2021). Relative inter-generational educational mobility captures the extent to which the disparity in outcomes between children from the highest- and lowest-educated backgrounds narrows in proportion to the parental gap; a ratio closer to zero indicates lower inter-generational persistence and stronger relative mobility. However, because this ratio is sensitive to shifts in the mean outcomes of both groups, analyzing absolute mobility is essential for isolating underlying

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distributional shifts. Absolute mobility is defined as the expected attainment gap between children and their parents at a given parental education level, with larger positive gaps indicating stronger upward mobility (Chetty et al., 2014). By comparing these gains across the parental education spectrum, researchers can more precisely identify the mechanisms driving variations in relative mobility.

Estimates of inter-generational educational mobility are highly sensitive to the metric employed; common indicators include educational attainment ranks, years of schooling, and categorical levels. Analyzing mobility using absolute years of schooling or ordinal levels is prone to nontrivial estimation bias, primarily due to cross-generational shifts in the marginal distributions (mean and variance) of attainment (Li et al., 2017). Utilizing rank-based measures effectively mitigates these biases as they are robust to such distributional changes. Chetty et al. (2014) systematically demonstrated the advantages of using parent-child rank correlations to measure income mobility—an approach that has gained broad consensus (Wang et al., 2019; Yang and Wang, 2020; Yuan and Liu, 2022) and is increasingly applied to educational mobility (Liu et al., 2018; Fletcher and Han, 2019; Lv et al., 2020; Asher et al., 2024). Following Chetty et al. (2014), we group the sample by region and the child's birth cohort. Within each stratum, we calculate each child's percentile rank relative to their peers, along with the corresponding rank of their parents relative to other parents in the same cohort. The slope coefficient from a linear regression of child ranks on parent ranks serves as the primary measure of relative mobility (or persistence). Furthermore, the intercept and slope of this regression allow us to estimate the expected educational rank of a child given a specific parental rank, thereby facilitating a robust analysis of absolute mobility.

The inter-generational correlation of educational outcomes is primarily rooted in the genetic inheritance of endowments and the transmission of household resources (Becker and Tomes, 1979; Solon, 2004). As a vital conduit for educational resources beyond the familial environment, investment in public education is a critical determinant of intergenerational mobility. Existing research on Chinese public expenditure generally yields a consistent finding: increased investment significantly fosters educational mobility (Li and Zhou, 2015; Liu and Duan, 2017; Fan, 2020; Peng and Zhao, 2022). However, a gross increase in public funding does not inherently translate into higher mobility; the progressivity of its allocation is the more decisive factor. Theoretical frameworks by Solon (2004) and Kotera and Seshadri (2017) demonstrate that the distributional equity of public resources is a fundamental driver of mobility outcomes. This is further corroborated by literature on higher education expansion, which suggests that if the benefits of increased investment accrue disproportionately to certain groups, mobility may stagnate or even deteriorate (Blanden and Machin, 2013; Yang, 2016; Zhang and Wan, 2018; Guo et al., 2019). Consequently, whether a specific public education initiative successfully promotes inter-generational mobility remains a question that demands rigorous, context-specific empirical validation.

While existing literature offers extensive theoretical and empirical insights into the relationship between public education investment, regional disparities, and social mobility, several critical analytical gaps remain. First, most studies adopt a fragmented framework, examining equalization effects either between urban and rural areas or within rural communities in isolation. This approach

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overlooks the complementary insights provided by an integrated analysis of both dimensions. Second, research on inter-generational mobility often relies on absolute attainment metrics and fails to distinguish between relative and absolute mobility, leaving room for methodological and conceptual refinement. Third, domestic scholarship occasionally overlooks the pivotal role of distributional equity, leading to the reductive premise that increased expenditure automatically translates into enhanced mobility—a conclusion that warrants further scrutiny. Specifically regarding the RDEP, while Bianchi et al. (2022) established its positive impact on long-term individual development, improved average outcomes are not synonymous with enhanced educational equity. Furthermore, their methodological approach does not fully account for the simultaneous evolution of human capital accumulation among both urban and rural cohorts. Consequently, it remains unclear whether the RDEP actively narrowed the urban-rural gap or merely staved off its further divergence. Given the project's significance as a pioneer in educational digitalization, this study investigates its impact on cross-sectoral disparities and intra-rural inter-generational mobility, seeking to provide a more comprehensive evaluation of its equity-enhancing effects.

2.2 Theoretical Framework

Building on human capital theory and drawing on the model framework developed by Solon (2004) to analyze inter-generational income mobility, this study extends the analysis to examine how public investment in human capital influences human capital accumulation and its inter-generational transmission. Thus, it provides a theoretical foundation for assessing the effects of the RDEP on urban-rural educational disparities and rural inter-generational educational mobility. Consider a family i consisting of a parent in period $t-1$ and a child in period t. In the absence of credit-worthiness and inter-generational transfers such as bequests, the family must allocate the parent's lifetime after-tax income, $(1\text{-}T)Y_{i,t\text{-}1,}$ between the parent's own consumption, $C_{i,t\text{-}1}$, and investment in the child's human capital, $E_{i,t\text{-}1}$, where taxation is modeled as a proportional tax with rate T. For analytical tractability, the family's utility function is assumed to take a Cobb-Douglas form:

$$U_i = (1-\alpha)\ln C_{i,t-1} + \alpha \ln Y_{i,t} \tag{1}$$

Where $0 < \alpha < 1$ denotes the weight the household assigns to the child's future income. The household's utility maximization problem is subject to the following budget constraint:

$$(1-T)Y_{i,t-1} = C_{i,t-1} + E_{i,t-1} \tag{2}$$

Human capital formation is determined by the specific inputs an individual receives and by other innate endowments. The human capital function is specified in a semi-logarithmic form as follows:

$$H_{i,t} = \theta \ln\left(E_{i,t-1}\right) + e_{i,t} \tag{3-1}$$

$$H_{i,t} = \theta \ln\left(E_{i,t-1} + G_{i,t-1}\right) + e_{i,t} \tag{3-2}$$

Equation (3-1) characterizes the baseline scenario involving only private human capital investment, whereas Equation (3-2) represents the augmented case that incorporates both private and public human capital inputs. Here, $G_{i,t\text{-}1}$ denotes public human capital investment, such as public expenditures on education or health. $\theta > 0$, and $e_{i,t}$ represents additional innate endowments, such as inherited intelligence or family-influenced learning aptitude. Given the inherent link

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between these endowments and family background, we assume that $e_{i,t}$ is correlated with $e_{i,t\text{-}1}$, following a first-order autoregressive process:

$$e_{i,t} = \delta + \lambda e_{i,t-1} + \varepsilon_{i,t} \tag{4}$$

Where $0 < \lambda < 1$ denotes the coefficient of inter-generational transmission (or the degree of persistence) of innate endowments, and $\varepsilon_{i,t}$ signifies the stochastic error term.

The link between individual income and human capital is specified as follows, where $p > 0$ represents the rate of return on human capital:

$$\ln Y_{i,t} = \mu + pH_{i,t} \tag{5}$$

Accordingly, the household utility function can be reformulated as:

$$U_i = (1-\alpha)\ln\left[(1-T)Y_{i,t-1} - E_{i,t-1}\right] + \alpha\left(\mu + pH_{i,t}\right) \tag{6}$$

From the first-order conditions (FOCs) for utility maximization:

$$\frac{\partial U_i}{\partial E_{i,t-1}} = \frac{-(1-\alpha)}{(1-T)Y_{i,t-1} - E_{i,t-1}} + \alpha p \frac{\partial H_{i,t}}{\partial E_{i,t-1}} = 0 \tag{7}$$

In the absence of public human capital investment, substituting this into Equation (3-1) yields the optimal level of private investment as:

$$E_{i,t-1} = \frac{\alpha p\theta}{1-\alpha(1-p\theta)}(1-T)Y_{i,t-1} \tag{8-1}$$

Substituting the first-order condition into Equation (3-2) gives the optimal level level when public investment is present:

$$E_{i,t-1} = \frac{\alpha p\theta}{1-\alpha(1-p\theta)}(1-T)Y_{i,t-1} - \frac{1-\alpha}{1-\alpha(1-p\theta)}G_{i,t-1} \tag{8-2}$$

In a steady state, and in the absence of public human capital investment, Equations (3-1) and (8-1) imply the following relationship between the child's human capital and parental income:

$$H_{i,t} = \theta \ln\left[\frac{\alpha p\theta}{1-\alpha(1-p\theta)}(1-T)Y_{i,t-1}\right] + e_{i,t} \tag{9-1}$$

In the presence of public human capital investment, Equations (3-2) and (8-2) yield the relationship between the child's human capital, parental income, and public human capital investment as follows:

$$H_{i,t} = \theta \ln\left[\frac{\alpha p\theta}{1-\alpha(1-p\theta)}(1-T)Y_{i,t-1} - \frac{1-\alpha}{1-\alpha(1-p\theta)}G_{i,t-1} + G_{i,t-1}\right] + e_{i,t} \tag{9-2}$$

A comparison of Equations (9-1) and (9-2) reveals that public human capital investment leads to higher human capital accumulation among offspring in generation *t*. Accordingly, we propose the following hypothesis:

Hypothesis 1 (H1): The targeted investment of the RDEP facilitates human capital accumulation among rural offspring, thereby narrowing the urban-rural educational gap.

To examine the impact of public human capital investment on the inter-generational mobility of human capital, we further simplify Equation (9-2). Following the analytical framework established by Solon (2004), we assume that:

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$$\frac{G_{i,t-1}}{(1-T)Y_{i,t-1}} = \varphi - \gamma\left(\mu + pH_{i,t-1}\right) \tag{10}$$

When $\gamma > 0$, the ratio of public human capital investment received by a household to its parental after-tax income decreases as parental human capital increases. That is, offspring from families with higher parental human capital receive relatively fewer benefits from public investment, characterizing a progressive distribution of public resources. Furthermore, a larger value of γ indicates a higher degree of progressivity, whereby households with lower parental human capital derive greater marginal benefits. Conversely, if $\gamma < 0$, the distribution is regressive, indicating that households with higher parental human capital capture a disproportionately large share of public investment.

The simplification of Equation (9-2) proceeds as follows:

$$\begin{aligned}
H_{i,t} &= \theta \ln\left[\frac{\alpha p\theta}{1-\alpha(1-p\theta)}(1-T)Y_{i,t-1} - \frac{1-\alpha}{1-\alpha(1-p\theta)}G_{i,t-1} + G_{i,t-1}\right] + e_{i,t} \\
&= \theta \ln\left[\frac{\alpha p\theta}{1-\alpha(1-p\theta)}(1-T)Y_{i,t-1} + \frac{\alpha p\theta}{1-\alpha(1-p\theta)}G_{i,t-1}\right] + e_{i,t} \\
&= \theta \ln\left\{\frac{\alpha p\theta}{1-\alpha(1-p\theta)}(1-T)Y_{i,t-1}\left[1 + \frac{G_{i,t-1}}{(1-T)Y_{i,t-1}}\right]\right\} + e_{i,t} \\
&= \theta \ln\frac{\alpha p\theta}{1-\alpha(1-p\theta)}(1-T) + \theta \ln Y_{i,t-1} + \theta \ln\left[1 + \frac{G_{i,t-1}}{(1-T)Y_{i,t-1}}\right] + e_{i,t}
\end{aligned}$$

When $\frac{G_{i,t-1}}{(1-T)Y_{i,t-1}}$ is sufficiently small, the above expression can be approximated as:

$$H_{i,t} \cong \theta \ln\frac{\alpha p\theta}{1-\alpha(1-p\theta)}(1-T) + \theta \ln Y_{i,t-1} + \theta\frac{G_{i,t-1}}{(1-T)Y_{i,t-1}} + e_{i,t}$$

Substituting the assumptions $\frac{G_{i,t-1}}{(1-T)Y_{i,t-1}} = \varphi - \gamma\left(\mu + pH_{i,t-1}\right)$ and $\ln Y_{i,t-1} = \mu + pH_{i,t-1}$ into the reduced form of Equation (10-2) yields:

$$\begin{aligned}
H_{i,t} &\cong \theta \ln\frac{\alpha p\theta}{1-\alpha(1-p\theta)}(1-T) + \theta\left(\mu + pH_{i,t-1}\right) + \theta\left[\varphi - \gamma\left(\mu + pH_{i,t-1}\right)\right] + e_{i,t} \\
&= \varphi\theta + \theta \ln\frac{\alpha p\theta(1-T)}{1-\alpha(1-p\theta)} + (1-\gamma)\theta\left(\mu + pH_{i,t-1}\right) + e_{i,t} \\
&= (1-\gamma)\theta\mu + \varphi\theta + \theta \ln\frac{\alpha p\theta(1-T)}{1-\alpha(1-p\theta)} + (1-\gamma)p\theta H_{i,t-1} + e_{i,t}
\end{aligned}$$

After simplifying Equations (9-1) and (9-2) and incorporating Equation (5), the structural relationships between the offspring's human capital and parental human capital—under the scenarios of zero and non-zero public human capital investment—are expressed as Equations (11-1) and (11-2), respectively.

$$H_{i,t} = \theta\mu + \theta \ln\frac{\alpha p\theta(1-T)}{1-\alpha(1-p\theta)} + p\theta H_{i,t-1} + e_{i,t} \tag{11-1}$$

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$$H_{i,t} \cong (1-\gamma)\theta\mu + \varphi\theta + \theta \ln \frac{\alpha p\theta(1-T)}{1-\alpha(1-p\theta)} + (1-\gamma)p\theta H_{i,t-1} + e_{i,t} \qquad (11\text{-}2)$$

In the absence of public human capital investment, the inter-generational correlation of human capital can be derived from Equations (11-1) and (4) as expressed in Equation (12-1). The derivation process is as follows:

From Equation (11-1) $H_{i,t} = \theta\mu + \theta \ln \frac{\alpha p\theta(1-T)}{1-\alpha(1-p\theta)} + p\theta H_{i,t-1} + e_{i,t}$, we have:

$$\frac{\partial H_{i,t}}{\partial H_{i,t-1}} = \frac{\operatorname{cov}(H_{i,t}, H_{i,t-1})}{\sqrt{\operatorname{var}(H_{i,t})}\sqrt{\operatorname{var}(H_{i,t-1})}} \times \frac{\sqrt{\operatorname{var}(H_{i,t})}}{\sqrt{\operatorname{var}(H_{i,t-1})}}$$
$$= \frac{\operatorname{cov}(H_{i,t}, H_{i,t-1})}{\operatorname{var}(H_{i,t-1})}$$

and

$$\operatorname{cov}(H_{i.t}, H_{i,t-1}) = \operatorname{cov}\left[\theta\mu + \theta \ln \frac{\alpha p\theta(1-T)}{1-\alpha(1-p\theta)} + p\theta H_{i,t-1} + e_{i,t}, H_{i,t-1}\right]$$
$$= p\theta \operatorname{cov}(H_{i,t-1}, H_{i,t-1}) + \operatorname{cov}(e_{i,t}, H_{i,t-1})$$
$$= p\theta \operatorname{var}(H_{i,t-1}) + \operatorname{cov}(e_{i,t}, H_{i,t-1})$$

Combining this with Equation (4) $e_{i,t} = \delta + \lambda e_{i,t-1} + \varepsilon_{i,t}$, we have:

$$\operatorname{cov}(e_{i,t}, H_{i,t-1}) = \operatorname{cov}(\delta + \lambda e_{i,t-1} + \varepsilon_{i,t}, H_{i,t-1})$$
$$= \lambda \operatorname{cov}(e_{i,t-1}, H_{i,t-1}) + \operatorname{cov}(\varepsilon_{i,t}, H_{i,t-1})$$
$$= \lambda \operatorname{cov}(e_{i,t}, H_{i,t})$$

and

$$\lambda \operatorname{cov}(e_{i,t}, H_{i,t}) = \lambda \operatorname{cov}\left[e_{i,t}, \theta\mu + \theta \ln \frac{\alpha p\theta(1-T)}{1-\alpha(1-p\theta)} + p\theta H_{i,t-1} + e_{i,t}\right]$$
$$= p\theta\lambda \operatorname{cov}(e_{i,t}, H_{i,t-1}) + \lambda \operatorname{cov}(e_{i,t}, e_{i,t})$$

It follows that:

$$\operatorname{cov}(e_{i,t}, H_{i,t-1}) = \lambda \operatorname{cov}(e_{i,t}, H_{i,t})$$
$$= p\theta\lambda \operatorname{cov}(e_{i,t}, H_{i,t-1}) + \lambda \operatorname{cov}(e_{i,t}, e_{i,t})$$
$$= \frac{\lambda \operatorname{var}(e_{i,t})}{1-p\theta\lambda}$$

and

$$\operatorname{var}(H_{i,t}) = \operatorname{var}\left[\theta\mu + \theta \ln \frac{\alpha p\theta(1-T)}{1-\alpha(1-p\theta)} + p\theta H_{i,t-1} + e_{i,t}\right]$$
$$= p^2\theta^2 \operatorname{var}(H_{i,t-1}) + \operatorname{var}(e_{i,t}) + 2p\theta \operatorname{cov}(e_{i,t}, H_{i,t-1})$$
$$= p^2\theta^2 \operatorname{var}(H_{i,t-1}) + \operatorname{var}(e_{i,t}) + 2p\theta \frac{\lambda \operatorname{var}(e_{i,t})}{1-p\theta\lambda}$$

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$$= \frac{\mathrm{var}\left(e_{i,t}\right) + 2p\theta \dfrac{\lambda\,\mathrm{var}\left(e_{i,t}\right)}{1-p\theta\lambda}}{1-p^2\theta^2}$$

$$= \frac{\left(1+p\theta\lambda\right)\mathrm{var}\left(e_{i,t}\right)}{\left(1-p\theta\lambda\right)\left(1-p^2\theta^2\right)}$$

Lastly, we obtain Equation (12-1):

$$\frac{\partial H_{i,t}}{\partial H_{i,t-1}} = \frac{\mathrm{cov}\left(H_{i,t}, H_{i,t-1}\right)}{\mathrm{var}\left(H_{i,t-1}\right)}$$

$$= \frac{p\theta\,\mathrm{var}\left(H_{i,t-1}\right) + \mathrm{cov}\left(e_{i,t}, H_{i,t-1}\right)}{\mathrm{var}\left(H_{i,t-1}\right)}$$

$$= p\theta + \frac{\mathrm{cov}\left(e_{i,t}, H_{i,t-1}\right)}{\mathrm{var}\left(H_{i,t-1}\right)}$$

$$= p\theta + \frac{\mathrm{cov}\left(e_{i,t}, H_{i,t-1}\right)}{\mathrm{var}\left(H_{i,t}\right)}$$

$$= p\theta + \frac{\dfrac{\lambda\,\mathrm{var}\left(e_{i,t}\right)}{1-p\theta\lambda}}{\dfrac{\left(1+p\theta\lambda\right)\mathrm{var}\left(e_{i,t}\right)}{\left(1-p\theta\lambda\right)\left(1-p^2\theta^2\right)}}$$

$$= \frac{p\theta+\lambda}{1+p\theta\lambda}$$

i.e.,

$$\frac{\partial H_{i,t}}{\partial H_{i,t-1}} = \frac{p\theta+\lambda}{1+p\theta\lambda} \tag{12-1}$$

In the presence of public human capital investment, the inter-generational correlation of human capital can be derived analogously from Equations (11-2) and (4) as follows:

$$\frac{\partial H_{i,t}}{\partial H_{i,t-1}} = \frac{\left(1-\gamma\right)p\theta+\lambda}{1+\left(1-\gamma\right)p\theta\lambda} \tag{12-2}$$

A comparison of Equations (12-1) and (12-2) shows that the impact of public human capital investment on the inter-generational relationship of human capital depends primarily on the parameter γ. When $\gamma > 0$—indicating that public human capital investment is progressive—an increase in such investment weakens the inter-generational correlation of human capital. This thereby enhances relative inter-generational educational mobility. Moreover, the stronger the degree of progressivity, the greater the improvement in relative educational mobility. By contrast, when $\gamma < 0$, public human capital investment is not progressive; instead, increased investment strengthens the intergenerational correlation of human capital, leading to a decline in relative educational mobility. Accordingly, this paper proposes the following hypothesis:

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Hypothesis 2 (H2): Whether the RDEP promotes inter-generational educational mobility in rural areas depends primarily on whether the distribution of benefits from this public educational investment is progressive.

3. Data, Variables, and Model

3.1 Data Sources and Processing

This study draws on three types of data: (i) project-level information on investment under the RDEP, (ii) micro-level household data, and (iii) region-level socioeconomic data. Data on project-specific investment are obtained from official Ministry of Education documents and include the number of project schools and the scale of central and local fiscal expenditures across 2,444 participating counties during 2004-2007.[2]

The micro-level household data comes from the 2015 National 1% Population Sample Survey, including information such as the district/county code of the household's location, housing, and vehicle ownership. Individual-level details within the household comprise *hukou* (household registration) location, gender, ethnicity, educational attainment, and other relevant variables. The region-level data primarily comes from the *China County Statistical Yearbook*, *China City Statistical Yearbook*, *China Regional Statistical Yearbook*, and various local statistical yearbooks or statistical compilations.

In compiling the RDEP investment data, this study applies several selection criteria aligned with the research design. First, samples from the Tibet Autonomous Region and Zhejiang Province are excluded because only province-level aggregate investment figures are publicly available, making it impossible to obtain precise county-level project data. Second, the Xinjiang Production and Construction Corps and most of Yichun City in Heilongjiang Province—excluding Jiayin County and Tieli City—are excluded from the sample because their administrative systems differ substantially from those of other regions[3], potentially compromising comparability. Third, the sample is further restricted to counties and county-level cities among the remaining project

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[2] Data for the Rural Modern Distance Education Project are derived from official documents jointly issued by the General Offices of the Ministry of Education, the National Development and Reform Commission (NDRC), and the Ministry of Finance: 2004: Data are sourced from the *Audit Opinions on the Pilot Work Plan for the Modern Distance Education Project in Rural Primary and Secondary Schools* (Jiao Ji Ting Han [2004] No. 30). 2005: Data are sourced from the *Audit Opinions on the 2004-2005 Implementation Plan for the Modern Distance Education Project in Rural Primary and Secondary Schools* (Jiao Ji Ting [2005] No. 13). 2006: Data are sourced from the *Audit Opinions on the 2006 Implementation Plan for the Modern Distance Education Project in Rural Primary and Secondary Schools for 14 Provinces including Hebei* (Jiao Ji Ting [2006] No. 8) and the *Audit Opinions on the 2006 Implementation Plan for the Modern Distance Education Project in Rural Primary and Secondary Schools for 7 Provinces and Autonomous Regions including Shanxi* (Jiao Ji Ting [2006] No. 10). 2007: Data are sourced from the *Audit Opinions on the 2007 Implementation Plan for the Modern Distance Education Project in Rural Primary and Secondary Schools for 13 Provinces, Autonomous Regions, and Municipalities* (Jiao Ji Ting [2007] No. 6) and the *Audit Opinions on the 2007 Implementation Plan for the Modern Distance Education Project in Rural Primary and Secondary Schools for 5 Provinces and Autonomous Regions* (Jiao Ji Ting [2007] No. 9).

[3] The Xinjiang Production and Construction Corps (XPCC) operates under a unique management system characterized by the highly unified integration of Party, administrative, military, and corporate authority. Yichun is a forest-based municipality where, with the exception of Jiayin County and Tieli City, all constituent areas transitioned from former forestry districts. Historically, these areas adopted a "government-enterprise nexus", in which forestry administration bureaus and district governments functioned as a single, unified entity.

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areas[4]. This restriction is imposed because non-agricultural populations dominate urban districts, and, in the absence of reliable county- or district-level data on rural students, calculating per-student investment would introduce substantial measurement error. Moreover, focusing exclusively on project-implementing regions avoids confounding differences with largely non-participating, more economically developed eastern counties. Applying these criteria yields a final sample of 1,692 counties and county-level cities that implemented the RDEP.

The 2015 China National 1% Population Sample Survey data were processed as follows. First, household heads, spouses, and children are identified as the offspring cohort, and parent-generation information is matched using the intra-household roster[5]: children are linked to household heads and spouses; household heads to their parents; and spouses to their parents-in-law. This strategy maximizes the number of matched child-parent pairs, with all relationships defined relative to the household head. Second, the offspring cohort's birth years are restricted to 1983-1996. Given that the RDEP was inaugurated in the fall semester of 2004, individuals born in 1988 or earlier had already aged out of compulsory education and were thus unaffected by the policy. Conversely, excluding those born after 1996 ensures that all observations had reached adulthood by the 2015 survey, allowing for more stable measurements of final educational attainment. Third, observations still in school at the time of the survey are excluded. Fourth, if a respondent's *de facto* residence differs from their *de jure* (*hukou*) registration, the regional identifier is adjusted to the *hukou* location to reflect the policy environment (Fan, 2020) accurately. Finally, aligned with the project's targeting criteria, rural status is proxied by the possession of land contractual rights (Kang et al., 2023). Analyses of the urban-rural education gap use the full integrated sample. In contrast, the investigation of intra-rural inter-generational mobility and its underlying mechanisms focuses exclusively on rural individuals with land rights. The final processed dataset comprises 131,410 child-parent observation pairs.

3.2 Key Variable Definitions

3.2.1 Child and parent educational ranks

Following Chetty et al. (2014), this study first groups all matched child-parent observations by province[6] and the child's birth year. Grouping by province is motivated by China's province-based college entrance examination system, under which relative educational standing within a province

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[4] The analytical focus is restricted to counties and county-level cities because municipal districts are predominantly urban and composed of non-agricultural populations. In the absence of granular data on rural students at the district and county levels, estimating per-student investment for beneficiaries based on aggregate regional data would introduce significant measurement error. Furthermore, the sample is limited to regions that implemented the Rural Distance Education Project. Given the project's broad geographic coverage, the excluded regions consist primarily of prosperous districts and counties in eastern China, which differ systematically from project areas. Restricting the sample in this manner ensures greater comparability between observations and mitigates potential selection bias.

[5] Specifically, for individuals classified as children, the corresponding parent-generation sample consists of the household head and the head's spouse. For individuals identified as household heads, the parent-generation sample comprises those recorded as their parents. For spouses, the parent-generation sample is drawn from parents-in-law. This matching procedure is designed to maximize the number of intergenerational (child–parent) pairs. Throughout, the terms "household head," "spouse," "child," "parent," and "parent-in-law" refer to each individual's relationship to the household head within the household structure.

[6] The primary rationale for calculating educational rank-orders at the provincial level is that college admissions in China are characterized by intra-provincial competition. Consequently, an individual's relative standing within their province is a critical determinant of their eventual educational attainment.

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is a determinative factor in final educational attainment. Within each province-cohort group, we calculate the proportion of individuals at each attainment level. An individual's educational rank is defined as the cumulative share of individuals with lower attainment plus one-half of the share at their own attainment level—a standard approach to generating percentile ranks for discrete data. For parents, educational attainment is defined as the higher of the two levels achieved by either parent. In the 2015 survey, educational attainment was classified into eight categories. In our calculations, general high school and vocational secondary school are collapsed into a single tier. For example, the rank of an unschooled child equals one-half of the share of unschooled children in their cohort; the rank of a primary-school graduate equals the full share of unschooled children plus one-half of the primary-school share, and so forth. While ranks are identical for individuals with the same attainment within a province-cohort group, spatial variation in educational composition across counties allows for the identification of heterogeneous inter-generational correlations. Crucially, the ranks assigned to rural individuals reflect their position within the pooled urban-rural sample, thereby capturing their relative standing in the aggregate national educational distribution.

3.2.2 Expected child educational rank

Given a specific Parental educational rank, the corresponding expected educational rank of the child is defined as the child's expected educational outcome. Operationally, within each project county or county-level city, matched child-parent observations are grouped according to the intensity of exposure to the RDEP. Within each group, a linear regression of child educational rank on parental educational rank is estimated. Let the intercept of the fitted regression be m, and the slope be n. The expected educational rank of a child whose parent ranks at the 25th percentile is then given by $m + n \times 25$. The accuracy of expected child rank estimates depends on the reliability of the fitted linear relationship, which, in turn, improves with greater variation and more child- and parent-rank observations in the regression.

3.2.3 Distance education project policy intensity

The policy variable is defined as the cumulative per-student treatment intensity an individual experiences during compulsory education. This measure is constructed by cross-referencing an individual's birth year with the RDEP's implementation timeline for their county. For example, in a county that inaugurated the project in 2004, individuals born in 1988 or earlier had already matriculated into senior secondary school or entered the labor market; they are therefore assigned a null treatment value. Individuals born in 1989 were in their final year of junior secondary school in 2004; their treatment intensity is defined as the county's per-student investment in that year. Per-student investment is calculated using primary school enrollment from the year before implementation.[7] This proxy is used because most counties report the aggregate enrollment across all secondary schools, making it difficult to isolate junior secondary students. However,

[7] The total number of students in compulsory education was not utilized because the vast majority of county-level administrative regions aggregate junior high and senior high school enrollments into a single category of "general secondary school students." Given the inability to accurately disaggregate these figures, and considering the stability of the ratio between primary and junior high school enrollments as well as the continuity of benefits from the Rural Distance Education Project across these stages, this study employs the number of primary school students as a proxy to calculate the per-capita investment of the project.

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given the stable ratio between primary and junior secondary enrollments, primary enrollment provides a reliable proxy for the target population. If no additional investment occurred after 2004, individuals born between 1990 and 1996 are assigned the same intensity as the 1989 cohort. If the county undertook a second round of investment in 2005, the 1990 cohort receives a cumulative dosage equal to the sum of the 2004 and 2005 per-student investments, with subsequent cohorts following an analogous accumulation logic.

3.2.4 Control variables

At the individual level, the set of control variables includes the child's gender and ethnicity. At the regional level, although the implementation of the RDEP constitutes an exogenous policy intervention, the design of local matching contributions implies that actual investment levels may still be correlated with pre-existing regional characteristics, such as economic development, population density, fiscal capacity, education expenditure preferences, telecommunications infrastructure, and school conditions. To mitigate potential endogeneity concerns, this study follows Liang and Wang (2020) and Duflo (2001) by interacting pre-policy regional characteristics with child birth-year dummy variables in the baseline regressions, thereby allowing baseline regional traits to exert cohort-specific or trend-differentiated effects across birth cohorts. Pre-policy regional characteristics are measured at the county or county-level city in 2003 and include the share of the agricultural population, the logarithm of population density, the logarithm of per capita GDP, fiscal self-sufficiency (defined as the ratio of general public budget revenue to general public budget expenditure), local education spending preference (the share of education expenditure in general public budget expenditure), the logarithm of per capita telecommunications business revenue (with prefecture-level data used as substitutes where county-level data are missing)[8], the primary school student-teacher ratio, and average primary school size.

Furthermore, several concurrent education policies were implemented alongside the RDEP. To isolate the project's effects from potential confounders, the analysis includes interaction terms between offspring birth-year dummies and variables that capture exposure to these policies. These include: the nationwide rollout of Free Compulsory Education in rural areas (2006-2007); the School Consolidation program (2001-2012); Higher Education Expansion; the second phase of the National Compulsory Education Project for Poor Areas; the "Two Basics" Program in the western region (specifically targeting the basic universalization of nine-year compulsory education and the basic elimination of illiteracy among youth and young adults); the Rural Boarding School policy; and the "Two Exemptions and One Subsidy" program (providing exemptions for tuition and textbook fees, alongside a living subsidy for boarding students from low-income families). For the Free Compulsory Education policy—which was implemented nationwide and lacks a clear intensity proxy—control is maintained by the number of semesters an individual was exposed to, calculated based on local implementation timing and birth year (Peng and Zhao, 2022). For other policies, treatment intensity or target-region indicators are interacted with birth-year dummies. Specifically, School Consolidation intensity is measured by the reduction in primary schools per

[8] Due to a substantial proportion of missing values in county-level per-capita telecommunications revenue, data from the respective prefecture-level cities are used as a proxy for the project counties and county-level cities.

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student between 2000 and 2012; Higher Education Expansion is proxied by provincial college enrollment per 10,000 residents in 1997 (Xing and Li, 2011); and the target area for both the National Compulsory Education Project for Poor Areas and the "Two Basics" Initiative is defined as the western region (Wang et al., 2019). Finally, the Rural Boarding School policy targets areas that had not achieved the "Two Basics" by the end of 2002 (Bianchi et al., 2022), while the "Two Exemptions and One Subsidy" targets poverty-stricken counties nationwide.

3.3 Econometric Model

To examine the impact of the RDEP on the urban-rural education gap and relative inter-generational educational mobility in rural areas, this study estimates the following econometric model:

$$\begin{aligned} RANK_{ijb} = {} & \alpha_0 + \alpha_1 Rural_{ijb} + \alpha_2 Treat_{jb} + \alpha_3 Treat_{jb} \times Rural_{ijb} + \alpha_4 RANK^0_{ijb} \\ & + \mathbf{X}'_{ijb}\boldsymbol{\alpha}_5 + \mathbf{Z}'_j f(b)\boldsymbol{\alpha}_6 + \mu_j + \eta_b + \gamma_t + \tau_{ijb} \end{aligned} \tag{13}$$

$$\begin{aligned} RANK_{ijb} = {} & \beta_0 + \beta_1 RANK^0_{ijb} + \beta_2 Treat_{jb} + \beta_3 Treat_{jb} \times RANK^0_{ijb} \\ & + \mathbf{X}'_{ijb}\boldsymbol{\beta}_4 + \mathbf{Z}'_j f(b)\boldsymbol{\beta}_5 + \mu_j + \eta_b + \gamma_t + \xi_{ijb} \end{aligned} \tag{14}$$

Here, i indexes individuals, j denotes the project county or county-level city in which the individual resides, and b indicates the child's birth year. $RANK_{ijb}$ represents the child's educational rank measured using educational attainment reported in the 2015 1% Population Sample Survey. $Rural_{ijb}$ is a dummy variable indicating whether the child belongs to a rural household (1 if rural, 0 otherwise). $Treat_{jb}$ captures the intensity of exposure to the RDEP for cohort b in county j. The coefficient α_3 on $Treat_{jb} \times Rural_{ijb}$ in Equation (13) is the primary coefficient of interest; a positive value indicates that the RDEP narrows the urban-rural education gap, while a negative value implies the opposite. $RANK_{ijb}{}^0$ denotes the corresponding parental educational rank. In Equation (14), the coefficient β_3 on $Treat_{jb} \times RANK_{ijb}{}^0$ is the key parameter of interest; a positive coefficient suggests that the project strengthens the correlation between children's and parents' educational ranks, thereby reducing relative inter-generational educational mobility, whereas a negative coefficient indicates increased mobility. $\boldsymbol{X}_{ijb}$ represents individual-level control variables, including gender and ethnicity. $\boldsymbol{Z}_j$ denotes a set of pre-policy regional characteristics measured in 2003 and contemporaneous education policy variables. Regional characteristic variables include the share of the agricultural population, the log of population density, the log of per capita GDP, the fiscal self-sufficiency rate, local government preference for education spending, the log of per capita telecommunications revenue, the primary school student-teacher ratio, and average primary school enrollment. Education policy variables encompass the number of semesters an individual was exposed to the Free Compulsory Education policy, the intensity of the school consolidation program, and the provincial college enrollment per 10,000 residents. Additionally, we include binary indicators for whether a location is in the western region (equal to 1 if so), whether it was a target area for the rural boarding school policy (equal to 1 if so), and whether it was a national poverty-stricken county (equal to 1 if targeted by the "Two Exemptions and One Subsidy" program). In the empirical specification, $f(b)$ represents birth-year dummy variables.[9] We incorporate county

[9] The Free Compulsory Education policy variable is directly represented by the number of semesters an individual was exposed to the policy; consequently, it is not interacted with the birth-year dummy variables $f(b)$.

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fixed effects μ_j and birth-year fixed effects η_b. Furthermore, to account for potential heterogeneity across different project rollout phases, we control for implementation-year fixed effects γ_t, defined by the year in which a county or county-level city first adopted the RDEP. Finally, τ_{ijb} and ξ_{ijb} represent the stochastic error terms for Equations (13) and (14), respectively. Standard errors in all regressions are clustered at the county level to account for potential within-region correlation.

To investigate the mechanisms through which the RDEP affects the urban-rural education gap and rural relative inter-generational educational mobility, this study further estimates the following econometric model to analyze the impact of the project on absolute educational attainment and absolute inter-generational mobility among rural samples:

$$Y_{ijb}=\omega_0+\omega_1 Treat_{jb}+\mathbf{X}'_{ijb}\omega_2+\mathbf{Z}'_j f(b)\omega_3+\mu_j+\eta_b+\gamma_t+v_{ijb} \quad (15)$$

When examining the mechanisms underlying changes in the urban-rural education gap, Y_{ijb} denotes the child's absolute educational attainment, including standardized years of schooling, a dummy variable for high school entry, and a dummy variable for college entry. When analyzing mechanisms underlying absolute intergenerational educational mobility in rural areas, Y_{ijb} denotes the expected educational rank of the child, conditional on a given parental rank. Specifically, expected child ranks at the 25th, 50th, and 75th percentiles of the parental educational rank distribution are examined and denoted as $E25$, $E50$, and $E75$, corresponding to children from lower-quartile, median, and upper-quartile parental education backgrounds, respectively. When estimating the impact of the RDEP on children's absolute educational attainment, $\boldsymbol{X}_{ijb}$ includes parental standardized years of schooling or categorical educational attainment, as well as the child's gender and ethnicity. When estimating effects on absolute inter-generational educational mobility, v_{ijb} includes only the child's gender and ethnicity. All remaining variables are defined as in Equation (13). The coefficient ω_1 on $Treat_{jb}$ is the main coefficient of interest; a positive estimate indicates that the RDEP promotes human capital accumulation or increases expected educational rank, while a negative estimate suggests the opposite. The results from Equation (15) provide insight into the underlying mechanisms driving the changes in the urban-rural education gap and rural relative inter-generational educational mobility identified in Equations (13) and (14). Descriptive statistics for the main variables are reported in Table 1.

TABLE 1. Descriptive Statistics of Key Variables

Variable	Sample unaffected by RDEP			Sample affected by RDEP		
	Observations	Mean	Standard deviation	Observations	Mean	Standard deviation
RDEP treatment intensity (100 yuan/student)	69702	0	0	61708	1.265	0.660
Offspring educational rank (%)	69702	45.947	25.347	61708	47.793	25.675
Parental educational rank (%)	69702	46.748	25.771	61708	48.099	24.579
Offspring educational attainment	69702	3.487	0.984	61708	3.539	0.937
Offspring high school enrollment (yes=1)	69702	0.367	0.482	61708	0.411	0.492
Offspring college enrollment (yes=1)	69702	0.148	0.355	61708	0.144	0.351
Parental educational attainment	69702	2.738	0.817	61708	2.821	0.743
Expected offspring rank at the 25th Parental percentile (%)	69606	39.432	7.527	60999	40.629	8.787
Expected offspring rank at the 50th Parental percentile (%)	69606	46.889	6.752	60999	48.153	7.429

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Table 1 Continued

Variable	Sample unaffected by RDEP			Sample affected by RDEP		
	Observations	Mean	Standard deviation	Observations	Mean	Standard deviation
Expected offspring rank at the 75th Parental percentile (%)	69606	54.322	8.678	60999	55.711	9.612
Offspring birth year	69702	1987	2.150	61708	1993	2.012
Offspring gender (male=1)	69702	0.696	0.460	61708	0.596	0.491
Offspring ethnicity (han=1)	69702	0.863	0.344	61708	0.851	0.356
Rural residency status (yes=1)	69702	0.750	0.433	61708	0.700	0.458
Year of initial RDEP implementation	69702	2005	0.998	61708	2005	0.935
Share of agricultural population	69702	0.848	0.113	61708	0.848	0.117
Log of population density	69702	5.501	0.985	61708	5.448	1.045
Log of per capita GDP	69702	8.518	0.581	61708	8.489	0.581
Fiscal self-sufficiency rate	69702	0.399	0.201	61708	0.384	0.201
Local education investment preference	69702	0.267	0.061	61708	0.266	0.061
Log of per capita telecommunications revenue	62602	5.203	0.696	54155	5.206	0.717
Student-teacher ratio in primary schools	62011	20.315	6.696	54819	21.187	6.903
Average primary school size (students per school)	63841	301	327	56379	324	394
Number of semesters impacted by free compulsory Education policy	69702	0.104	0.503	61708	6.010	4.060
Intensity of the school merger program	57870	0.003	0.006	50857	0.002	0.004
Provincial higher education enrollment per 10,000 people	69702	22.528	8.432	61708	22.006	8.260
Western region dummy (yes=1)	69702	0.323	0.467	61708	0.397	0.489
Target region for rural boarding school policy (yes=1)	69702	0.144	0.351	61708	0.152	0.359
Target region for the “two exemptions and one subsidy” policy (yes=1)	69702	0.265	0.441	61708	0.280	0.449

Notes: Educational attainment for both children and parents is coded on a seven-point scale: 1 = unschooled, 2 = primary school, 3 = junior high school, 4 = general or vocational high school, 5 = college diploma, 6 = bachelor’s degree, and 7 = postgraduate education. The following variables are measured using 2003 data from project regions: agricultural population share, logarithm of population density, logarithm of per capita GDP, fiscal self-sufficiency (the ratio of general public budget revenue to expenditure), local education expenditure preference (education spending as a share of the general public budget), logarithm of per capita telecommunications business revenue, primary school student-teacher ratio, and average primary school size. The number of semesters in which a child benefited from the Free Compulsory Education policy is calculated based on the individual’s birth date and the timing of policy implementation in the corresponding province. The intensity of the school consolidation policy is measured as the difference between the number of primary schools per student in 2000 and in 2012. The intensity of the Higher Education Expansion policy is proxied by the number of college students per 10,000 population at the provincial level in 1997. Target regions for the rural boarding school policy are those that had not achieved the “Two Basics” by the end of 2002, and target regions for the “Two Exemptions and One Subsidy” policy are nationally designated poverty counties.

4. Main Regression Results and Robustness Checks

4.1 Impact on the Urban-Rural Education Gap

Table 2 reports estimates from Equation (13) assessing the impact of the RDEP on the urban-rural education gap. Column (1) examines baseline educational disparities while controlling for regional and birth-year fixed effects. Column (2) adds the policy treatment variable and its interaction with the rural indicator, as well as fixed effects for the year of initial policy implementation. The interaction coefficient is positive and statistically significant at the 1% level, indicating that the RDEP significantly narrows the urban-rural education gap. Based on Column (2), Columns (3) and (4) sequentially incorporate interactions between pre-policy regional characteristics, contemporaneous education policies, and birth-year dummy variables.

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The results show that even after accounting for pre-existing regional conditions and overlapping policy influences, the RDEP continues to exert a robust effect in reducing the gap. The coefficient of 1.24 in Column (4) implies that a 100 yuan increase in per-student project investment offsets approximately 12.80% of the prevailing urban-rural education gap (1.24 divided by 9.69).

4.2 Impact on Rural Relative Inter-generational Educational Mobility

Table 3 presents estimates from Equation (14) evaluating the effect of the RDEP on relative inter-generational educational mobility within rural areas. Column (1) analyzes the correlation between children's and parents' educational ranks while controlling for regional and birth-year fixed effects. Column (2) adds the policy intensity variable and fixed effects for the year of policy rollout; the coefficient on policy intensity is positive and statistically significant at the 5% level, indicating that the project increases educational ranks among beneficiary rural children overall. Column (3) introduces the interaction between policy intensity and parental educational rank. The interaction coefficient, approximately 0.02 and significant at the 1% level, indicates that higher policy intensity is associated with a stronger correlation between children's and parents' educational ranks, implying a decline in relative inter-generational educational mobility in rural areas. Columns (4) and (5) further incorporate interactions between pre-policy regional characteristics, other education policies, and birth-year dummy variables. The interaction coefficient remains highly stable in both magnitude and statistical significance. Quantitatively, the coefficient of 0.02 implies that a 100 yuan increase in per-student project investment raises the correlation between children's and parents' educational ranks by approximately 9.52% (0.02 divided by 0.21), thereby reducing relative inter-generational educational mobility.

TABLE 2. Impact of the RDEP on the Urban-Rural Education Gap

Variable	Offspring educational rank			
	(1)	(2)	(3)	(4)
Treat×Rural		1.470***	1.329***	1.235***
		(0.229)	(0.263)	(0.273)
Treat		-0.809***	-0.770***	-0.615**
		(0.239)	(0.280)	(0.293)
Rural Sample	-9.685***	-10.582***	-10.908***	-10.946***
	(0.250)	(0.296)	(0.333)	(0.348)
Parental educational rank	0.273***	0.273***	0.264***	0.264***
	(0.004)	(0.004)	(0.004)	(0.004)
Individual controls	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes
Policy wave fixed effects	No	Yes	Yes	Yes
Region characteristics × Birth cohort dummies	No	No	Yes	Yes
Education policy controls × Birth cohort dummies	No	No	No	Yes
Observations	131,410	131,410	108,565	102,273
R-squared	0.200	0.201	0.183	0.182

Notes: Individual-level control variables include the offspring's gender and ethnicity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Cluster-robust standard errors are reported in parentheses and are clustered at the county level.

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TABLE 3. Impact of the RDEP on Rural Relative Inter-Generational Educational Mobility

Variable	Offspring educational rank				
	(1)	(2)	(3)	(4)	(5)
Treat×Parental educational rank			0.017***	0.020***	0.023***
			(0.005)	(0.005)	(0.005)
Treat		0.453**	-0.339	-0.553*	-0.644*
		(0.206)	(0.294)	(0.336)	(0.350)
Parental educational rank	0.213***	0.213***	0.203***	0.199***	0.198***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Individual controls	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Policy wave fixed effects	No	Yes	Yes	Yes	Yes
Region characteristics×Birth cohort dummies	No	No	No	Yes	Yes
Education policy controls×Birth cohort dummies	No	No	No	No	Yes
Observations	95,461	95,461	95,461	81,605	77,048
R-squared	0.151	0.151	0.151	0.134	0.133

Notes: Same as Table 2.

4.3 Identification Validity

The causal identification strategy in this study relies on utilizing pre-treatment cohorts as a counterfactual for later-born cohorts. The fundamental identifying assumption is that, in the absence of the RDEP, the cross-regional differences in the urban-rural education gap and rural inter-generational rank correlations would have followed a stable trend across birth cohorts. Following the methodology of Lin (2021) and Xiao et al. (2017), we test this parallel trends assumption using the 1983-1988 cohorts, which were not exposed to the policy. Specifically, the project's implementation dates are temporally back-shifted by one to five years to create placebo treatment assignments. Using these fictitious timings, we reconstruct the policy intensity variables and re-estimate Equations (13) and (14). Figure 1 illustrates the resulting coefficients for the key interaction terms. Notably, for the urban-rural gap and rural relative mobility, the interaction coefficients under these placebo scenarios are statistically insignificant, with point estimates tightly bounded around zero. These results confirm that no divergent trends existed before the policy shock, thereby validating the causal interpretation of our findings and the overall credibility of the research design.

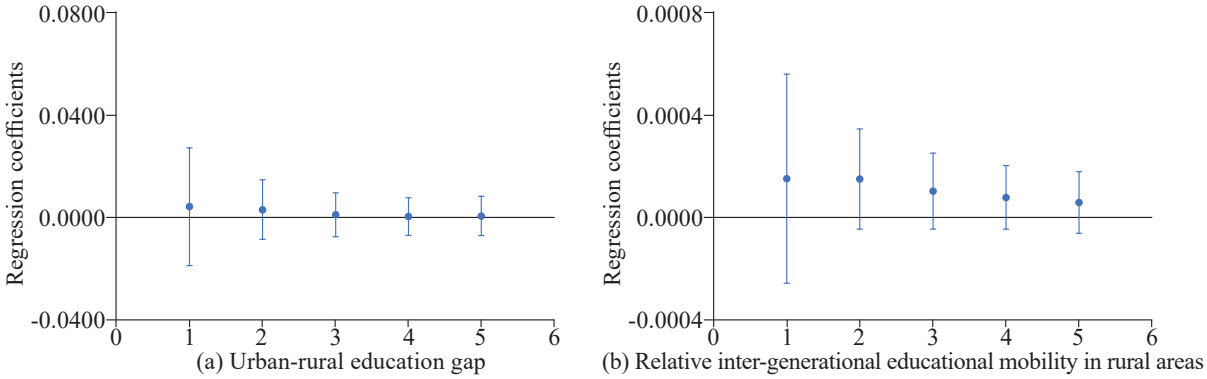

Fig. 1. Identification Validity

Note: Figure 1 reports regression results based on Equations (13) and (14) using the 1983-1988 birth cohorts that were not exposed to the RDEP. The policy implementation year is artificially advanced by one to five years. The horizontal axis indicates the number of years by which the policy timing is shifted forward, and the vertical line segments represent 95% confidence intervals.

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4.4 Robustness Checks

To further assess the reliability of the main regression results, a series of robustness checks is conducted.

4.4.1 Alternative measures of distance education project intensity

First, the baseline policy variable is replaced with the number of project schools per student, calculated using a method analogous to that used to construct the per-student investment variable. Second, following the approach of Bianchi et al. (2022), the policy is redefined as a binary treatment indicator equal to one if the individual's county implemented the project before they completed compulsory education, and zero otherwise. Third, drawing on Peng and Zhao (2022), the cumulative duration of exposure—measured by the actual number of semesters an individual spent in treated schools—is used as a proxy for treatment intensity. The regression results presented in Table 4 demonstrate that the directionality and statistical significance of the interaction terms remain remarkably stable across all alternative specifications. These results provide strong evidence that the baseline findings are robust to different definitions of policy intensity.

TABLE 4. Robustness Checks: Alternative Measures of Distance Education Project Intensity

Variable	Offspring educational rank					
	Number of project schools per student		Binary treatment dummy (0/1)		Number of treatment semesters	
	(1)	(2)	(3)	(4)	(5)	(6)
	Urban-rural education gap	Relative educational inter-generational mobility (rural)	Urban-rural education gap	Relative educational inter-generational mobility (rural)	Urban-rural education gap	Relative educational inter-generational mobility (rural)
Treat×Rural sample	0.217*** (0.064)		2.836*** (0.394)		0.388*** (0.042)	
Treat×Parental educational rank		0.006*** (0.001)		0.025*** (0.008)		0.003*** (0.001)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Policy wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region characteristics×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Education policy controls×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102,273	77,048	102,273	77,048	102,273	77,048
R-squared	0.182	0.133	0.183	0.133	0.183	0.133

Note: To conserve space, coefficients on the corresponding standalone terms of the interaction variables are not reported. All other notes are identical to those in Table 2.

4.4.2 Alternative measures of educational outcomes

We further examine whether measuring educational outcomes in absolute terms, rather than by rank order, significantly alters the baseline findings. Columns (1) and (2) of Table 5 report the regression results in which the education of both child and parent is measured as ordinal attainment

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levels. Columns (3) and (4) convert these categorical measures into linear years of schooling and re-estimate the model using standardized versions of these variables. Across these alternative specifications, the estimated coefficients remain highly consistent with those obtained in the baseline regressions. These results demonstrate that the main findings are robust to the choice of measurement and remain valid even after accounting for cross-generational shifts in mean attainment and distributional variance.

TABLE 5. Robustness Checks: Alternative Measures of Educational Outcomes

Variable	Offspring educational attainment (categorical)		Standardized offspring years of schooling	
	(1)	(2)	(3)	(4)
	Urban-rural education gap	Relative rural inter-generational educational mobility	Urban-rural education gap	Relative rural inter-generational educational mobility
Treat×Rural	0.059*** (0.010)		0.058*** (0.010)	
Treat×Parental educational attainment		0.034*** (0.007)		0.039*** (0.006)
Individual controls	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes
Policy wave fixed effects	Yes	Yes	Yes	Yes
Region characteristics×Birth cohort dummies	Yes	Yes	Yes	Yes
Education policy controls×Birth cohort dummies	Yes	Yes	Yes	Yes
Observations	102,273	77,048	102,273	77,048
R-squared	0.208	0.140	0.198	0.140

Note: In Columns (1) and (2), child and parental educational attainment are measured using categorical variables with the following values: 1 = unschooled, 2 = primary school, 3 = junior high school, 4 = general or vocational high school, 5 = college diploma, 6 = bachelor's degree, and 7 = postgraduate degree. In Columns (3) and (4), child and parental education are measured using standardized years of schooling. Before standardization, years of schooling were coded as follows: 0 = unschooled, 6 = primary school, 9 = junior high school, 12 = general or vocational high school, 15 = college diploma, 16 = bachelor's degree, and 19 = postgraduate degree. All other notes are identical to those in Table 2.

4.4.3 Accounting for county-to-district conversions

During the period between the implementation of the RDEP and the 2015 survey, several pilot areas underwent urban administrative conversions from counties or county-level cities to municipal districts. Given the limited number of such cases and the potential for these areas to introduce idiosyncratic shocks, they were initially excluded from the baseline regressions. To assess whether this reclassification affects our findings, we perform two supplementary analyses. First, we re-incorporate units that were classified as counties at the time of implementation but had been converted to municipal districts by 2015. Second, we further refine this sample by excluding areas that experienced cross-jurisdictional boundary shifts during their conversion, thereby ensuring more precise identification of policy exposure. Columns (1) and (2) of Table 6 report estimates including all converted areas, while Columns (3) and (4) provide estimates excluding those with boundary adjustments. The coefficients on the key interaction terms remain positive and statistically significant at the 1% level across all specifications. These results substantiate

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the robustness of our primary findings: while the RDEP successfully narrowed the urban-rural education gap, it simultaneously reduced relative inter-generational educational mobility within the rural sector.

TABLE 6. Robustness Checks: County-to-District Conversions

Variable	Offspring educational rank			
	(1)	(2)	(3)	(4)
	Urban-rural education gap	Relative rural inter-generational educational mobility	Urban-rural education gap	Relative rural inter-generational educational mobility
Treat×Rural	1.192*** (0.272)		1.315*** (0.271)	
Treat×Parental educational rank		0.022*** (0.005)		0.022*** (0.005)
Individual controls	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes
Policy wave fixed effects	Yes	Yes	Yes	Yes
Region characteristics×Birth cohort dummies	Yes	Yes	Yes	Yes
Education policy controls×Birth cohort dummies	Yes	Yes	Yes	Yes
Observations	106,707	80,262	104,771	78,940
R-squared	0.183	0.133	0.183	0.134

Note: Columns (1)-(4) add individuals from areas that experienced county or county-level city to municipal district conversions between the implementation of the RDEP and 2015. Columns (1) and (2) include all such converted areas, while Columns (3) and (4) further exclude areas in which cross-county-level jurisdictional adjustments occurred during conversion, allowing for more precise identification of treatment exposure. All other notes are identical to those in Table 2.

4.4.4 Accounting for urban-rural classification

Following Kang et al. (2023), rural status is determined by land contractual rights. This strategy is constrained by the omission of explicit agricultural *hukou* indicators in the 2015 1% Population Sample Survey; however, land rights serve as a robust proxy for individuals who were de facto rural residents during their formative years but subsequently transitioned to non-agricultural status. While conceptually sound, this criterion is susceptible to potential misclassification, warranting a robustness check. A primary concern is that certain urban residents retain land contract rights despite limited exposure to the RDEP. To address this, we restrict the rural sample to individuals who both possess land rights and reside in rural areas (as identified by the 2015 residence classification code 220), thereby excluding land-rights holders currently in urban settings. Although this adjustment entails a trade-off in sample size, it substantially enhances the internal validity of treatment identification. Conversely, institutional rigidities in land allocation may mean that some genuinely rural children do not personally hold land rights. We therefore expand our definition to include individuals whose parents possess land rights and whose own permanent residence is rural. This multi-layered refinement minimizes classification errors for the offspring cohort. The regression results under these alternative criteria, reported in Table 7, demonstrate that the interaction coefficients remain entirely consistent with the baseline findings in both directionality and significance, further substantiating the reliability of our primary results.

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TABLE 7. Robustness Checks: Urban-Rural Classification

Variable	Offspring educational rank			
	(1)	(2)	(3)	(4)
	Urban-rural education gap	Relative rural inter-generational educational mobility	Urban-rural education gap	Relative rural inter-generational educational mobility
Treat×Rural	1.287*** (0.286)		0.808*** (0.307)	
Treat×Parental educational rank		0.025*** (0.007)		0.025*** (0.006)
Individual controls	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes
Policy wave fixed effects	Yes	Yes	Yes	Yes
Region characteristics×Birth cohort dummies	Yes	Yes	Yes	Yes
Education policy controls×Birth cohort dummies	Yes	Yes	Yes	Yes
Observations	70,863	45,628	70,863	52,223
R-squared	0.214	0.140	0.226	0.137

Note: Columns (1) and (2) exclude individuals who possess land contractual rights but whose permanent residence is non-rural. Columns (3) and (4) build on this restriction by additionally classifying as rural those individuals whose parents hold land contractual rights, who themselves do not, and whose permanent residence is rural. All other notes are identical to those in Table 2.

5. Mechanism Analysis

To clarify the underlying mechanisms through which the RDEP both narrowed the urban-rural education gap and reduced relative inter-generational mobility within rural areas, this section is organized into three analytical components. First, we examine the project's impact on human capital accumulation among the rural offspring cohort. Second, we analyze the project's effects on expected child rank orders conditional on parental standing—effectively explaining shifts in relative mobility through the lens of absolute intergenerational mobility. Finally, we investigate how the project's specific implementation design influenced the aggregate distribution of benefits.

5.1 Effects on Absolute Educational Attainment of Rural Individuals

In accordance with Hypothesis 1, the primary channel through which the RDEP narrows the urban-rural education gap is by augmenting public education investment. This thereby catalyzes the accumulation of human capital among rural beneficiaries. We test this mechanism using Equation (15) to estimate the project's impact on absolute educational outcomes. Column (1) of Table 8 reports estimates for standardized years of schooling. The coefficient on per-student project investment is positive and statistically significant, indicating that increased funding significantly raises attainment levels. Column (2) presents the results for high-school enrollment, showing that a 100-yuan increase in per-student investment raises the probability of matriculation by 1.30 percentage points. Column (3) reports similar effects on college enrollment, where the same investment increase raises the probability of university entry by 0.60 percentage points. Taken together, these results demonstrate that the project substantially promotes human capital

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accumulation at both the intensive margin (years of schooling) and the extensive margin (educational thresholds), ultimately serving as the primary conduit for the observed reduction in the urban-rural education gap.

5.2 Effects on Absolute Inter-generational Educational Mobility in Rural Areas

Columns (4) through (6) of Table 8 present estimates from Equation (15), characterizing the heterogeneous impacts of the RDEP on expected child educational ranks conditional on parental standing. These estimates provide a granular view of the project's effect on absolute inter-generational mobility within rural areas. In Column (4), for children whose parents are at the 25th percentile (low-attainment), the coefficient on project intensity is positive (0.24) but statistically insignificant. Conversely, Column (5) shows that at the parental median (50th percentile), the coefficient rises to 0.81, significant at the 1% level. For children at the 75th percentile (high-attainment) in Column (6), the impact further escalates to 1.42, likewise significant at the 1% level. Since these expected ranks are derived from a linear rank-rank specification, the coefficients are directly comparable and reveal a stark monotonic gradient: the RDEP significantly bolsters educational outcomes for children from middle- and high-attainment families while failing to generate statistically significant gains for those from the most disadvantaged backgrounds. Consequently, while the project fosters aggregate human capital growth, it disproportionately benefits the rural elite, thereby exacerbating inter-generational persistence and reducing relative mobility. Therefore, this empirical pattern substantiates the theoretical inference that regressive public investment—wherein benefits accrue more heavily to advantaged households—inherently constrains social fluidity.

Table 8: Mechanism Analysis: Effects of the RDEP on Rural Absolute Educational Attainment and Absolute Inter-generational Mobility

Variable	Standardized offspring years of schooling	Offspring high school enrollment	Offspring college enrollment	*E*25	*E*50	*E*75
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.016* (0.009)	0.013*** (0.005)	0.006* (0.003)	0.240 (0.293)	0.814*** (0.223)	1.424*** (0.338)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Policy wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region characteristics×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Education policy controls×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,048	77,048	77,048	76,504	76,504	76,504
R-squared	0.139	0.140	0.085	0.674	0.763	0.679

Note: In Column (1), individual-level controls include parental standardized years of schooling, child gender, and ethnicity. In Columns (2) and (3), the dependent variables are binary indicators equal to 1 if the child enters high school or university and 0 otherwise; Individual controls additionally include parental educational attainment categories (defined as in Table 5), along with child gender and ethnicity. All other notes are identical to those in Table 2.

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5.3 Differential Benefits Across Project School Types

The RDEP classified participating schools into three types: CD-based teaching sites (Mode I), satellite reception sites (Mode II), and computer classrooms (Mode III). Mode I targeted rural teaching points that geographic constraints necessitated retaining, with investments consisting of televisions, DVD players, and grade-specific instructional discs. Mode II focused on village complete primary schools and township central schools; in addition to the equipment and discs for Grades 1-6 provided under Mode I, these schools received computers, satellite reception systems, and one to two multimedia classrooms. Mode III was directed at rural junior high schools and included all hardware and software from Mode II, plus the construction of a computer lab equipped with 30 terminals to provide students with basic internet-based learning environments. In terms of spatial reach, Modes I and II could be deployed to dispersed villages, whereas Mode III schools—typically rural junior high schools—were usually located in township centers, often far from villages (Jia and Zeng, 2012). Infrastructure requirements also escalated across modes. Mode I required only basic electricity; Mode II required access to the China Education Satellite Broadband Network; Mode III demanded substantially stronger network infrastructure. Moreover, the project guidelines stipulated that selected schools must ensure the equipment operates normally.[10] As a result, Mode III schools were relatively few and were more likely to be located in areas with better information infrastructure and higher levels of economic development.

Table 9 presents estimates from Equation (15), wherein treatment intensity is disaggregated by project school type. Given that Modes I and II were designed to penetrate village-level schools, we aggregate these categories to compare their impact against the more advanced Mode III (Computer Classrooms). Columns (1) and (4) examine the impacts on children from the bottom quartile (25th percentile) of parental education. The results indicate that while Modes I and II significantly bolster the expected ranks of children from low-education backgrounds, the Mode III coefficient is not statistically significant for this disadvantaged group, despite its larger point estimate. The remaining columns illustrate the effects at the median and 75th parental percentiles. While all three modes significantly improve expected outcomes, the impact of Mode III far exceeds that of Modes I and II. Furthermore, while the benefits of Modes I and II are relatively uniform across the distribution, Mode III exhibits significant heterogeneity, with the largest gains accruing disproportionately to children from high-education families. Essentially, while computer laboratories generate the most potent educational dividends, they are the least equitably distributed. These findings substantiate Lucas's (2001) theory of Effectively Maintained Inequality (EMI): even as quantitative access to education is equalized, advantaged social classes leverage qualitative disparities in school type and resource quality to secure a competitive edge for their offspring. Although the RDEP expanded the reach of digital resources, the inherent differences in implementation modes and local conditions created a regressive benefit structure. Ultimately, this intensified inter-generational persistence, as the "digital dividend" was captured more effectively

[10] *Notice of the Ministry of Education, the National Development and Reform Commission (NDRC), and the Ministry of Finance regarding the Implementation of the Pilot Work Plan for the Modern Distance Education Project in Rural Primary and Secondary Schools* (Jiao Ji [2003] No. 22).

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by those with pre-existing familial advantages.

TABLE 9. Mechanism Analysis: Differential Benefits Across Project School Types

Variable	DVD player stations+satellite receiving stations			Computer classrooms		
	*E*25	*E*50	*E*75	*E*25	*E*50	*E*75
	(1)	(2)	(3)	(4)	(5)	(6)
Mode I & Mode II Treatment	0.156** (0.063)	0.304*** (0.049)	0.434*** (0.078)			
Mode III treatment				0.475 (0.615)	1.390*** (0.505)	2.459*** (0.819)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Policy wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region characteristics×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Education policy controls×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76,681	76,681	76,681	76,607	76,607	76,607
R-squared	0.713	0.792	0.709	0.688	0.775	0.690

Note: The Mode I + Mode II *Treat* variable is defined as the per-student total number of CD-based teaching sites (Mode I) and satellite reception sites (Mode II). The Mode III *Treat* variable is defined as the per-student number of computer-classroom project schools. All other notes are identical to those in Table 2.

5.4 The Role of Information Infrastructure Development

The implementation of various project school modes necessitates a robust foundation of supporting information infrastructure. This subsection examines whether the local developmental level of such infrastructure moderates the realized benefits of the RDEP. Since most infrastructure indicators are aggregated at the provincial level—thereby obscuring marked intra-provincial disparities—we follow Zhu and Liu (2022) in employing prefecture-level per capita telecommunications revenue as a proxy. Compared with static construction metrics, this indicator more accurately captures the effective utilization rate of local digital resources. Table 10 reports estimates from Equation (15), partitioning the sample based on whether a region's 2003 per capita telecommunications revenue fell above or below the median. Notably, the results reveal that in high-infrastructure regions, the project significantly bolsters expected educational ranks across the entire parental distribution, with relatively uniform magnitudes. Conversely, in low-infrastructure regions, the gains are highly concentrated, with statistically significant improvements observed only in the 75th percentile (advantaged) cohort. Taken together with the previous analysis of school modes, these findings suggest that a robust information infrastructure is a critical complement, enabling the project's benefits to be fully realized and fostering a more egalitarian distribution of educational gains. In the absence of such infrastructure, the digital intervention is constrained, unintentionally favoring those from advantaged backgrounds who can better navigate or compensate for a resource-poor environment.

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TABLE 10. Mechanism Analysis: The Role of Information Infrastructure Development

Variable	Low per capita telecommunications revenue			High per capita telecommunications revenue		
	*E*25	*E*50	*E*75	*E*25	*E*50	*E*75
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.270 (0.420)	0.458 (0.328)	1.309** (0.538)	0.803** (0.408)	1.167*** (0.318)	1.539*** (0.453)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Policy wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region characteristics×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Education policy controls×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,179	37,179	37,179	39,325	39,325	39,325
R-squared	0.679	0.742	0.655	0.683	0.786	0.705

Notes: Same as Table 2.

6. Heterogeneity Analysis

Recognizing that various individual and regional factors may moderate the distributional impacts of the RDEP, this section explores heterogeneity across four dimensions: gender, household economic background, regional education spending preferences, and county-level fiscal responsibilities.

6.1 Gender Differences in Rural Benefits

Table 11 reports the heterogeneous effects of the project by gender among rural individuals. The shifts in expected educational ranks suggest that the project yields larger dividends for females than for males. This divergence is likely attributable to gender-specific developmental trajectories. A robust body of pedagogical and neurodevelopmental literature indicates that during compulsory schooling, boys typically exhibit slower cognitive maturation than their female peers, often resulting in weaker self-regulation and attenuated attentional persistence. Compared with traditional pedagogical methods, remote education requires greater learner autonomy to facilitate effective knowledge transfer. Furthermore, the efficacy of digital learning is heavily contingent upon the recipient's ability to maintain focus and resist online distractions. These developmental and behavioral differences likely explain the differential returns to the RDEP observed between male and female students.

6.2 Heterogeneity by Family Economic Background among Rural Individuals

Following the methodology of Cai et al. (2022), we construct a Family Economic Background Score using Principal Component Analysis (PCA) of dwelling-based proxies from the 2015 1% Population Sample Survey[11]. These indicators—encompassing floor area, housing structure,

[11] The housing condition data utilized in this study encompass the total floor area, structural type, total number of stories in the building, availability of toilet facilities, and the source of acquisition of the sample households' dwellings.

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TABLE 11. Heterogeneity Analysis: Gender Differences in Rural Benefits

Variable	Male			Female		
	***E*25**	***E*50**	***E*75**	***E*25**	***E*50**	***E*75**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Treat	0.213 (0.291)	0.770*** (0.224)	1.345*** (0.342)	0.272 (0.316)	0.878*** (0.238)	1.553*** (0.357)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Policy wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region characteristics×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Education policy controls×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,134	51,134	51,134	25,358	25,358	25,358
R-squared	0.688	0.773	0.691	0.679	0.767	0.687

Note: Fisher combination tests of coefficient equality yield a p-value of 0.060 for Columns (2) and (5), and 0.000 for Columns (3) and (6), rejecting the null hypothesis of equal coefficients. All other notes follow Table 2.

building height, sanitation facilities, and housing tenure—serve as a multidimensional measure of household wealth. The offspring cohort is then stratified into low- and high-background groups based on the intra-regional median score. Table 12 reports the estimates from Equation (15) regarding the project's impact on absolute inter-generational mobility across these two strata. The qualitative results are consistent with our full-sample analysis: in both groups, children of higher-attainment parents derive greater dividends from the project. However, a cross-group comparison of the coefficients reveals a clear socioeconomic gradient. For children at the 50th and 75th parental percentiles, the policy effects are markedly larger among the high-economic-background group than their less affluent counterparts. This suggests that household economic capital serves as a complementary input, enabling children from better-off families to capture the dividends of the RDEP disproportionately.

TABLE 12. Heterogeneity Analysis: Family Economic Background and Rural Benefits

Variable	Low family economic background score			High family economic background score		
	***E*25**	***E*50**	***E*75**	***E*25**	***E*50**	***E*75**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Treat	0.385 (0.315)	0.778*** (0.244)	1.220*** (0.379)	0.179 (0.328)	0.860*** (0.250)	1.555*** (0.361)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Policy wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region characteristics×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Education policy controls×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,350	36,350	36,350	37,505	37,505	37,505
R-squared	0.688	0.770	0.681	0.677	0.767	0.695

Note: Fisher combination tests of coefficient equality yield a p-value of 0.100 for Columns (2) and (5), and 0.000 for Columns (3) and (6), rejecting the null hypothesis of equal coefficients. All other notes follow Table 2.

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6.3 Heterogeneity by Local Education Investment Preferences

Local governments' pre-existing fiscal effort toward education may moderate the realized benefits of the RDEP. We proxy local education investment preferences with the share of education expenditure in the 2003 general public budget and partition regions into low- and high-preference groups based on the median ratio. Table 13 reports the estimates from Equation (15). Consistent with our primary findings, children with higher parental education ranks derive greater benefits across both groups. However, cross-group comparisons reveal a notable trade-off between aggregate gains and distributional equity. In regions with lower preferences for education investment, the coefficients across parental percentiles are relatively uniform, suggesting a more balanced distribution of benefits. Conversely, regions with higher preferences exhibit larger absolute gains but greater disparities across parental ranks. These divergent patterns likely stem from two distinct mechanisms. First, pre-existing local investment may crowd-in additional resources, creating a synergistic effect that amplifies the project's impact. Second, as noted by Fan and Zhang (2013), the project's matching-fund structure reduces the marginal cost of providing digital educational public goods. High-preference regions likely leverage this subsidy to prioritize the intensive deployment of capital-heavy Mode III (computer classroom) schools. In contrast, lower-preference regions may opt for less expensive modes requiring minimal local matching. Consequently, while high-preference areas realize greater absolute dividends, they also experience a regressive intensification of educational outcomes, whereas low-preference areas maintain a more equitable, albeit modest, benefit profile.

TABLE 13. Heterogeneity Analysis: Local Education Investment Preferences

Variable	Low local education investment preference			High local education investment preference		
	*E*25	*E*50	*E*75	*E*25	*E*50	*E*75
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.479	0.606*	0.739	0.031	1.013***	2.048***
	(0.409)	(0.322)	(0.477)	(0.430)	(0.308)	(0.473)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Policy wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region characteristics×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Education policy controls×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,268	36,268	36,268	40,236	40,236	40,236
R-squared	0.695	0.751	0.653	0.663	0.780	0.713

Notes: Same as Table 2.

6.4 Heterogeneity by County-Level Fiscal Responsibility

Since 2001, China has operated under a county-led financing system for compulsory education. However, county governments often face binding fiscal constraints; furthermore,

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because the returns on basic education are long-term and subject to inter-jurisdictional spillovers, local authorities may lack the incentive to ensure optimal investment. Consequently, scholars have frequently advocated for the upward shifting of fiscal responsibilities to higher levels of government (Gao, 2004; Qiao et al., 2005; Li and Yin, 2012). The 2004 project data reveal marked heterogeneity in how sub-provincial governments allocated matching-fund responsibilities for the RDEP. To examine whether these fiscal arrangements moderate policy outcomes, we partition the sample into regions in which county governments were required to provide matching funds and those in which they were exempt. Table 14 presents the results for absolute inter-generational mobility across these two groups. In regions where counties were exempt from matching requirements, the gains across parental percentiles were relatively uniform—suggesting a more balanced distribution—yet the estimates fail to reach statistical significance. Conversely, where counties bore matching-fund responsibilities, we observe larger absolute gains alongside weaker distributional equity. A plausible explanation is that funds drawn from local tax revenues are "costlier" than upper-level transfers. This higher opportunity cost of local capital likely heightens fiscal accountability and performance monitoring, leading to more intensive resource utilization targeted toward high-yield cohorts, ultimately resulting in larger but less egalitarian dividends.

TABLE 14. Heterogeneity Analysis: County-Level Fiscal Responsibility

Variable	Counties exempt from matching funds			Counties required to provide matching funds		
	*E*25	*E*50	*E*75	*E*25	*E*50	*E*75
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.246 (0.427)	0.570 (0.347)	0.866 (0.552)	0.239 (0.552)	1.028** (0.414)	1.849*** (0.542)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Policy wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region characteristics×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Education policy controls×Birth cohort dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,183	36,183	36,183	18,050	18,050	18,050
R-squared	0.675	0.732	0.639	0.658	0.805	0.762

Notes: Same as Table 2.

7. Conclusions and Policy Implications

The RDEP is a large-scale national endeavor to leverage information technology to deliver premium instructional resources to rural primary and secondary schools. Its primary objective was to promote the sharing of high-quality assets and catalyze improvements in teaching quality, while simultaneously exploring the feasibility of distance learning as a vehicle for the balanced development of compulsory education. Grounded in the theoretical nexus between public investment, human capital accumulation, and inter-generational mobility, this study utilizes data from the 2015 1% Population Sample Survey to evaluate the project's dual impact on urban-rural

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disparities and intra-rural mobility. Our analysis yields the following critical insights:

First, while the project significantly narrowed the urban-rural attainment gap, it also reduced relative intergenerational educational mobility in rural areas. Specifically, each additional 100 yuan of per-student project funding reduced the urban-rural education gap by approximately 12.80% and increased the correlation between children's and parents' educational rankings by 9.52%. This indicates a heightened degree of inter-generational persistence, a result that remains robust across alternative measures of variables and after accounting for administrative reclassifications and various urban-rural identification criteria.

Second, although the project bolstered aggregate human capital accumulation—thereby reducing the urban-rural gap—the internal distribution of these benefits was markedly uneven. We observe a clear regressive benefit structure: the project yielded no statistically significant improvement in expected educational outcomes for children in the bottom quartile (25th percentile) of parental education. In contrast, the gains for those in the top quartile (75th percentile) significantly outstripped those at the median. This capture of dividends by the rural elite explains why relative mobility declined even as absolute attainment rose.

Third, this regressive pattern is rooted in stratification arising from disparities in school modes and regional infrastructure. Consistent with the theory of Effectively Maintained Inequality (EMI) (Lucas, 2001), advantaged rural households were better positioned to secure higher-quality remote education. Furthermore, we find that the level of regional information infrastructure is a critical moderator; higher levels of such infrastructure enable the project's policy effects to be fully realized, thereby enhancing the equilibrium of benefit distribution across groups.

Finally, heterogeneity analyses reveal that female students and children from affluent households derived the greatest dividends. Furthermore, local governments' preferences for education spending and fiscal management incentives significantly shaped outcomes. Regions with higher education spending priorities realized larger absolute gains but lower distributional equity. In contrast, regions where county governments were exempt from matching-fund requirements exhibited more balanced, albeit markedly weaker, policy effects due to diminished local administrative incentives.

Based on the empirical evidence presented above, this study offers the following policy implications:

(1) Sustaining and Enhancing the Digital Pathway, with a Focus on Equity. The digitalization and informatization of rural basic education should be further strengthened as indispensable tools for rural revitalization, since the sharing of high-quality resources remains a primary engine for narrowing urban-rural disparities. Although our empirical results indicate that the project was associated with a decline in relative inter-generational mobility within rural areas, the underlying logic of this impact warrants careful interpretation. Specifically, the reduction in mobility reflects a scenario in which the educational outcomes of individuals from the most disadvantaged backgrounds remained statistically unchanged, while other rural cohorts experienced significant gains. That is, while the educational rank of children from low-ranking parental backgrounds remained unchanged, the ranks of children from middle- and high-ranking backgrounds ascended. Although this increases the ratio of child-to-parent educational rank variance—thereby statistically

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lowering relative mobility—it simultaneously reduces the absolute gap between a substantial portion of the rural population and their urban counterparts. From the perspective of aggregate rural welfare, this pattern constitutes a Pareto improvement, demonstrating that distance-based compulsory education is a viable and effective means of providing premium basic education in rural China.

(2) Enhancing Progressivity and Balancing Equity with Efficiency. In future development, greater emphasis should be placed on enhancing the progressivity of benefits from compulsory education in rural areas, thereby gradually mitigating quality disparities arising from differences in school types and levels of information infrastructure. The empirical findings of this study indicate that the regressive distribution of benefits under the RDEP was closely linked to shortcomings in policy implementation. In particular, requirements for local fiscal matching and supporting ICT infrastructure significantly affected the equity of benefit allocation, favoring relatively better-endowed areas. As educational digitalization and informatization continue to advance, policy design should more clearly embody compensatory principles by channeling high-quality basic education resources toward remote teaching sites and geographically indispensable rural schools. This approach is essential to ensuring smooth access to quality educational resources at the "first mile" of rural education delivery. Although infrastructure constraints on distance education have eased at this stage, sustained and targeted investment in lagging regions remains necessary to narrow persistent regional disparities. For rural individuals who are unable to relocate from impoverished, remote areas due to structural disadvantages, promoting educational equity requires a more effective balance between efficiency and fairness. Enhancing their access to high-quality basic education is therefore a fundamental component of advancing equitable educational development.

(3) Refining Governance and Oversight of Earmarked Educational Funds. There is a pressing need to improve further the oversight and management mechanisms for earmarked funds in basic education, as effective supervision is key to enhancing the efficiency of public spending. Our heterogeneity analysis of the Project's impacts under different county-level fiscal responsibility regimes reveals a salient trade-off. When earmarked investments for basic education are allocated through county-level matching requirements, the local "skin in the game" tends to lead to more efficient use of funds. However, because county governments vary significantly in their fiscal capacities and educational priorities, this structure can lead to a "regressive" pattern of benefits. This often results in a "Matthew Effect"—where "the strong become stronger, and the weak become weaker"—further entrenching existing disparities. Conversely, while shifting fiscal responsibility to higher levels of government and reducing or eliminating matching-fund obligations can promote geographic equity in fund distribution, it may simultaneously erode the incentives for local governments to manage those funds diligently, thereby undermining the full realization of policy benefits. Consequently, any upward reallocation of fiscal responsibility must be coupled with a strengthened emphasis on performance-based management. Thus, it is essential to implement robust, full-cycle monitoring systems to ensure that education funds are deployed with maximum efficiency and impact, balancing the dual goals of equity and effectiveness.

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References:

Asher S., Novosad P., Rafkin C. Intergenerational Mobility in India: New Measures and Estimates across Time and Social Groups [J]. American Economic Journal: Applied Economics, 2024(2): 66-98.

Becker G. S., Tomes N. An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility [J]. Journal of Political Economy, 1979(6): 1153-1189.

Bianchi N., Lu Y., Song H. The Effect of Computer-Assisted Learning on Students' Long-Term Development [J]. Journal of Development Economics, 2022, 158, 102919.

Blanden J., Machin S. Educational Inequality and the Expansion of United Kingdom Higher Education [J]. Scottish Journal of Political Economy, 2013(5): 597-598.

Cai W. X., Shen X. Y., Chen L. L. Human Capital Enhancement Effect of China Nutrition Improvement Program[J]. Journal of Quantitative & Technological Economics, 2022(10): 150-169.

Chetty R., Hendren N., Kline P., Saez E. Where Is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States [J]. The Quarterly Journal of Economics, 2014(4): 1553-1623.

Duflo E. Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment [J]. American Economic Review, 2001(4): 795-813.

Fan Y., Yi J., Zhang J. Rising Intergenerational Income Persistence in China [J]. American Economic Journal: Economic Policy, 2021(1): 202-230.

Fan Z. Y., Zhang J. Transfer Payments, Public Goods Provision and the Expansion of the Size of Government[J]. World Economic Papers, 2013(2): 1-19.

Fan Z. Y. Financial Transfer Payments and the Intergenerational Mobility of Human Capital[J]. Social Sciences in China, 2020(9): 48-67+205.

Fletcher J., Han J. Intergenerational Mobility in Education: Variation in Geography and Time [J]. Journal of Human Capital, 2019(4): 585-634.

Gao R. F. A Positive Analysis Current Financial System of Rural Compulsory Education in China[J]. Educational Research, 2004(5): 3-10.

Guo Y., Song Y., Chen Q. Impacts of Education Policies on Intergenerational Education Mobility in China [J]. China Economic Review, 2019(55): 124-142.

Haider S., Solon G. Life-Cycle Variation in the Association between Current and Lifetime Earnings [J]. American Economic Review, 2006(4): 1308-1320.

Hu Z. A. Intergenerational Mobility of Education in China: Methods and Facts[J]. Economic Science, 2022(5): 164-176.

Jia Y. H., Zeng X. The Negative Impact of Rural Primary and Secondary School Layout Adjustment on the Equity of the Starting Point of Education - A Survey Based on Nine Provinces (Districts) Across the Country[J]. Journal of Central China Normal University(Humanities and Social Sciences), 2012(3): 143-153.

Kang Y. K., Hou J. Y., Chen B. K. Government Educational Investment, Human Capital and Common Prosperity[J]. The Journal of World Economy, 2023(7): 140-164.

Kotera T., Seshadri A. Educational Policy and Intergenerational Mobility [J]. Review of Economic Dynamics, 2017, 25: 187-207.

Li C. L. Expansion of Higher Education and Inequality in Opportunity of Education: A Study on Effect of "Kuozhao" Policy on Equalization of Educational Attainment[J]. Sociological Studies, 2010(3): 82-113+244.

Li L. X., Zhou G. S. Family Credit Constraint, Public Education Expenditure, and Social Mobility in China[J]. China Economic Quarterly, 2015(1): 65-82.

Li R. Y., Chen X. R., Gan L. Intergenerational Mobility and its Decomposition: Growth and Structural Effects[J]. Economic Research Journal, 2017(9): 165-181.

Li S. G., Yin H. An External Analysis of the County-level Expenditure on Basic Education: With an Analysis of the Effectiveness of the "County-based" System[J]. Social Sciences in China, 2012(11): 81-97+205.

Liang C., Wang S. S. The Influence of Public School Allocation on Human Capital: Evidence from the School Consolidation in China[J]. Economic Research Journal, 2020(9): 138-154.

中国知网 https://www.cnki.net

Lin J. H. Free Compulsory Education Policy and the Urban-rural Gap in Education[J]. China Rural Survey, 2021(3): 128-144.

Liu N. N., Duan Y. D. The Impact of Fiscal Expenditure on the Educational Intergenerational Mobility: An Education Transition Perspective[J]. Finance & Economics, 2017(9): 35-45.

Liu X. G., Si H. P., Pang J. W. Regional Intergenerational Mobility and Well-Being: A Study Based on Intergenerational Education Mobility[J]. The Journal of World Economy, 2018(9): 171-192.

Lucas S. R. Effectively Maintained Inequality: Education Transitions, Track Mobility, and Social Background Effects [J]. American Journal of Sociology, 2001(6): 1642-1690.

Luo C. L., Liu X. X. Educational Expansion and Intergenerational Educational Mobility[J]. Social Sciences in China, 2018(2): 121-140+207.

Lv W., Guo M. M., Wang W. T. Equity of Educational Opportunity and Social Trust of Residents: Empirical Measurement and Micro-evidence from Urban Intergenerational Mobility of Education[J]. China Industrial Economics, 2020(2): 80-99.

Lv W., Liu G. H. Research on Some Influencing Factors of China's Educational Equalization[J]. Journal of Quantitative & Technological Economics, 2010(5): 20-33.

Peng J., Zhao X. L. Free Compulsory Education Policy and Equality of Educational Opportunity in Rural China: An Empirical Analysis from the Perspective of Intergenerational Mobility of Education[J]. China Rural Survey, 2022(2): 144-164.

Qiao B. Y., Fan J. Y., Feng X. Y. Fiscal Decentralization and Compulsory Primary Education in China[J]. Social Sciences in China, 2005(6): 37-46+206.

Solon G. A Model of Intergenerational Mobility Variation over Time and Place[J]. Generational Income Mobility in North America and Europe, 2004: 38-47.

Solon G. Intergenerational Income Mobility in the United States[J]. The American Economic Review, 1992: 393-408.

Torche F. Educational Mobility in Developing Countries[J]. Social Mobility in Developing Countries, 2021.

Wang D. H., Zou J., Mao Z. G. Schooling and Income Effect of Education Development in China: Evidence from the National Compulsory Education Project in China's Poor Areas[J]. Economic Research Journal, 2019(9): 155-171.

Wang W. T., Xie J. S., Zhang L. Research on the Measurement of Intergenerational Mobility Level and the Influencing Factors in China[J]. Journal of Quantitative & Technological Economics, 2019(1): 78-95.

Wang X. Q., Shao Y. H. Are We Better off than Our Parents? A Study on Intergenerational Income Upward Mobility in China[J]. The Journal of World Economy, 2021(3): 157-183.

Xiao Y., Li L., Zhao L. Education on the Cheap: The Long-Run Effects of a Free Compulsory Education Reform in Rural China [J]. Journal of Comparative Economics, 2017(3): 544-562.

Xing C. B., Li S. Higher Education Expansion, Education Opportunity, and Unemployment of College Graduates[J]. China Economic Quarterly, 2011(4): 1187-1208.

Yang C. R., Zhang Y. S., Zhang H. Basic Education Equity and Economic and Social Development[J]. Journal of Management World, 2021(10): 152-166.

Yang M., Wang Y. Research on the Trend and Channels of Intergenerational Income Mobility of China[J]. Journal of Management World, 2020(3): 60-76.

Yang Z. C. Does Higher Education Expansion Promote Intergenerational Mobility?[J]. Chinese Journal of Sociology, 2016(6): 180-208.

Yuan Q. Q., Liu Z. Y. Trends in Intergenerational Income Mobility in China[J]. Economic Perspectives, 2022(1): 117-131.

Zhang J. H., Wang Q. Higher Education Expansion and Intergenerational Transmission of Education[J]. The Journal of World Economy, 2018(4): 168-192.

Zhang N., Lin J. B., Li J. J. Research on Inequality of Opportunity in Basic Education[J]. China Industrial Economics, 2020(8): 42-60.

Zhu Z. Y., Liu C. C. Impact of Digital Infrastructure on the Urban-Rural Income Gap and Its Threshold Effect[J]. Journal of South China Agricultural University(Social Science Edition), 2022(5): 126-140.

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