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The long-run human capital benefits of the one-village-one-preschool pilot in rural northwestern China

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ABSTRACT

Since its inception in 2009, the One Village One Preschool (OVOP) initiative has emerged as one of China's most extensive social experiments in rural early childhood education (ECE), distinguished by stringent teacher entry standards and sustained professional development. Utilizing variations in OVOP's access cross villages and cohorts, we find that high-school-aged students exposed to OVOP have gained human capital benefits. Specifically, an additional one-year of OVOP exposure generates a 4.6 percentage point (pp) increase in the likelihood of attending selective senior high schools and a 3.8 pp reduction in the probability of grade retention. Further examination suggests that the quality of OVOP centers, particularly teacher qualifications, plays a crucial role in generating these benefits. Moreover, the program's impact is mediated through boosting preschool skill development and subsequent academic performance in compulsory education. Notably, students from upper-middle ability distribution derive more substantial benefits from OVOP exposure. Finally, a preliminary benefit-cost analysis indicates a return of at least 4.1:1 on OVOP investments, with the marginal value of public funds spanning from 6.2 to infinity. These findings underscore the efficacy of OVOP as a scalable model for enhancing educational equity and human capital development in rural China.

1. Introduction

Over past three decades, educational intergenerational mobility in developing countries has stagnated (World Bank, 2018), primarily due to the widening urban-rural divide in academic performance during high school tracking (Rozelle and Hell, 2020). In China, this disparity is particularly pronounced. By 2020, only 50% of rural youth aged 20–24 had completed senior high school, a significant 30 percentage points (pp) gap compare to their urban counterparts (State Council Census Office, 2022). This educational disadvantage manifests in limited access to selective high schools and higher-grade repetition rates among rural students (Chen et al., 2010; Rozelle and Hell, 2020). Such setbacks hinder opportunities for selective university admission and future income growth, perpetuating cycles of poverty across generations (Li et al., 2024). Given that neural development is most rapid during early childhood and that skills

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developed during this period are complementarity[1] (Cunha and Heckman, 2008; Cunha et al., 2010), constrained access to quality early childhood education (ECE) emerges as a critical determinant perpetuating these disparities.

While ECE has been established as an effective policy tool for fostering child development and upward mobility (Heckman and Masterov, 2007; Duncan et al., 2023), many rural ECE programs in developing countries[2] remain trapped in a low-quality equilibrium, particularly due to inadequate teacher qualifications (Özler et al., 2018; Wang et al., 2020; Wong et al., 2013), undermining its long-term benefits. Some studies indicate that rural ECE benefits children's educational attainment, cognitive and non-cognitive skills (Berlinski et al., 2008, 2009; Bietenbeck et al., 2019; Krafft, 2015; Brinkman et al., 2017; Arapa et al., 2021; Kim, 2022), while others report no impact or even negative short-term effects (Morabito et al., 2018; Wong et al., 2013; Bouguen et al., 2018; Lassassi et al., 2021; Özler et al., 2018). This mixed evidence arises from the lack of rigorous natural experimental designs, long-term follow-up data, and detailed information on program features. Therefore, unpacking the "black box" of program quality is essential for a deeper understanding of long-term benefits of rural ECE.

This paper aims to address these problems by assessing the impact of a teacher support-based rural ECE pilot on human capital outcomes of high-school-aged students. The One Village One Preschool (OVOP) pilot, launched in 2009 by the China Development Research Foundation, represents a distinctive social experiment in rural ECE. It is characterized by stringent teacher qualification standards and systematic in-service professional development, distinguishing from other ECE interventions in developing countries (Duncan et al., 2023). Initially implemented in the Ledu county, Qinghai Province, OVOP has expanded to over 2300 centers across ten provinces, serving more than 170,000 children by 2019 (Zhao et al., 2020), making it one of the largest rural ECE interventions in China. The program established three key requirements for each OVOP teacher: (1) a restrictive standard for teachers' educational qualification, allowing only those with a college degree in any field or those with a secondary vocational school diploma in ECE to be eligible; (2) on-site in-service training, where teachers attended an eight-hour training session every two weeks, delivered by experienced teachers from urban demonstration preschools; and (3) online training, with faculty from Beijing Normal University conducting systematic training (more than two times per semester) on curriculum implementation, child development, and educational psychology. These features enable us to address an important question: Whether enhancing teacher qualifications in rural ECE help it escape the low-quality trap and yield long-term benefits?

To evaluate the long-term effects of the OVOP initiative, we integrated survey data collected in 2022 with administrative records on household registration, students' ECE attendance and academic performance. Our survey tracked students who graduated from primary schools in Ledu County between 2016 and 2018[3] and achieved a 75% response rate.[4] We also surveyed OVOP teachers who had worked for these students. Additionally, we obtained each child's household registration information from the Public Security Authorities, enabling accurate identification of their birth place, and mitigating measurement error in assessing OVOP exposure (Bailey et al., 2021). The Ledu Education Bureau provided administrative records, including: (1) types of ECE programs attended by students; (2) registration records of each OVOP center; and (3) students' scores on junior and senior high school entrance exams. Building on this, leveraging the village-by-village rollout of OVOP, we employed a cohort difference-in-differences (DID) approach to examine its impact on rural students' human capital outcomes.

Our analysis reveals that exposure to OVOP yields significant long-term human capital benefits for high school-aged rural students. Specifically, an additional year of OVOP exposure is associated with a 4.6 pp increase in the likelihood of attending selective high schools and a 3.8 pp decrease in the probability of grade retention. However, no significant effects were observed on academic high school attendance. To ensure the validity of our findings, we conducted several robustness checks. An event-study specification confirmed the strength of our identification strategy, while controlling for predetermined village characteristics and performing placebo tests further validated our results. Additionally, we found a 21 pp ECE enrollment gain from three-year exposure to OVOP, similar to the macro-level data that Ledu achieved a 24-pp lead in ECE enrollment over the national average after three years of OVOP's implementation, thereby supporting the relevance assumption.[5]

We examined four potential mechanisms through which OVOP may influence educational outcomes: (1) early childhood skill

[1] That said, skills produced in early life help raise the productivity of investment at subsequent stages, which are concluded as "skills beget skills" (Cunha and Heckman, 2008; Cunha et al., 2010).

[2] Early childhood education interventions include home visitation programs (Emmers et al., 2021), such as the Jamaica Home Visiting Program (Gertler et al., 2014), universal (Dietrichson et al., 2020) and targeted ECE programs (Duncan et al., 2023), like Perry Preschool Project and Abecedarian Program (García et al., 2023; Heckman et al., 2013). Due to budget constraints, preschool classrooms were built on public primary schools in many developing countries to expand access to ECE for rural children. Such initiatives have been implemented in countries like Indonesia (Brinkman et al., 2017), Argentina and Uruguay (Berlinski et al., 2008; 2009), Zambia (Bietenbeck et al., 2019), Ethiopia (Kim, 2022), Algeria (Lassassi, 2021) and China (Rao et al., 2017).

[3] These students, assuming on-time progression, would enroll in primary school between 2010 and 2012. Given that the first OVOP centers were established in Ledu in 2009, their exposure to OVOP, based on birth cohort and village, generates substantial exogenous variation, strengthening the validity of our research design.

[4] These students can reflect local-born populations and provide rich internal comparability. The household registration records verified by the Public Security Authorities show that, 99% of primary school graduates in 2016-2018 on the roster were born in Ledu. In the 2022 follow-up survey, we not only visited students who remained in the local school system but also tracked those who had migrated, attended schools outside Ledu or had left the school system. Such students are often overlooked in previous studies, leading to potential bias in the estimated effects (Chetty et al., 2011).

[5] Our analysis of OVOP's impact on ECE enrollment is based on rural student samples. The macro-level data, provided by the Ledu Education Bureau, encompass both rural and urban students. Also, available ECE options in Ledu includes not only OVOP, but also county seat ECE and private township ECE providers, the latter also exhibited nationwide growth.

accumulation, (2) performance in junior and senior high school entrance exams, (3) family care environment during preschool age, and (4) family educational investment and parenting practices during high school age. Our findings provide evidence for the first two mechanisms. Children aged 3–6 who attended OVOP centers showed a 23% improvement in overall cognitive, memory, language, and social skills. Furthermore, one year of OVOP exposure led to an increase of 5.0 points in junior high school entrance exam scores and 16.0 points in senior high school entrance exam scores. Quantile Treatment Effect (QTE) estimates indicate that the benefits of OVOP are more pronounced among students in the upper-middle ability distribution, which may explain its stronger positive effects on selective high school enrollment. No significant effects were found on parenting practices, suggesting that the primary mechanism is skill development rather than changes in family behavior. Taken together, our analysis of the underlying mechanisms paints a consistent picture of "skills beget skills".

Our analyses of OVOP center quality and county-level cost data reveal that centers with more qualified teachers play a better role in reducing students' grade retention, indicated by the presence of higher qualified OVOP teachers' certification, preschool education specialization, and experience. More qualified teachers also play a critical role in improving students' enrollment in academic high schools. Given the annual cost of approximately CNY 1700 (USD 239) per child, a back-of-the-envelope calculation yields a benefit-cost ratio of 5.1:1, with the marginal value of public funds (MVPF) estimated at least 9.3. We also included OVOP-induced crowding-out of selective school enrollment slots for local urban students, resulting in a revised return of 4.1:1 (the MVPF of at least 6.2). Subsequent robustness checks confirmed the substantial social returns of OVOP.

This study contributes to the literature in three key ways. First, it sheds light on the new focus of burgeoning ECE literature that "quality matters" and extends its scope by focusing on a teacher support-based rural ECE polit. Given the early developmental disadvantages of rural children in developing countries, the mixed impacts of rural ECE programs there warrants attention (Bouguen et al., 2018; Duncan et al., 2023; Emmers et al., 2021). Previous studies have attributed the failures to poor teacher qualifications, such as inexperience and low educational attainment (Bouguen et al., 2018; Morabito et al., 2018; Wong et al., 2013), though most evidence remains qualitative. Nevertheless, some small-scale interventions targeting teacher training in developing countries have also faltered, including those in Mauritius (Morabito et al., 2018), Ghana (Wolf et al., 2019), and Malawi (Özler et al., 2018). In comparison, OVOP stands out by combining strict teacher entry requirements with intensive and targeted teacher training, which remains uncommon among rural ECE interventions in developing countries. Our analyses demonstrate that OVOP generates sustained human capital benefits on rural students, with teacher qualifications constituting the critical quality dimension driving the long-term impacts.

Second, this paper advances the understanding of the "high school trap" among rural children in developing countries by offering novel empirical evidence on the role of teacher support-based ECE in improving rural students' educational attainment, especially the probability of selective high school enrollment. Many rural children in middle- and low-income countries, face structural constraints in accessing quality educational resources during post-compulsory education, limiting their potential for upward mobility (Rozelle and Hell, 2020). Even though some studies have examined the drivers of high school failure in rural areas, most of them focus on impacts of school and family factors at compulsory stage rather than impacts of ECE at earlier stage (Hu, 2012; Pilařová and Kandakov, 2017; Yang et al., 2014), while neglecting inequality in selective high school admissions. This study demonstrates that OVOP enhances rural students' long-term educational attainment by fostering continuous skill accumulation from preschool through junior high school. Notably, these benefits are more pronounced among students in upper-middle ability distribution and those from disadvantaged backgrounds.

Finally, this paper provides the first causal and cost-benefit estimates for the OVOP pilot, offering one of the first cost-benefit analyses of rural ECE programs in developing countries (Özler et al., 2018). While previous evaluation of OVOP have examined its correlation with primary school outcomes (Chen et al., 2019, 2023), this study extends the analysis to high school years and leverages cross-village variation in OVOP's introduction for the causal identification. Moreover, although most existing evidence has established the benefit-cost ratio of ECE above unity (Dietrichson et al., 2020; Duncan et al., 2023), the estimated returns exhibit remarkable heterogeneity across settings, spanning from less than 1:1 to over 16:1, with particularly limited evidence from developing countries (Belfield et al., 2006; Meadows, 2011; Hojman et al., 2022). This study extends the literature by demonstrating that ECE programs in underdeveloped rural areas prioritizing investment in teachers yield significant returns.

Our findings have direct policy implications for public investments in expanding access to ECE services in developing countries. With more than 30% of children in developing countries still lack access to one year of ECE before the official primary entry age (The United Nations, 2024), three is substantial potential for further investment. Given the disappointing outcomes of previous low-quality investments, it is essential to carefully formulate strategies to ensure the effectiveness of ECE investments. As China serves as one of the most populous developing countries, the impact of the OVOP pilot estimated in this study is particularly relevant for policymaking in these countries. We not only highlight the long-term impact of a quality ECE pilot on students' long-term human capital, but also emphasize the importance of effectively providing qualified teachers. Overall, we support the policy perspective of Heckman and Masterov (2007) that *"investing in disadvantaged young children is a rare public policy with no equity-efficiency tradeoff"*.

The remainder of our paper is organized as follows. In Section 2, we introduce the OVOP pilot and educational tracking in the post-compulsory education of rural China. Section 3 describes the data and sample of this paper, followed by an empirical framework in Section 4. Section 5 presents the empirical findings and discusses the potential mechanisms. Section 6 presents the results of cost-benefit analyses. The final section concludes.

2. Background

2.1. The One Village One Preschool (OVOP) pilot

To enhance access to quality ECE in rural China, the China Development Research Foundation (CDRF)[6] launched the OVOP pilot program in 2009 in Ledu County, Qinghai Province. This pilot aimed to provide free, high-quality ECE services to 3–6-year-old children in less-developed, rural, mountainous areas of central and western China (Fig. A.1). By 2019, around 2300 OVOP centers had been set up across 10 provinces, serving more than 170,000 children at no charge (Zhao et al., 2020).

To select the pilot sites for OVOP in Ledu, Ledu county government took a two-step procedure. First, the county education bureau selected nine townships based on their topography, of which five townships from its valley plain area (named "Chuan Shui") and four from its hilly area (named "Nao Shan").[7] In the second step, within each pilot township, all villages that meet the following criteria simultaneously are eligible for OVOP: One was the existence of any primary school that can provide necessary classrooms and space for OVOP. The other is the presence of more than ten 3- to 6-year-old children in the village so that stable enrollment can be ensured. As a result, 81 villages from these nine pilot townships were eligible and each had one OVOP center established in 2009. Afterwards, OVOP centers gradually expanded to all the 18 townships outside of the county seat of Ledu county by 2019 (Fig. 1).

There are several features of OVOP centers that are designed to ensure their quality. The first is the facilities. Like most rural ECE programs in developing countries (Berlinski et al., 2008, 2009; Brinkman et al., 2017), OVOP centers were converted or redecorated from abandoned classrooms of village primary schools to save costs. Consequently, most OVOP centers were situated within walking distance of rural children's households. Moreover, CDRF provided each center with basic tables, chairs, toys, as well as television sets, DVD players, and educational CDs. On average, an OVOP center enrolled ten to 17 children per semester from nearby villages.

The second feature is about teachers. The OVOP pilot program set specific criteria for teacher recruitment, selecting only two types of candidates: those who had completed local vocational teacher training and obtained at least a secondary vocational diploma, and those who, though not trained in normal schools or preschool education, held a college degree or higher. Most OVOP teachers resided in nearby villages or townships. To ensure classroom quality, a series of training sessions were implemented. Teachers were required to attend a full day offline training every two weeks at a public demonstration preschool in the county, where experienced senior-ranking teachers provided training and assessed its effectiveness. During winter and summer holidays, professors from Beijing Normal University offered more specialized guidance online, covering topics such as curriculum design based on the syllabus, addressing the needs of children with language and developmental disabilities, managing conflicts among children and so on.

The third feature is about curriculum. CDRF provided OVOP centers with textbooks and syllabus for their teachers to organize activities for children in accordance with the syllabus. The syllabus lists a series of regular activities such as singing songs, storytelling, and math learning (e.g., counting numbers). Teachers are supposed to organize these activities five to six hours per weekday, three to five times a week.

The above features make Ledu county a suitable study setting for three reasons. First, it is one of the first pilot counties of OVOP by CDRF.[8] The long-term operation of OVOP in Ledu since 2009 allows us to assess its long-term benefits on children. Second, Ledu used to be a nationally designated poverty-stricken county. Compared with other counties in China, Ledu is less developed, with larger proportion of rural population and ethnic minorities,[9] which are the key target population criteria of OVOP. Third, access to preschool education in rural areas of Ledu was very limited before 2009, with only two preschools (which were private) in rural areas outside the county seat. Since the introduction of OVOP in 2009, and its subsequent expansion, it has become the primary provider of ECE services in rural Ledu.

The introduction of OVOP has led to a significant increase of the overall ECE enrollment rate in Ledu County. By 2012, Ledu had achieved an ECE enrollment rate 24 pp higher than the national average (Fig. 2).[10] This remarkable growth was largely driven by OVOP, which expanded from serving 1429 children in 2010 to approximately 3000 children in 2012, accounting for over 40% of total ECE enrollment in the county. It is worth noting that since China launched the targeted poverty reduction policy in 2013, both the number of OVOP centers and their enrollment have been declining as many rural parents have taken their children to migrate with them to urban cities. Therefore, this study focuses on children who were exposed to OVOP before 2013.

During the same period as the implementation of OVOP (starting in September 2009), Ledu County also launched its first Nutrition Package Program (NPP) for infants and young children aged 6 to 24 months. This program provided a daily sachet of a complementary

[6] The CDRF serves as a public foundation affiliated with the Development Research Center (DRC) of the State Council of China.

[7] Chuan Shui and Nao Shan are the two major landforms in rural Ledu (except for the township which serves as the location of county seat). Comparatively speaking, Chuan Shui area is economically more developed than the Nao Shan area.

[8] Ledu County, located in Haidong Prefecture, Qinghai Province in northwestern China (Figure A.2). It comprises an area of about 3,050 km^2, with 354 villages in 19 townships. By 2013, 122 villages had established OVOP centers. In 2009, Ledu's per capita GDP was CNY 9,427 (approx. USD 1,380), less than 40% that of the national average.

[9] Just to put it into context, we compare Ledu County with other counties in China. As shown in Table A.1, Ledu County is comparable to an average lower-middle-income county in many socio-economic variables (Panel A). Panel B shows that in terms of gender and age structure of the population, Ledu is comparable to an average middle-income county. However, Ledu has higher proportions of rural residents, ethnic minorities and a less educated adult population.

[10] The data were provided by the Ledu Education Bureau. Fig. 2 encompasses all the preschool-aged children in Ledu, including those born in county seat and rural areas. Thus, the ECE enrollment rate in Ledu reflects contributions from both rural ECE expansion and growth in urban ECE provision.

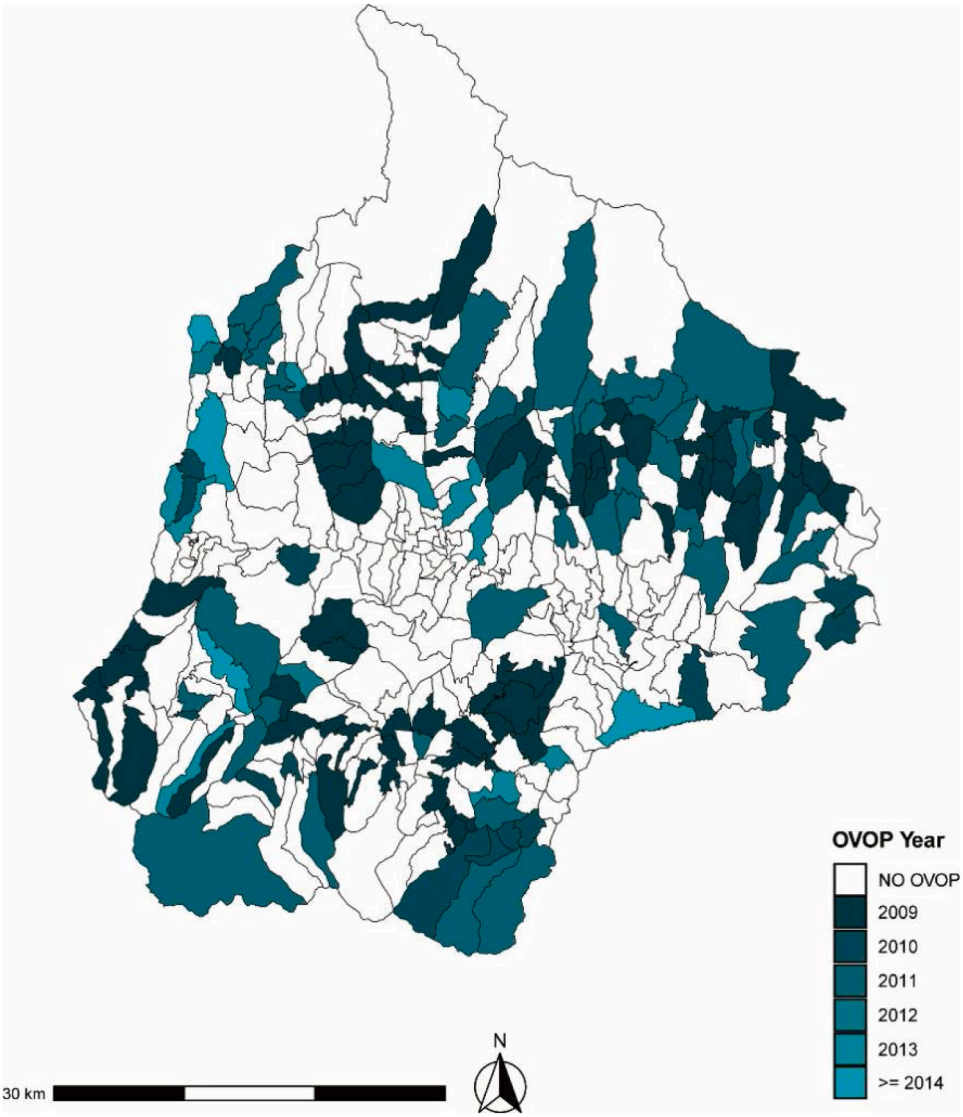

Fig. 1. Village-by-village roll-out of the OVOP over time.
Notes: The village rollout data for the OVOP construction in Ledu are from Ledu County government.

food supplement known as Yingyangbao, which was developed by the China Center for Disease Control and Prevention (China CDC). NPP is based on soybean protein and enriched with nine micronutrients, including iron, zinc, and calcium. It was distributed to all eligible rural children in the county through township health centers and village clinics, where caregivers were encouraged to pick it up free of charge. Among the 18 rural townships in Ledu, nine were randomly selected to be the intervention group, while the other nine served as the control group. As we will demonstrate in Section 4.2, the estimated human capital benefits of OVOP remain robust even after controlling for this concurrent policy.

2.2. Educational stratification in China's post-compulsory education

Chinese students will be involved in the educational tracking after completing the nine-year compulsory education. Four primary pathways stand out: labor market, upper-secondary technical and vocational education and training (TVET) schools, selective or non-selective academic high schools. The tracking process is primarily determined by performance on the Senior High School Entrance Exam (Zhongkao), a prefecture-level unified examination (Anderson et al., 2016).[11] Students know of their scores and prefecture

[11] The subjects of Zhongkao includes: Chinese, mathematics, English, history, geography, political science, physics, chemistry, biology and physical education.

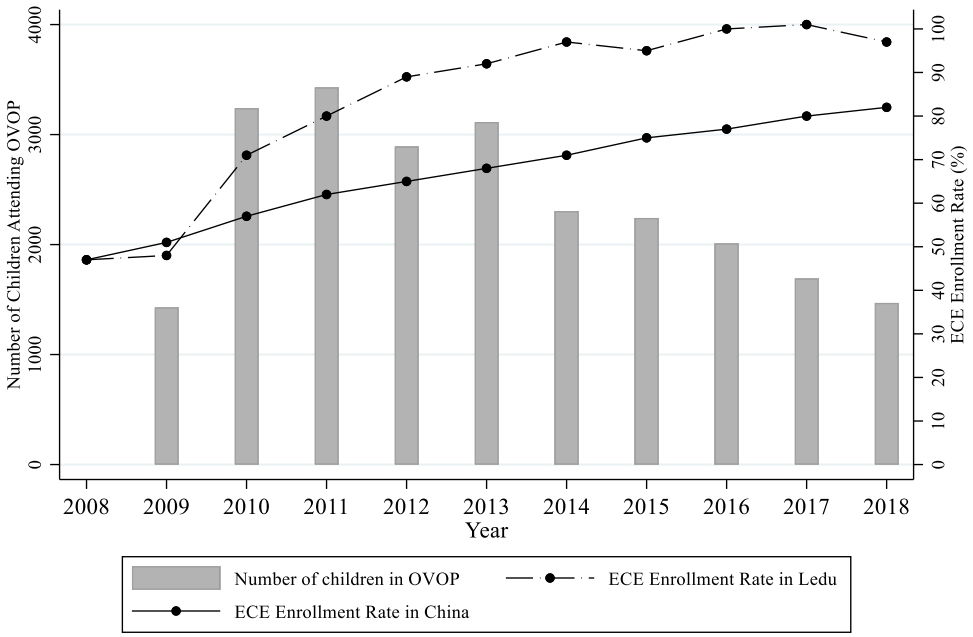

Fig. 2. Number of children attending OVOP in Ledu and ECE enrollment rate in Ledu County and China.
Notes: Data on the number of children attending OVOP in Ledu, ECE enrollment rate in Ledu comes from the Ledu county government. Data on ECE enrollment rate in China are from the Educational Statistics Yearbook of China, 2008–2018.

rankings approximately two weeks after the exam, and fill in their applications. Following this application phase, high schools then set their minimum admission scores and enroll students accordingly (Anderson et al., 2016). In general, the better the performance of the high school in the subsequent National College Entrance Exam (NCEE), the higher the admission score line.[12] Those failing to meet academic high school requirements would enter TVET schools, which do not require Zhongkao scores. However, Zhongkao scores are not the sole determinants, individual attitude and family background also matter for the tracking results. For instance, some students opt out of the exam due to perceived academic inadequacy or financial constraints, while some parents send their children to private or non-local high schools for better educational opportunities.

TVET schools provide students with occupational competencies for the future work through a three-year program. The standard TVET curriculum consists of three components: general academic instruction, vocational skills training, and mandatory internships with partner companies (Yi et al., 2018). As TVET schools do not charge tuition fees (unlike academic high schools), over 70% of their students in China come from rural areas.[13] However, TVET schools come with their challenges in two aspects. First, previous studies document concerning quality of TVET, with many programs failing to meeting their goals. Yi et al. (2018) found that approximately 90% of TVET students showed no measurable improvement in either vocational or general skills after one academic year. Moreover, under the selective examination system of China, both policymakers and the public generally view TVET as a secondary option for students after compulsory education stage, particularly as labor market demands increasingly prioritize college degrees.

Academic high schools in China, including selective or non-selective schools, focus on cultivating students' academic competencies to prepare them for NCEE. In 2022, the average county in Qinghai Province, where Ledu County is located, had 3.9 high schools.[14] The facilities, teaching staff and courses in these high schools are guaranteed to a certain extent (Liu et al., 2009). Laboratory compliance rates, student-teacher ratios, and teacher qualifications there are comparable to those in urban schools and even surpass those in many developing countries (Liu et al., 2009). Yet, the competitive high school admission system of China stratifies student quality among different academic high schools, and those non-selective high schools enrolled in lower-performing students exhibit inadequate learning conditions and counterproductive peer dynamics (Jackson, 2013).

Among academic high schools, selective high schools are officially designated by provincial education bureaus and focus on developing students' academic capabilities to prepare them for top-tier universities. In China, most counties like Ledu have only one such selective high school. They can receive prioritized financial support from both prefecture and provincial governments, along with preferential allocation of top teaching staff, and are also characterized by the concentration of high-achieving students (Jackson, 2013). It has been shown that the higher-achieving peers help boost students' academic performance, which can translate to higher

[12] Take Ledu as an example. After the 2019 high school entrance examination, the minimum admission score for academic high schools was 362 points (Out of 750 points), while the admission score for the only selective high school in Ledu was as high as 482 points.
[13] Data source: White Paper on the Development of Vocational Education in China, 2023.
[14] Data source: Qinghai Provincial Department of Education.

starting salary (Jackson, 2013; Démurger et al., 2024). Take Ledu for example, in the 2022 NCEE, in the best No.1 High School, 47% (11%) met the admission thresholds for Project 211 (985) universities,[15] demonstrating a substantial gap compared to the No.4 High School with the lowest admission scores, where only 1% (0%) of students reached the Project 211 (985) universities' admission scores. Therefore, attending selective high schools is regarded by many as an opportunity to gain upward mobility.[16]

3. Sampling, data and variables

3.1. Sampling and data

To identify the benefits of the OVOP pilot on students' long-term human capital development, we draw on data from four sources. Specifically, data from the first three modules are used for main regression analyses and mechanism analyses, and data from the last module was used only for mechanism analyses. First, given a three-step student sample construction procedure, we conducted a survey of high school aged students in 2022, where we asked them about their personal, parental and household characteristics. The other data source is administrative data, including the OVOP registration form from county education bureau and the household registration information of sample students from county public security bureau. Third is the village geographical data. Finally, we use the survey data for preschool-aged children in Ledu and two other comparison countries in 2011, where trained numerators ask children about their language, motor, cognitive, memory and social skills and ask their parents about their parental and household characteristics.

3.1.1. Study sample construction and data

We took a three-step approach to construct the sample for this study (Fig. 3) with the county education bureau of Ledu. In the first step, in March and April of 2022, we got the roster of primary school graduates in Ledu County between 2016 and 2018, which contains 8928 students. Then we obtained information from the Qinghai School Registration System for each of the 8928 students about whether she/he is still attending school in spring 2022, and if yes, which school she/he is attending. In this way, we were allowed to obtain the whereabouts information for 7472 (84%) students in spring 2022. For the rest of 1456 students (16%), we continued to check the roster of junior high school graduates in Ledu County between 2019 and 2021, which provided us with the where-about information in spring 2022 for 661 students (7%). For the remaining 795 students (9%), we continued to check with their junior high school class captains or classmates and obtain the whereabouts information for 204 students (2%). In this way, we got the whereabouts information in spring 2022 for 8337 students, which we called prospective sample students for this study. Among them, 7096 students (or 85.1%) were studying in academic senior high schools, 1069 students in vocational high schools (12.8%), 39 students in junior high schools (0.5%), the rest 133 students (1.6%) were not in schools in spring 2022.

In the second step, we invited all the 8337 prospective sample students to participate in a survey online during June and July 2022. As a result, 6690 students (or 80%) were connected and surveyed successfully. The survey was administered in their computer rooms on campus by their class captains with support from our trained enumerators online.[17] We collected rich information at three levels. The first is students themselves, where we ask questions about their basic social economic characteristics (including date of birth, gender, ethnicity, number of siblings, Hukou status and kindergarten experience[18]), their educational attainment (ever attend academic high school, attend selective academic high school, and grade retention). The second includes parental characteristics, such as their age, years of schooling, migration status, marital status, and parenting style. The last level is household characteristics, including household asset index.[19]

The third step is to identify sample students from prospective sample students. To do so, we draw on information about the place of birth of students from the administrative data (which we will describe later). This information allows us to tell whether a student was born in rural areas of Ledu. As a result, 4681 prospective children were born in rural Ledu and they became the sample for the rest of

[15] The "211 universities" denote those included in China's 211 Project, generally considered the Top 100 universities in China. The "985 universities" denote a more elite subset of the 211 group, designated under the 985 Project and representing the Top 39 universities in China.

[16] Notably, selective high schools in China differ from elite high schools in the United States and other western countries to a large extent. In China, the admission to selective high schools is determined primarily by students' performance in Zhongkao, and these schools confer no formal privilege in the subsequent NCEE (Anderson et al., 2016). In contrast, socioeconomically disadvantaged students were strikingly under-represented in elite high schools' ear-marked for high ability students (Birkelund et al., 2021).

[17] In cases where students were not able to meet in the computer rooms on campus (16%), they completed the questionnaire on their mobile phones with help and monitoring from trained enumerators online.

[18] The kindergarten is often organized within rural primary schools and offers a one-year pre-primary curriculum. It is highly academic, mainly teaches phonetics, arithmetic, or even the curriculum for the first grade in advance. The teachers are often from elementary schools (Rao et al., 2017).

[19] The index is generated by counting 21 types of fixed assets of the household, with 21 of them indicating having all the assets whereas zero none, and then standardizing the count. These fixed assets cover large animals such as horses, cows, and sheep, washing machines, computers, tractors, refrigerators, Internet connections, motorcycles, microwave ovens, iPad/tablets, tricycles, range hoods, children's separate desk, large farm equipment, gas stoves, separate room of children, truck, TV, water heater, family car, combination speaker and water pump. Moreover, when we compare our sample students against those prospective sample children who are missed from our sample, our data show among eight observable characteristics, six cannot predict interview participation significantly (Table A.2). It seems that older boys among the prospective students are more likely to be missed. Therefore, we controlled for the age and gender of sample children later. Also, in later analyses, we also conducted heterogeneous analyses to examine whether the benefits of OVOP differ by gender or age.

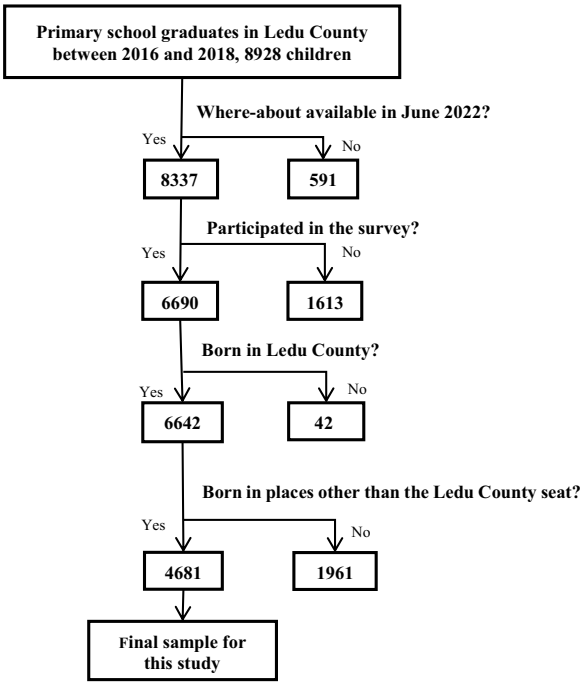

Fig. 3. Study sample construction procedure.
Notes: This figure shows the construction procedure of our study sample. Our sample consists of individuals who: (1) graduated from primary school in Ledu County between 2016 and 2018; (2) were born in rural areas of Ledu, as verified by their registered birth address; and (3) were successfully tracked and interviewed in the 2022 survey conducted by authors.

the study.

3.1.2. OVOP teacher survey

To obtain more precise information on teacher qualification, we conducted an online survey targeting OVOP teachers. Given that our sample students took secondary school entrance examinations between 2016–2018 (implying they should have entered primary school by 2012 at the latest), we focused on teachers employed by the OVOP centers during 2009–2012. The survey captured 118 respondents (representing 83% of all OVOP teachers during this period), who reported their employment duration, degree, major, teaching certifications, and years of teaching experience at initial OVOP employment. We subsequently matched these data with OVOP registration form to compute preschool-level averages of teacher qualification metrics.

3.1.3. Administrative data for OVOP and students

We obtained administrative data from both the education bureau and public security bureau of Ledu county. The former not only provided us with individual sample students' information on the type of ECE they ever attended, but also detailed information of each OVOP (including its location, establishment and closing dates, facilities, degree and majors of individual teachers), together with the junior (senior) high school entrance exam scores for 2016–2018 (2019–2021). As to the county public security bureau, it provided us with detailed information of individual sample students, including their name, gender, ID number and birth location. Leveraging these data sources, we employed Python to identify students' birth villages.

3.1.4. Geographical data for students' birth villages

We obtained raw grid data (30 × 30-meter grid size) from the Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences (CAS). With these data, we are able to construct eight geographical measures for each village in 2008 where our sample students were born: distance from the village seat to the county seat (km), whether the village is the township seat (yes=1), area of the village (km^2), slope of the village (%), the proportion of arable land (%), the proportion of forest and grass land (%), distance to the nearest railway station (km) and distance to the nearest highway entrance (km). Table A.3 shows the summary statistics of these village characteristics.

3.1.5. Preliminary sampling survey data in 2011

In 2011, a sampling survey was conducted in Ledu and two comparison counties, where child development assessments were performed for preschool-aged children. In further analyses, we draw on this survey data to examine the benefits of OVOP on children's development during their preschool age. To be specific, a three-step approach is used to construct our sample. In the first step, two

comparison counties (Ping'an and Jianzha county in Qinghai) were selected by the OVOP office of CDRF, due to that they are representative of the socioeconomic characteristics of the agricultural and pastoral areas of Qinghai Province, respectively. In the second step, Population Proportionate Sampling (PPS) method is used to choose the sample townships, which brings us eight, three and four sample townships in Ledu, Ping'an and Jianzha County, respectively. Finally, PPS method is used to choose 16 OVOP centers among sample townships in Ledu, and similar method is used to choose six villages in Ping'an and eight villages in Jianzha. Finally, all the 3–6 aged children in chosen OVOP centers in Ledu and sample villages in Ping'an and Jianzha were surveyed, which left us 823 sample children in total.

For further mechanism analyses, we draw on information from two modules in the 2011 survey. The first is the psychological evaluation scale for children aged 36–72 months.[20] The scale focuses on children's skills in their language, cognition, motor, memory and social rules. To ensure the quality of the information collected, the survey was undertaken by trained enumerators on a one-on-one basis. The second is the caregiver survey, which collects information on the characteristics at children, parental and household level, respectively by the caregiver questionnaire.

3.2. Variables

3.2.1. Human capital indicators in students' high school age

Following the literature (Bailey et al., 2021; Berlinski et al., 2008, 2009; Bietenbeck et al., 2019; Gray-Lobe et al., 2023; Heckman et al., 2013; Thompson, 2018), we focus on educational attainment as the measure of human capital, including ever attended academic high school, ever attended selective academic high school, and ever had grade retention (Amadon et al., 2022; Bailey et al., 2021; Barnett and Jung, 2021; De Haan and Leuven, 2020; Heckman et al., 2013; Reynolds et al., 2011; Thompson, 2018).

3.2.2. Years of exposure to OVOP

Following Huang and Liu (2023) and Chen et al. (2022), we measure student's exposure to OVOP by the number of years that an OVOP center was available within three kilometers (km) of a student's birth village when she/he was three to six years old, which ranges from 0 to 4.[21] Therefore, if a student was less than three years old when an OVOP was established within three km of her/his birth village, her/his years of exposure was 4 years. In contrast, if a student was older than 7 years already when an OVOP was established within three km of her/his birth village, her/his years of exposure was 0.

3.2.3. Variables used for mechanism analyses

The psychological evaluation scale for preschool-aged children. We use the scale for children aged 36–72 months to measure child development outcomes during their preschool age, which is helpful for us to understand whether OVOPs help children get prepared for their study in primary school. During the survey, trained enumerators asked the child to answer questions or complete actions on a two-point scale, ranging from zero (cannot answer the question or complete the action, and their caregivers think they do the same in daily life), one (cannot answer the question or complete the action, while their caregivers think they can answer or complete them successfully in daily life) and two (can answer the question or complete the action successfully on the spot). These questions or actions include five dimensions: language, cognition, motor, memory and social rules, with the score of each dimension ranging from 0 to 100, and the overall score is the average of the above five dimensions.[22]

Scores of junior (senior) high school entrance exam. The junior high school entrance exam has a total score of 300 points, divided into three subjects: Chinese, Mathematics, and English. The senior high school entrance exam has a total score of 750 points, divided into seven subjects: Mathematics, English, Chemistry, Physics, History, Morality and Law, and Physical Education. All of them are original scores. We obtained each student's total score and matched it with the student survey data using information from the exam score sheets, including each student's name, school, grade, and class. In the end, 4544 out of 4681 sample children (97%) were matched with junior high school entrance exam scores, and 4222 (90%) were matched with senior high school entrance exam scores.

Family care environment during preschool age. We use the Parent-Child Interaction Scale (PCIS) to measure the parenting practice of caregivers during the sample students' preschool age. PCIS has been extensively used in previous studies, such as in Evans et al. (2000) and Gelber and Isen (2013), among others. Specifically, we ask students about their experiences in three types of interactions (telling stories, singing songs, or playing games) with three types of caregivers (their parents, grandparents and other caregivers) before they entered primary school, respectively. Based on their responses, we construct six dummy variables. The first three dummy variables indicate whether the student under discussion often had interactions of telling stories, singing songs or playing games with any

[20] Source: https://www.cdrf.org.cn/jjh/pdf/yunnan.pdf

[21] We use three km as distance of commuting following Jensen and Miller (2018) and Miguel and Kremer (2004). We also confirmed the reasonableness of this distance setting through interviews with OVOP office officials and OVOP teachers in Ledu. According to their reports, OVOP centers primarily enroll children from nearby areas, and in most cases, grandparents walk the children to school. The time it takes for children to get to school ranges from five minutes to one hour. It is estimated that for preschool children, a one-hour walk roughly corresponds to three kilometers.

[22] For children aged 3, 4, 5, and 6 years, the total number of items differed: 55 for 3-year-olds, 47 for 4-year-olds, and 69 for 5-year-olds. To make the scores comparable among different age groups, the full score for each dimension has been adjusted to 100 points.

caregivers before they entered primary school, respectively; the rest three dummy variables indicate whether they had similar interactions with their parents before entering primary school.

Parental involvement and investment during high school age. We measure parental involvement and educational investment during students' high school years using variables across three dimensions: (1) Educational investment, including the number of books in the household and a strict parenting index ;[23] (2) Companionship, which includes students' reports of lack of parental care (yes=1) and perceived closeness to parents (yes=1); and (3) Fertility decisions, including whether the student has younger siblings (yes=1) and the total number of younger siblings.

Variables used for heterogenous analyses. Following the literature (Bailey et al., 2021; Blanden et al., 2016, 2021; Berlinski et al., 2009; Dietrichson et al., 2020; Gray-Lobe et al., 2023; Heckman et al., 2013; Heckman and Masterov, 2007; Thompson, 2018), we draw on the following two modules of variables to examine whether the benefits of OVOP differ by different group of students. The first module is related to students' personal characteristics, including gender (girl=1), ethnicity (ethnic minorities=1) and age. The second module is related to their parental and household characteristics, including parental migration (yes=1), parental education (both parents do not attend senior high school=1) and ever being poverty-registered household (yes =1).

3.3. Descriptive statistics

Our data show the ECE enrollment rate of the 4681 sample students is comparable to that of Ledu County in 2011 (80%). 80% of them had ECE experience, of which 65% attended OVOP, 10% attended township private preschools, and 5% attended county seat preschools, respectively. Among those students who attended OVOP, they were exposed to OVOP for 1.6 years on average before their age of seven. As to their human capital, 81% of them attended academic high school, 28% attended selective academic high school, and 19% ever had grade retention, respectively (Table 1). In comparison, the proportion of sample students attending academic high school and selective academic high school are higher than that of their peers aged 16–19 in rural China (69% attended academic high school and 22% attended selective academic high school).[24] Also, the proportion of grade retention of sample students is slightly lower than the national average of rural junior school students (23%).[25]

Table 1 also shows the social economics characteristics of sample students. Half of them are girls, 21% of them are ethnic minorities, 12% own non-agricultural Hukou and 66% have attended kindergarten, with 0.9 siblings on average. Their parents are in their forties, with 82% of them being married. On average, the years of schooling are 8.7 for fathers and 7.4 for mothers, respectively. The household asset index ranges from −8.2 to 2.6.

4. Estimation framework

4.1. Difference-in-Differences model

To examine the impacts of early-life exposure to the OVOP on students' long-run human capital, we employ a cohort difference-in-differences (DID) approach. Specifically, following Bailey et al. (2021), Huang and Liu (2023) and Duflo (2001), we estimate a DID specification as follows:

$$Y_{ctvi} = \alpha_{ctvi} + \beta Exposure_{cv} + \mathbf{X}_{ctvi}\boldsymbol{\delta} + \phi_v + \varphi_{tc} + \partial_c + \mathbf{Z}_{v,2008} Timetrend_c + \varepsilon_{ctvi} \quad (1)$$

Where *i, c, v* and *t* denote individual, birth cohort, birth village and birth township, respectively. Y_{ctvi} denotes students' educational attainment. $Exposure_{cv}$ denotes the years that students were exposed to OVOP when they were 3 to 6 years old and is a function of their birth village and birth year, as introduced above. $\mathbf{X}_{ctvi}$ denotes the vector of student and household characteristics, including students' age, gender, number of siblings, age of parents, parental years of schooling, marital status and household asset index. For each specification, we include fixed effects for birth village, township-by-cohort, the availability of ECE service before the OVOP establishment-by-cohort and village specific linear cohort trends.[26] We cluster all standard errors at the village level.

[23] The index is composed of the sum of three dummy variables, which ask students whether their parents are strict with them regarding academics, friendships, and their use of the internet or television. A score of 1 is assigned if they answer "yes". Therefore, this variable ranges from 0 to 3.

[24] Data source: China Family Panel Studies (CFPS) 2018 survey. Covering 25 provinces and autonomous regions, the CFPS survey utilizes a multistage probability sampling approach, proportional to size, with an implicit stratification based on administrative districts and socioeconomic status as the primary stratification factors. This methodology guarantees that the study is a comprehensive, nationally representative, and longitudinal examination of Chinese families and society.

[25] Data source: China Education Panel Survey, 2013-2014, we focus on rural junior high school students (N = 9998).

[26] By introducing the village specific linear cohort trends, we allow the trend to be related to villages' initial characteristics in the year of 2008, prior to the construction of OVOP. These features contain of the determinants of OVOP construction, including the existence of village primary school and the presence of no less than 10 three- to six-year-old children in that village in the year prior to the introduction of OVOP.

Table 1
Descriptive statistics.

	Obs.	Mean	SD	Min	Max
Panel A: Dependent variables					
Human capital indicator in high school age					
Attend academic high school (yes =1)	4681	0.81	0.39	0.00	1.00
Attend selective high school (yes =1)	4681	0.28	0.45	0.00	1.00
Grade retention (yes =1)	4681	0.19	0.39	0.00	1.00
ECE experience					
Attend OVOP (yes =1)	4681	0.65	0.48	0.00	1.00
Attend township private ECE (yes =1)	4681	0.10	0.30	0.00	1.00
Attend county seat ECE (yes =1)	4681	0.05	0.22	0.00	1.00
Attend any ECE (yes =1)	4681	0.80	0.40	0.00	1.00
Academic performance in compulsory education stage					
Score of junior high school entrance test [0–300]	4544	233.41	44.33	55.00	298.00
Score of senior high school entrance test [0–750]	4222	422.23	96.10	20.00	692.50
Panel B: ECE exposure					
Years of exposure to OVOP	4681	1.11	1.15	0.00	4.00
Years of exposure to township private ECE	4681	0.37	0.96	0.00	4.00
Panel C: Covariates					
Girls (yes =1)	4681	0.50	0.50	0.00	1.00
Ethnic minorities (yes =1)	4681	0.21	0.41	0.00	1.00
Number of siblings	4681	0.90	0.58	0.00	7.00
Years of schooling of fathers	4681	8.66	2.38	0.00	19.00
Years of schooling of mothers	4681	7.39	3.08	0.00	19.00
Father's age	4681	45.96	4.34	28.00	64.00
Mother's age	4681	43.37	4.49	29.00	60.00
Non-agricultural hukou (yes =1)	4681	0.12	0.33	0.00	1.00
Parents are married (yes =1)	4681	0.82	0.39	0.00	1.00
Attended kindergarten (yes =1)	4681	0.66	0.47	0.00	1.00
Household asset index	4681	−0.47	2.13	−8.21	2.62
Panel D: Variables used for heterogenous analyses					
At least one parent migration (yes=1)	4681	0.76	0.43	0.00	1.00
Both the parents migration (yes=1)	4681	0.47	0.50	0.00	1.00
Poverty-registered households (yes=1)	4681	0.21	0.41	0.00	1.00
Lower position in the social ladder (yes=1)	4681	0.29	0.45	0.00	1.00
Neither parent attended senior high school (yes=1)	4681	0.78	0.42	0.00	1.00
Neither parent attended junior high school (yes=1)	4681	0.17	0.38	0.00	1.00
Panel E: Family care environment during preschool age					
Storytelling with any caregivers (yes=1)	4681	0.57	0.50	0.00	1.00
Play games with any caregivers (yes=1)	4681	0.60	0.49	0.00	1.00
Sing songs with any caregivers (yes=1)	4681	0.51	0.50	0.00	1.00
Storytelling with parents (yes=1)	4681	0.17	0.37	0.00	1.00
Play games with parents (yes=1)	4681	0.15	0.36	0.00	1.00
Sing songs with parents (yes=1)	4681	0.18	0.39	0.00	1.00
Panel F: Parental educational investment, companion and fertility decisions					
Number of books	4681	62.12	93.54	5	500
Strict parenting index	4551	0.81	0.98	0	3
Lack parental care (yes=1)	4681	0.43	0.49	0	1
Close to parents (yes=1)	4681	0.42	0.49	0	1
Having younger siblings (yes=1)	4681	0.39	0.49	0	1
Number of younger siblings	4681	0.42	0.56	0	3

Notes: The table shows the observation, mean, standard deviation, minimum and maximum values of the key variables for sample students. Data sources are from the survey conducted by us during June and July 2022, focusing on children from 2016–2018 Ledu Primary School Graduation Album. The sample consists of individuals who: (1) graduated from primary school in Ledu County between 2016 and 2018; (2) were born in rural areas of Ledu, as verified by their registered birth address; and (3) were successfully tracked and interviewed in the 2022 survey. Variables related to family care environment ask about students' experience before they enter primary school. The household asset index is generated by counting 21 types of fixed assets of the household, with 21 of them indicating having all the assets whereas zero none, and then standardizing the count. These fixed assets cover large animals such as horses, cows, and sheep, washing machines, computers, tractors, refrigerators, Internet connections, motorcycles, microwave ovens, iPad/tablets, tricycles, range hoods, children's separate desk, large farm equipment, gas stoves, separate room of children, truck, TV, water heater, family car, combination speaker and water pump.

4.2. Identification assumptions

Before presenting the regression results, we discussed potential three challenges associated with estimating this model. The first and key identification assumption is that absent OVOP's introduction, the human capital outcomes for students born in treated villages

would have followed the same trend as those born in untreated villages. This assumption is untestable but can be studied using pre-trends. To do so, we estimate the following event study specification:

$$Y_{ctvi} = \alpha_{ctvi} + \sum_{j<=3}^{>=10} \beta_j D_{cvj} + \mathbf{X}_{ctvi}\boldsymbol{\delta} + \phi_v + \varphi_{tc} + \partial_c + \mathbf{Z}_{v,2008} Timetrend_c + \varepsilon_{ctvi} \quad (2)$$

Where D_{cvj} are dummy variables indicating that the sample student was age j when the OVOP center within three km of students' birth village was introduced.[27] The reference group is the cohorts who were at least seven years old when OVOP centers were introduced within three km of their birth village, where age seven is the omitted group. All other variables are consistent with those in Eq. (1). In the meantime, the coefficients of interest in Eq. (2) are represented by the vector β_j. In Fig. 4, we found that the estimates for OVOP exposure at age seven and beyond are small in magnitude and statistically insignificant, suggesting no evidence of pre-trends in students' human capital outcomes that might lead to spurious findings.[28]

Another primary threat to this identifying assumption is that villages introducing OVOP centers were not randomly selected. In other words, the selection criteria might be related to some other socio-economic characteristics at village level. To address the concern, we study the exogeneity of OVOP introduction in three ways. First, following Li et al. (2016) and Thompson (2018), we examine which village characteristics predict the introduction of OVOP.[29] As shown in Table 4, except to the two site selection criteria for OVOP, which have been included in our model, significantly predict the establishment of OVOP. In contrast, among the additional eight other socio-economic characteristics, only one is statistically significant with a much smaller magnitude. Nevertheless, we add interactions of abovementioned socioeconomic characteristics[30] in 2008 and the linear cohort trend into Eq. (1) and rerun the regressions. The results in Table A.4 support the robustness of our main findings.

We also investigate whether the estimates for years of exposure might be confounded by other concurrent policies. We focus on three strands of them, the expansion of private rural preschools,[31] other CDRF-led interventions in Ledu (i.e., China rural nutrition improvement program, Smart village school program, Huiyu home visiting program and Nutrition package program[32]), and other central-government-led programs (i.e., The minimum living standard scheme, or named "Dibao", and Relocation-based poverty alleviation program[33]). To address this concern, we first construct a variable to measure students' years of exposure to private preschools, using the same method like years of exposure to OVOP, and add it to Eq. (1). We then leveraged program beneficiary lists from CDRF and questionnaires to construct dummy variables representing beneficiaries of the abovementioned intervention programs. After additionally controlling these confounding factors in Tables A.5 and A.6, we do not find substantial changes in our main results. To further assess whether our results are driven by chance, we conduct a placebo test by randomly reassigning years of OVOP among

[27] Age classification is based on calendar month-year. Specifically, we calculate students' age at first OVOP exposure by computing the difference between the establishment month-year of exposed OVOP and their birth date. For instance, a difference of −6 months indicates exposure beginning at age 0, while a difference of 36 months corresponds to initial exposure at age 3. Correspondingly, on the x-axis of Figs. 4 and 5, the event time "<=3" denotes OVOP introduction before or at age three, indicating the fully exposed cohorts.

[28] We also re-estimated the event study applying the estimator developed by Sun and Abraham (2021) (see Figure A.3), and the results remain robust.

[29] We focus on two sets of village characteristics measured in 2008, before the introduction of OVOP. One set consists of two site selection criteria for OVOP, having a primary school before 2009 (yes = 1) and having at least 10 children aged 3–6 years (yes = 1). The other set includes eight village characteristics, including distance from the village seat to the county seat (km), whether the village is the township seat (yes=1), area of the village (km2), slope of the village (%), the proportion of arable land (%), the proportion of forest and grass land (%), distance to the nearest railway station (km) and distance to the nearest highway entrance (km).

[30] They include distance from the village seat to the county seat (km), whether the village is the township seat (yes=1), area of the village (km2), slope of the village (%), the proportion of arable land (%), the proportion of forest and grass land (%), distance to the nearest railway station (km) and distance to the nearest highway entrance (km).

[31] China has increasingly invested in rural ECE service since 2010 by constructing public preschools and subsidizing private preschools (Rao et al., 2017). In Ledu county, all the public rural preschools have been OVOP centers since 2009, and private preschools have expanded during the same period.

[32] The China Rural Nutrition Improvement Program was initiated in Ledu in 2010 under the coordination of CDRF and was gradually expanded to a national policy after 2011. We surveyed students about their participation in the program through questionnaires. The Smart Village School Program was implemented by CDRF since 2015 among three primary schools in Ledu. We obtained the beneficiary student list directly from CDRF and matched them with our sample students. The Nutrition Package Program (NPP), launched in 2009, provided nutritional supplements to children aged 6-24 months across nine townships in Ledu. The Huiyu Home Visiting Program, launched in 2018, delivered home visits for rural children aged 0-3 in Ledu. However, the beneficiary children from the Huiyu program alternated with our sample students, resulting in non-overlapping populations.

[33] In addition to the programs implemented by CDRF, Ledu, as an underdeveloped area, has also benefited from the minimum living standard scheme named "Dibao" (since 2004) and the Relocation-based Poverty Alleviation Program (RPAP, since 2013). To be specific, rural hukou holders with their families' annual per capita income lower than the rural minimum living allowance standard can become "Dibao" beneficiares. Students from those families will receive benefits such as tuition reduction, living and accommodation fee reduction during the high school stage. We surveyed students about their participation in the "Dibao" program and subsequent benefits through questionnaires. Meanwhile, since the implementation of RPAP in Ledu, 59 villages in Ledu have been relocated as a whole. As the policy is implemented at the village level, we control for village fixed effects in Eq. (1) to minimize the potential impact of relocation policies on students' subsequent educational outcomes. It is also worth noting that the RPAP was implemented since 2013, whereas all sampled students in our study had already entered primary school by 2012. Consequently, this policy is unlikely to have influenced whether these students attended preschools outside their birthplace.

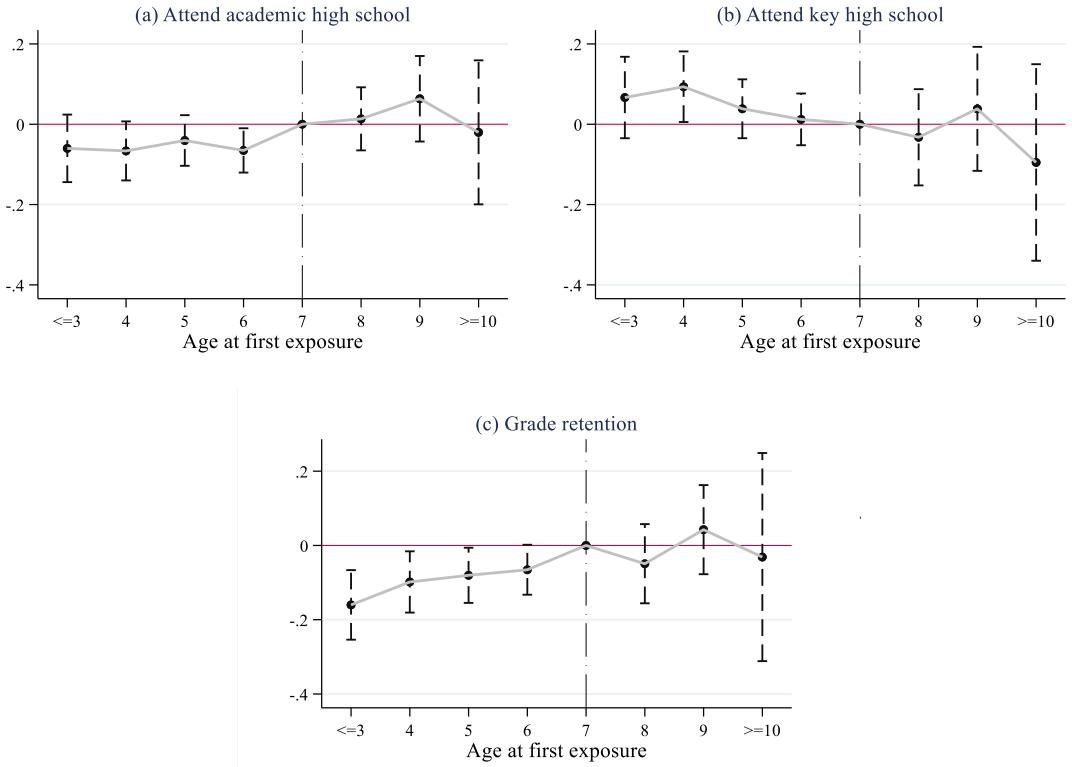

Fig. 4. Event study - Effects of OVOP on children's human capital outcomes by age at first exposure.
Notes: The figure depicts coefficients of β_j in Eq. (2), with corresponding 90 percent confidence intervals, where the key independent variables are a set of categorical measures of age when the OVOP was introduced within 3 km of commuting distance. The outcome variables are attending academic high school (yes=1), selective high school (yes=1), and grade retention (yes=1), respectively. Covariates include girls, ethnic minorities, number of siblings, years of schooling of fathers and mothers, age of fathers and mothers, non-agricultural hukou, parents are married, kindergarten experience, and household asset index, as in Eq. (1). In the model, we include fixed effects for birth village, township-by-cohort, the availability of ECE service before the OVOP establishment-by-cohort and village specific linear cohort trends. The standard errors are clustered at the village level. Age 7 is the omitted group. Estimates of exposure in early childhood (i.e., <=3, 4, 5, 6) are shown in the left of the dash dotted line, those of exposure in later childhood (i.e., 8, 9, >=10) are shown in the right of the dash dotted line.

sample students, following a permutation test procedure with 500 repetitions. Fig. A.4 shows that the resulting placebo coefficients cluster around zero, alleviating this concern.

Finally, years of exposure to OVOP must increase students' OVOP participation to generate long-term effects. Following Bailey et al. (2021), we substitute the dependent variable in Eq. (1) with students' participation across ECE types. Table 2 shows that one additional year of exposure increases OVOP attendance by 8.9 pp while modestly crowding out county seat ECE enrollment (refer to Table A.7 for more details).[34] Overall, there is a net 7.0 pp total ECE enrollment gain per exposure year, implying that the full exposure (at least three years) would increase ECE enrollment probability by at least 21 pp.[35] Macro data further validate these findings, showing that after three years of OVOP's implementation, the 2012 ECE enrollment in Ledu (including OVOP centers, county seat and township private ECE) was 24 pp above the national average. The gap likely reflects OVOP's impact on ECE enrollment given concurrent nationwide private ECE expansion, closely to the findings based on our micro-level estimates (21 pp) and supporting the relevance assumption.

[34] This substitution pattern is economically rational, as county seat ECE participation involves substantially higher costs, both in terms of tuition fees (with rural children being constrained to fee-paying private ECE options in county seat) and transportation expenses, while OVOP remains completely free

[35] For an additional assessment of pre-existing trends, we conduct a similar event study, and find that the effects of OVOP exposure on ECE attendance are salient among those exposed during their preschool age, with little impact for those exposed in later childhood (i.e., ages 7 and above) (Fig. 5).

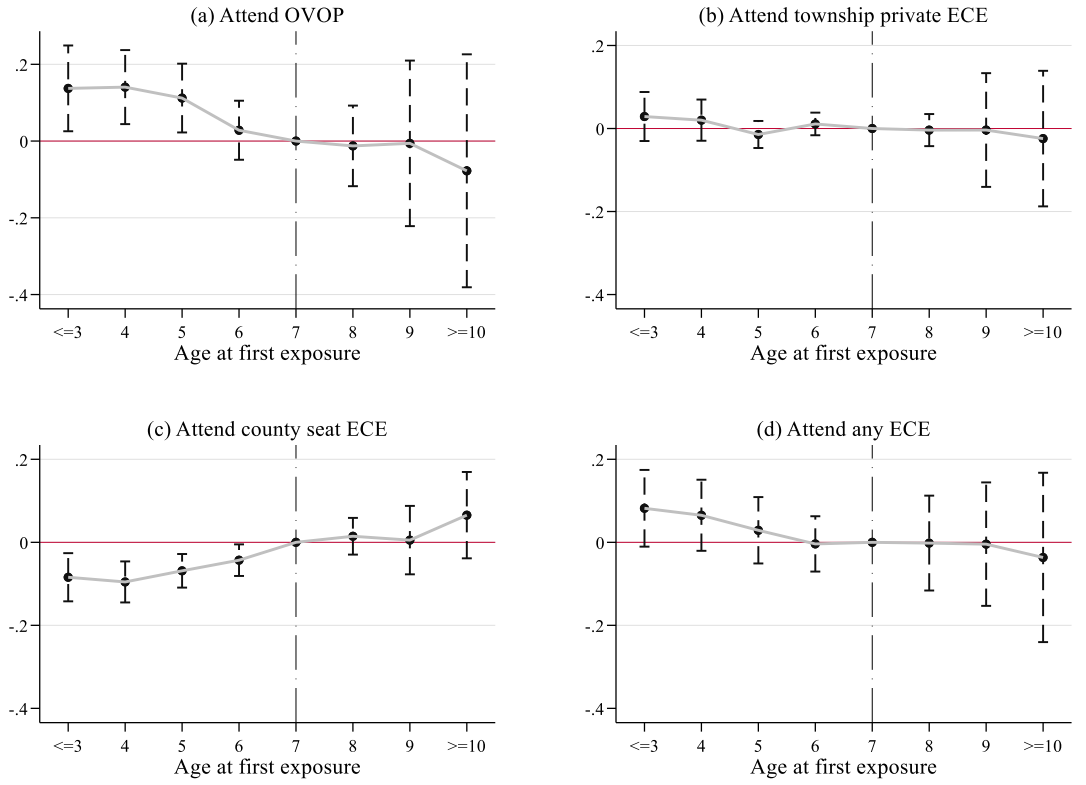

Fig. 5. Event study - Effects of OVOP on ECE enrollment by age at first exposure.
Notes: The figure depicts coefficients of β_j in Eq. (2), with corresponding 90 percent confidence intervals, where the key independent variables are a set of categorical measures of age when the OVOP was introduced within 3 km of commuting distance. The outcome variables have been replaced with attending OVOP (yes=1), township private ECE (yes=1), county seat ECE (yes=1) and any ECE (yes=1), respectively. Covariates include girls, ethnic minorities, number of siblings, years of schooling of fathers and mothers, age of fathers and mothers, non-agricultural hukou, parents are married, kindergarten experience, and household asset index, as in Eq. (1). In the model, we include fixed effects for birth village, township-by-cohort, the availability of ECE service before the OVOP establishment-by-cohort and village specific linear cohort trends. The standard errors are clustered at the village level. Age 7 is the omitted group. Estimates of exposure in early childhood (i.e., <=3, 4, 5, 6) are shown in the left of the dash dotted line, those of exposure in later childhood (i.e., 8, 9, >=10) are shown in the right of the dash dotted line.

Table 2
Effect of OVOP exposure to the ECE attendance of high school-aged children.

	Attend OVOP	Attend township private ECE	Attend county seat ECE	Attend any ECE
	(1)	(2)	(3)	(4)
Years of exposure	0.089***	0.007	−0.026**	0.070***
	(0.021)	(0.012)	(0.011)	(0.019)
Covariates	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Township-by-cohort FE	Yes	Yes	Yes	Yes
ECE before 2009-cohort FE	Yes	Yes	Yes	Yes
Village specific linear cohort trend	Yes	Yes	Yes	Yes
N	4660	4660	4660	4660
R2	0.215	0.151	0.168	0.256

Notes: This table shows the DID estimates of the effects of OVOP exposure on ECE enrollment, based on Eq. (1) with the dependent variable replaced by dummy variables indicating different types of ECE participation. The sample consists of individuals who: (1) graduated from primary school in Ledu County between 2016 and 2018; (2) were born in rural areas of Ledu, as verified by their registered birth address; and (3) were successfully tracked and interviewed in the 2022 survey. Covariates include girls, ethnic minorities, number of siblings, years of schooling of fathers and mothers, age of fathers and mothers, non-agricultural hukou, parents are married, kindergarten experience, and household asset index. In the model, we include fixed effects for birth village, township-by-cohort, the availability of ECE service before the OVOP establishment-by-cohort and village specific linear cohort trends. Standard errors clustered at the village level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Results

5.1. Impacts of years of exposure to OVOP on students' human capital

Our regression results show that years of OVOP exposure has statistically significant and positive effects on students' educational attainments. The estimates, presented in Table 3, control for a comprehensive set of individual and household covariates, village fixed effects, township-by-cohort fixed effects, cohort-specific ECE availability before 2009, and village-specific linear cohort trends (refer to Table A.8 for more details). We find that one year of OVOP exposure is associated with a 4.6 pp increase in one's probability of attending selective high school, and 3.8 pp reduction in one's probability of ever being retained in a grade. In contrast, the coefficients for academic high school attendance are small and statistically insignificant.

These results are consistent with prior literature. For instance, Chen et al. (2019, 2022) show that OVOP attendance improves students' academic performance during their early years of primary school. Chen et al. (2022) find further evidence that a higher dosage of OVOP attendance yields greater academic gains for children in primary school. Additionally, studies of ECE programs in developed countries suggest substantial benefits for students. Bailey et al. (2021) find that the Head Start program significantly increased the likelihood of high school completion. Similar positive effects have been documented for the Boston Preschool Program (Gray-Lobe et al., 2023) and the Child-Parent Center Program (Reynolds et al., 2011). Moreover, our findings regarding grade retention are in line with those from two targeted programs in the United States (Barnett et al., 2021; Reynolds et al., 2011), while larger in magnitude than those of two universal ECE programs (Amadon et al., 2022; Felfe et al., 2015).

5.2. Robustness checks

5.2.1. Heterogeneous treatment effects

Recent studies highlight potential biases in difference-in-differences (DID) estimators with staggered treatment timing (or cohorts) when treatment effects are heterogeneous or when already-treated units act as controls for later-treated units (de Chaisemartin and D'Haultfoeuille, 2023; Callaway and Sant'Anna 2021). To address this concern, we apply the estimator developed by de Chaisemartin and D'Haultfoeuille (2023), Sun and Abraham (2021) and Callaway and Sant'Anna (2021). Table A.9 shows that our main findings remain robust to heterogeneous treatment effects and the inclusion of already-treated units as controls.

5.2.2. Alternative empirical specifications

(1) Different measure of dependent variables. We replaced the dummy variable of grade retention with times of grade retention. (2) Different measure of independent variables. Following Huang and Liu (2023), we replaced years of exposure to OVOP with the fraction of exposure years before seven years old. Moreover, since OVOP centers are not opened in summer, those born after June and exposed for no more than three months were adjusted to zero exposure group. We also adjusted the exposure year to no more than three years. Finally, we adjust the bandwidths for the distance to identify neighboring OVOP centers, from 3 km to 3.5 or 4 km from sample students' birth villages. (3) Other adjustments, including dropping ECE before 2009-cohort fixed effects, clustering the standard errors at the township level, adding measures of quality of students' secondary school and parental emotions as covariates. As shown in Tables A.10–A.13, our results are robust to these alternative empirical specifications.

5.2.3. Alternative samples

(1) Excluding some sample students. First, we excluded students born in villages with private preschools before 2009. Secondly, we

Table 3
Effect of OVOP exposure to the human capital outcomes of high school-aged children.

	Attend academic high school	Attend selective high school	Grade retention
	(1)	(2)	(3)
Years of exposure	0.011	0.046**	−0.038**
	(0.016)	(0.022)	(0.016)
Covariates	Yes	Yes	Yes
Village FE	Yes	Yes	Yes
Township-by-cohort FE	Yes	Yes	Yes
ECE before 2009-cohort FE	Yes	Yes	Yes
Village specific linear cohort trend	Yes	Yes	Yes
N	4660	4660	4660
R^2	0.142	0.120	0.184

Notes: This table shows the DID estimates on the human capital benefits of OVOP exposure, based on the estimates of Eq. (1). The sample consists of individuals who: (1) graduated from primary school in Ledu County between 2016 and 2018; (2) were born in rural areas of Ledu, as verified by their registered birth address; and (3) were successfully tracked and interviewed in the 2022 survey. Covariates include girls, ethnic minorities, number of siblings, years of schooling of fathers and mothers, age of fathers and mothers, non-agricultural hukou, parents are married, kindergarten experience, and household asset index. In the model, we include fixed effects for birth village, township-by-cohort, the availability of ECE service before the OVOP establishment-by-cohort and village specific linear cohort trends. Standard errors clustered at the village level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4
The association between village characteristics and the construction of OVOP centers.

	Have OVOP center			
	OLS (1)	OLS (2)	Probit (3)	Probit (4)
Have primary school in the village (yes=1)	0.594***	0.576***	1.804***	1.831***
	(0.048)	(0.052)	(0.209)	(0.228)
Have at least 10 3- to 6-year-old children in the village (yes=1)	0.149***	0.207***	0.484***	0.746***
	(0.055)	(0.055)	(0.187)	(0.203)
Distance from the village seat to county seat (km)		0.001		0.003
		(0.003)		(0.014)
Being the resident of the township government (yes=1)		0.125		0.556
		(0.081)		(0.345)
Area of the village (km^2)		−0.003		−0.009
		(0.002)		(0.006)
Slope of the village (%)		0.015**		0.056**
		(0.007)		(0.026)
The proportion of arable land (%)		0.851		3.846
		(0.619)		(2.675)
Proportion of forest and grass land (%)		0.811		3.826
		(0.566)		(2.485)
Distance to the nearest railway station (km)		−0.001		−0.005
		(0.008)		(0.031)
Distance to the nearest highway entrance (km)		0.010		0.036
		(0.007)		(0.028)
N	275	275	275	275
R^2	0.371	0.418		

Notes: This table examines the association between village characteristics and the construction of OVOP centers, drawing on both the OLS and Probit estimation. The data of the first two variables comes from the list of OVOP centers provided by Ledu education bureau. The remaining variables are constructed by the original grid data, with the unit of observation of a 30 × 30-meter grid cell. Standard errors clustered at the village level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

excluded those born in township G, which tends to be the townships closest to the county seat. Thirdly, we excluded those students born in rural areas while attending preschools in county seat. Finally, we excluded those whose self-reported birth township and Hukou registration information were inconsistent. (2) Adding comparison group from other regions in Qinghai.[36] (3) Adjusting sample weights. Considering that students enrolled in schools are more likely to be interviewed, we made the following two adjustments accordingly. First, we deleted students not in school by setting their weight as zero. Secondly, we increased the weight of sample students not in school in 2022 survey from 1% to 4%, as 4% of students whose whereabouts are known but not interviewed are not at schools. As shown in Tables A.14–A.16, our results remain robust.

5.3. Impacts adjusted by quality of OVOP

The benefits identified in the previous sections hinge on two key assumptions. First, compared with other ECE programs, OVOP is sufficiently competitive in quality, which enables it to attract rural students. Second, high-quality OVOP centers play a positive role in enhancing students' human capital. To verify this, we begin by comparing the quality of various types of ECE services in Ledu, drawing on administrative data on OVOP centers and a complementary preschool principal survey.[37] Specifically, we compare four types of ECE services: OVOP centers, township private ECE, county seat public ECE, and county seat private ECE. We also compare the ECE quality in Ledu County with the national rural average and national average for China.

As shown in Table 5, compared to other types of ECE institutions, OVOP centers are smaller in scale and have fewer resources, such as books and toys, which may be attributed to the relatively small number of children there. Nevertheless, the quality of facilities in OVOP centers also far exceeds those of other rural preschools across China during the same period (Luo et al., 2012; Wong et al., 2013). The comparative advantage of OVOP may be attributed to the fact that OVOP centers receive funding from multiple sources, including

[36] To mitigate the threat posed by the relatively small number of control groups, we conducted a similar children survey in seven academic/vocational high schools in four other counties in Qinghai in August 2022. The survey and sample selection follow a three-step process: first, the research team selected four counties with relatively better/worse economic conditions than the sample county. Among them, the former two counties were randomly selected from the provincial capital city of Xining; The latter two counties were randomly selected from the agricultural and pastoral counties of Qinghai province, respectively. Second, in each county, one-two local academic/vocational high schools with the largest scale were selected for investigation. Thus, five academic high schools and two vocational high schools were surveyed. Third, two classes were randomly selected from each grade in each school to conduct the survey. Finally, among all the children interviewed by us, 1,138 born in rural areas (i.e., excluding those born in county seats) were added to the control sample.

[37] Principals from private or county seat public preschools operated between 2009 and 2012 in the sample county reported the basic characteristics of facilities and teachers during this period. It is notable that such self-reported information might be threatened by potential recall bias.

Table 5
Quality characteristics of OVOP centers and other types of ECE.

	OVOP center	Township private ECE	County seat public ECE	County seat private ECE	National average in rural areas	National average
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Facility characteristics						
Floor space (mu)	1.19	2.34	5.40	3.82	-	-
Construction space (m^2)	163.30	976.20	2400.00	1296.00	-	-
Number of books	107.20	508.90	1500.00	823.30	-	-
Number of big toys	1.00	2.89	10.00	3.25	-	-
Panel B: Teacher qualifications						
Child-teacher ratio	11:1	18:1	15:1	13:1	30:1	16:1
Proportion of teachers with at least college degree (%)	60	57	48	57	42	54
Proportion of teachers majoring in preschool education (%)	78	47	48	47	-	-
Proportion of teachers with a professional ranking (%)	0	0	8	0	24	30
Panel C: Other Characteristics						
Operating time (h/day)	6	7	7	7	-	-
Monthly salaries of teachers (2010 CNY yuan)	1500	1792	2000	2086	-	-

Notes: This table shows the average quality of different types of ECE institutions in Ledu, compared with the national levels. Data source: Indicators of OVOP comes from the OVOP registration form, taking average for the OVOP centers founded from 2009 to 2012; Indicators of township private ECE, county seat public ECE and county seat private ECE comes from the preschool principal survey, principals reported basic characteristics of their preschools from 2009–2012. National data comes from the *Educational Statistics Yearbook of China*, taking average of the indicators ranging from 2009 to 2012. In China, mu is a traditional unit of land measurement, and one mu of land is equal to about 0.06667 hectares or 666.7 square meters.

foundations, and local and central governments, while other types of ECE services rely primarily on investment from local governments or private investors. Also, it is notable that OVOP centers lag behind other types of ECE services in terms of available hours (due to their remote location) and teachers' salaries.

Moreover, substantial differences exist between OVOP centers and other types of ECE services with respect to teacher qualifications and child-teacher ratios. OVOP centers have the highest proportion of teachers with college degree or higher (60%) and majoring in preschool education (78%) and have the lowest child-teacher ratio of 11:1. In fact, OVOPs outperform the national average on these indicators. OVOP teachers appear to have better qualifications than their counterparts in rural preschools in Henan, Guizhou, or other provinces of China (Luo et al., 2012; Wong et al., 2013; Wang et al., 2020). Moreover, OVOP centers and county seat private preschools are more likely to meet the standards of the child-teacher ratio standards set by Ministry of Education (2013). However, as only teachers in public preschools are eligible for professional ranking evaluations, those from OVOPs and other private preschools do not meet the criteria for ranking, regardless of their performance.

In this case, a natural question arises, do higher-quality OVOP centers lead to greater improvements in students' human capital outcomes? To answer this question, as we do not directly observe which OVOP a student attended, we use the quality of the nearest OVOP to the student's birth village before age seven as a proxy. While this variable might be subject to measurement error to some extent, it has the advantage of being more exogenous for two reasons (Hojman and Lopez Boo, 2022). First, it depends solely on the housing decisions of families, not on their choice of preschools. Second, it is difficult for families to obtain information about the quality of different OVOPs, let alone base decisions on it. Therefore, we assume that these quality measures are uncorrelated with unobservable factors. We estimate the following equation in practice:

$$Y_{ctvi} = \alpha_{ctvi} + \beta_1 Exposure_{cv} + \beta_2 Exposure_{cv} Q_s + \mathbf{X}_{ctvi}\boldsymbol{\delta} + \phi_v + \varphi_{tc} + \partial_c + \mathbf{Z}_{v,2008} Timetrend_c + \varepsilon_{ctvi} \quad (3)$$

Q_s represents quality of the nearest OVOP to students' birth village before age seven. Four indicators[38] were utilized for assessing the quality, including hardware facility index,[39] child-teacher ratio, teacher qualifications (including the proportion of teachers with at least college degree or majoring in preschool education). All of them are recorded data from the county education bureau.

The effects of OVOP, adjusted for its quality, reveal significant benefits of attending a high-quality OVOP on students' human capital outcomes (Table 6). Notably, teacher qualifications, including indicated by certification, preschool education specialization, and experience, play a critical role in reducing students' likelihood of grade retention (Panel C-E). More experienced teachers majoring in preschool education further contribute to their probability of attending academic high schools (Panel D and E). However, more facilities and lower child-teacher ratios show no significant effects (Panel A-B), nor do the advanced degrees of OVOP teachers (Panel F). Interviews with officials from the county education bureau and OVOP teachers provide us with the potential explanation. That said,

[38] Due to that the remaining quality indicators listed in Table 5 differ little among different OVOP centers, we only consider the impact of the four quality indicators mentioned above.

[39] The index of facilities is constructed drawing on polychoric principal components on these variables: building area (m^2), outdoor activity area (m^2), number of books and number of large toys.

Table 6
Effect of OVOP exposure, adjusted by quality indicators.

	Attend academic high school (1)	Attend selective high school (2)	Grade retention (3)
Panel A:			
Years of exposure	0.015	0.049**	−0.044***
	(0.018)	(0.022)	(0.017)
Years of exposure × Index of facilities	−0.005	0.000	0.005
	(0.005)	(0.006)	(0.007)
N	4034	4034	4034
R^2	0.146	0.123	0.187
Panel B:			
Years of exposure	0.014	0.055**	−0.043***
	(0.017)	(0.022)	(0.016)
Years of exposure × Reasonable Child-teacher ratio	−0.016	−0.025	0.015
	(0.016)	(0.020)	(0.019)
N	4034	4034	4034
R^2	0.146	0.124	0.187
Panel C:			
Years of exposure	0.018	0.039	−0.034*
	(0.017)	(0.024)	(0.017)
Years of exposure × Proportion of teachers with teaching certifications (%)	−0.002	−0.023	−0.045**
	(0.016)	(0.025)	(0.021)
N	3684	3684	3684
R^2	0.152	0.121	0.190
Panel D:			
Years of exposure	0.006	0.027	−0.023
	(0.018)	(0.025)	(0.017)
Years of exposure × Proportion of majoring in preschool education (%)	0.042**	0.033	−0.058***
	(0.019)	(0.022)	(0.020)
N	3684	3684	3684
R^2	0.153	0.122	0.192
Panel E:			
Years of exposure	0.002	0.031	−0.032*
	(0.018)	(0.024)	(0.018)
Years of exposure × Average years of experience (%)	0.024***	0.008	−0.011**
	(0.007)	(0.006)	(0.005)
N	3684	3684	3684
R2	0.156	0.121	0.190
Panel F:			
Years of exposure	0.023	0.036	−0.035**
	(0.017)	(0.024)	(0.017)
Years of exposure × Proportion of teachers holding college degree or above (%)	−0.015	−0.002	−0.012
	(0.014)	(0.021)	(0.018)
N	3684	3684	3684
R2	0.152	0.121	0.190
Covariates	Yes	Yes	Yes
Village FE	Yes	Yes	Yes
Township-by-cohort FE	Yes	Yes	Yes
ECE before 2009-cohort FE	Yes	Yes	Yes
Village specific linear cohort trend	Yes	Yes	Yes

Notes: This table shows the DID estimates on the human capital benefits of OVOP exposure adjusted by different quality indicators, based on the estimates of Eq. (3). Quality indicators in Panel A-B come from the OVOP registration form provided by Ledu education bureau. Specifically, the facility index was constructed using polychoric principal component analysis on the following variables: building area (m^2), outdoor activity space (m^2), number of books, and number of large toys. Additionally, a child-teacher ratio that meets the standards set by the Ministry of Education (2013) is classified as "reasonable". Quality indicators in Panel C-F come from a complementary OVOP teacher survey conducted by authors, where 83% of OVOP teachers employed by the OVOP centers during 2009–2012 reported their employment duration, degree, major, teaching certifications, and years of teaching experience at initial OVOP employment. We subsequently matched these data with OVOP registration form to compute preschool-level averages of teacher qualification metrics. The sample consists of individuals who: (1) graduated from primary school in Ledu County between 2016 and 2018; (2) were born in rural areas of Ledu, as verified by their registered birth address; and (3) were successfully tracked and interviewed in the 2022 survey. Covariates include girls, ethnic minorities, number of siblings, years of schooling of fathers and mothers, age of fathers and mothers, non-agricultural hukou, parents are married, kindergarten experience, and household asset index. In the model, we include fixed effects for birth village, township-by-cohort, the availability of ECE service before the OVOP establishment-by-cohort and village specific linear cohort trends. Standard errors clustered at the village level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

lower child-teacher ratios in OVOPs are generally linked to remote locations, where longer teacher commutes reduce their attention to children. Additionally, OVOP teacher recruitment does not require preschool education majors for college-educated hires, and this lack of specialization may explain why better educated teachers show no significant effects.

Overall, our results emphasize the importance of improving ECE quality in rural areas. These findings are consistent with those from other developing countries (Bouguen et al., 2018; Morabito et al., 2018) or developed countries (Blanden et al., 2016, 2021; Thompson, 2018), which highlight the importance of high-quality ECE service in promoting long-term child development in their discussions. Building on this foundation, our study provides the following implications that, policymakers should give more attention to ECE teachers' qualifications, rather than just focusing on facilities.

5.4. Potential mechanisms

So far, our results have shown the long-term benefits of OVOP on students' educational attainment. Why is it like this? In theory, two possible causal pathways exist, leading us to conduct four empirical analyses. First, the theory of skill formation emphasizes the concept of "skills beget skills" (Cunha and Heckman, 2008). That said, early childhood investments like quality ECE lay a solid foundation for human capital accumulation, enhancing subsequent investment productivity, while early skill deficits may persist (Cunha et al., 2010). We test these mechanisms by examining whether and how children at preschool age and compulsory education stage benefit from OVOP in skill development. Second, quality ECE programs might reshape family environment, fostering parent-child interaction (García et al., 2023; Gelber and Isen, 2013), and crucially, influence later-stage family investments, an understudied but important dimension for sustaining early childhood intervention effects (Cunha et al., 2010). We therefore analyze the impacts of OVOP on preschool-aged parent-child interaction and later parental investments.

5.4.1. Effects on early childhood skill accumulation

We first investigate whether OVOP has laid the foundation for children's human capital accumulation during their early childhood. Due to that sample children's early childhood development outcomes are not available in our 2022 survey, we draw on a preliminary survey conducted in Ledu and two other comparison counties in Qinghai province in 2011 (see Section 3). Among all the 823 surveyed children aged 3 to 6 years old, 244 are preschoolers in OVOP centers in Ledu, 579 are children without any ECE experience in comparison counties. To address the underlying self-selection bias of OVOP attendance,[40] we rely on the entropy balancing (EB) techniques to balance these pre-treatment variables between the OVOP group and No OVOP group.[41] Specifically, we estimate the following equation:

$$Y_{is} = \beta_0 + \beta_1 OVOPer_{is} + \mathbf{X}_{is}\boldsymbol{\beta} + \gamma_s + \varepsilon_{is} \tag{4}$$

Where Y_{is} denotes the skill indicators of student i in township s. $OVOPer_{is}$ is a dummy variable, which takes the value of one if children were enrolled in OVOP. $\boldsymbol{X_{is}}$ denotes an array of covariates including personal characteristics (gender, age, ethnicity), parental characteristics (parental education and parents working outside home) and household income (in 2011 CNY yuan). γ_s is the township fixed effects, which are employed to account for characteristics that influence student achievement at the class level and beyond. ε_{is} is the i.i.d. error term. We cluster the standard errors at the child level. Meanwhile, the entropy balancing method is applied to equalize the pre-treatment variables between groups, thereby reducing potential selection bias.[42]

Our results in Table 7 show that OVOP significantly benefits children's cognitive and language development during preschool (refer to Appendix A.19 for more details). Compared with the peers not attending any ECE, children attending OVOP perform better in memory by 10.9 points, in cognition by 13.0 points, in language by 10.2 points, in social rules by 8.1 points respectively, and show an average improvement of 10.0 points in the overall score. Given the comparison group's average score of 43.3, attending OVOP resulted in a 23% improvement in students' skill scores during preschool age. That said, years of OVOP exposure significantly benefits students' human capital development in high school by fostering skills in early childhood. Our findings are also consistent with Heckman et al. (2013) and Gray-Lobe et al. (2023), which have shown that human capital accumulation in earlier stage serves as the channels by which ECE programs produce the long-term effects.

[40] As shown in Table A.17, children with OVOP experience are less likely to be ethnic minorities, owning better educated parents and older than their peers with OVOP experience.

[41] Due to the survey on preschool-aged children did not include their names, ID numbers and precise birth addresses, we cannot employ the DID approach for these sample children.

[42] Moreover, we use the balancing method to make sure the balanced control group has almost the same mean, variance, and skewness in these variables. To do so, we draw on nine covariates: girl, ethnic minorities, age 4, age 5, complete junior high school (father), complete junior high school (mother), work outside home (father), work outside home (mother), and family annual income (in 2011 CNY). Table A.18 summarizes the entropy balancing results. Columns (1) to (3) compare the mean, variance, and skewness of the variables between the treatment and the comparison group. In the upper panel, large differences are evident in these statistics. In the lower panel, the balanced control group has roughly the same statistics as the treatment group. We also regress the treatment dummy on these variables and present the results in column (7) for the non-balanced sample and the balanced sample, respectively, to investigate whether these variables can predict the assignment of the treatment. We find that these coefficients become much smaller and are no longer statistically significant. This result suggests that these covariates can no longer predict the OVOP attendance after balancing. We also compare both the pre- and post-differences in the nine covariates in the outcome equation to ensure that the balancing method makes the treatment and the comparison group comparable. It turns out that the differences between these covariates are eliminated after balancing (Fig. A.5).

Table 7
Benefits of OVOP on students' early childhood human capital development.

	Motor		Memory		Cognition		Language		Social rules		Overall	
	OLS	EB	OLS	EB	OLS	EB	OLS	EB	OLS	EB	OLS	EB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Attend OVOP	11.607**	5.459	12.972**	10.883*	12.480***	13.008***	10.626***	10.151***	7.823**	8.090*	11.389***	9.984***
	(4.755)	(5.240)	(5.352)	(6.242)	(3.432)	(3.745)	(3.176)	(3.606)	(3.342)	(4.455)	(2.928)	(3.316)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Township FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	823	823	823	823	823	823	823	823	823	823	823	823
R^2	0.161	0.179	0.195	0.173	0.348	0.309	0.208	0.252	0.581	0.588	0.351	0.308

Notes: This table shows the OLS and Entropy Balancing (EB) estimates on benefits of OVOP on students' early childhood human capital development, based on the estimates of Eq. (4). Data come from the preliminary sampling survey in 2011 focusing on preschool-aged children. The sample includes 823 children aged 3–6 from Ledu and two comparison counties (Ping'an, and Jianzha) in Qinghai. The sample is constructed through a multi-stage process: (1) Based on similarities in socioeconomic characteristics, two counties in Qinghai without OVOP centers were selected as the comparison group. (2) townships in above three counties were selected using the Population Proportionate Sampling (PPS) method, yielding eight, three, and four sample townships in Ledu, Ping'an, and Jianzha, respectively; and (3) within these townships, a total of 16 OVOP centers in Ledu and six and eight villages in Ping'an and Jianzha were selected, drawing on similar PPS method. Finally, all children aged 3–6 in the selected OVOP centers and villages were surveyed, resulting in a final sample of 823 children. Covariates at individual level include girls, ethnic minorities, age 4 years old (yes=1) and age 5 years old (yes=1). Covariates at household level complete junior high school (father), complete junior high school (mother), work outside home (father), work outside home (mother), and family annual income (2011 CNY yuan). We include township fixed effects in the model. Standard errors clustered at the village level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.4.2. Effects on performance in junior (senior) high school entrance exam

We now return to our main survey data and find that OVOP further enhances the academic performance of students during compulsory education stage. Specifically, one year of OVOP exposure during students' preschool age is associated with a 4.9 (15.4) point increase in junior (senior) high school entrance exam scores (Table 8). The event study in Fig. A.6 confirms the validity of the results. Given the average performance of children who did not attend OVOP, this translates to an improvement of 2.2 (3.8) pp in the junior (senior) high school entrance exams, respectively. These findings suggest that the benefits of OVOP on children's academic performance may not diminish over time; rather, it may continue to amplify. This aligns with the findings of Chen et al. (2019), where the academic performance gap between children who attended OVOP and those who did not is larger by Grade 5 than it was by Grade 3. To conclude, these findings point to a potential mechanism underlying the concept of "skills beget skills."

Moreover, to better understand why OVOP promotes enrollment in selective senior high schools rather than regular ones, we employ the quantile treatment effects (QTE) approach to examine its impacts across different grade distributions. As shown in Fig. 6, students in the 60th-80th grade percentiles benefit the most from OVOP. Combined with the fact that only 28% of the sample students attend selective senior high schools (Table 1), the bias of OVOP's benefits on upper-middle-performing students explains why it promotes enrollment in selective rather than non-selective schools. Additionally, the lowest-performing students benefit the least from OVOP, whether in junior or senior high school entrance exams.

These findings are consistent with several important prior studies that help explain non-linear benefits of OVOP. In the study of Israeli high school achievement awards, Angrist and Lavy (2009) find that the benefits for girls are driven by marginal students for whom certification is "within reach", because they are more likely to adjust test-taking strategies or study time when incentivized. Yi et al. (2015) also show that Early Commitment of Financial Aid (ECFA) did not motivate significant behavioral changes among ninth graders to prepare for high school, due to the competitive education system effectively screened out poorer performers while promoting better-performing students. This pattern emerges even earlier, e.g., additional instructional time in preschools benefit higher achievers more (Hayes and Gershenson, 2016). Combined with the concept of "skill begets skill", which showing that a strong early foundation enables acquisition of more advanced skills (Cunha et al., 2010), it is reasonable that OVOP enhances the academic competitiveness of children with emerging potential by effective early interventions, resulting in nonlinear returns to human capital accumulation.

5.4.3. Effects on parent-child interactions during preschool age

Given that OVOPs foster students' early childhood development, is it likely that they play the role in reshaping family care behaviors and other decisions? In this section, we return to the data from our 2022 survey, where we gathered detailed information on family parenting practices during students' preschool years. Our data reveal a concerning family care environment of sample rural students during their early years. Descriptive statistics in Table 1 show that only 57%, 60% and 51% of caregivers regularly told stories, sang nursery rhymes and played games with the sample students before they entered primary school. Even less than 20% of parents did so regularly. Intergenerational caregivers, particularly grandparents, constitute a substantial proportion of these caregiving interactions. For example, 48% of storytelling sessions are led by grandparents, followed by 31% by mothers and 21% by fathers or other family members.

Can years of OVOP exposure enhance preschool-aged parent-child interactions? However, our regression results show no significant effect, irrespective of caregiver type (Table A.20). According to the meta-analyses of Emmers et al. (2021), the potential channel of the success of parental training programs tends to be the increase of caregivers' engagement in stimulating parenting practices and that of their parenting knowledge. However, in the first few years of the introduction of OVOP, the connection between OVOP and

Table 8
Effect of OVOP exposure on children's academic performance at compulsory education stage.

	Score of junior high school entrance exam [0–300]		Score of senior high school entrance exam [0–750]	
	(1)	(2)	(3)	(4)
Years of exposure	6.596***	4.888***	16.486***	15.378***
	(2.021)	(1.059)	(5.150)	(5.058)
Covariates	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Township-by-cohort FE	Yes	Yes	Yes	Yes
ECE before 2009-cohort FE	Yes	Yes	Yes	Yes
Village specific linear cohort trend	Yes	Yes	Yes	Yes
Exam Year FE	No	Yes	No	Yes
N	4526	4526	4202	4202
R2	0.231	0.718	0.165	0.188

Notes: This table shows the DID estimates of the effects of years of exposure to OVOP on children's academic performance, based on Eq. (1) with the dependent variable replaced by scores of junior (senior) high school entrance exam. Students' name, school, ID number and test scores were provided by the Ledu Education Bureau. The sample consists of individuals who: (1) graduated from primary school in Ledu County between 2016 and 2018; (2) were born in rural areas of Ledu, as verified by their registered birth address; and (3) were successfully tracked and interviewed in the 2022 survey. Covariates include girls, ethnic minorities, number of siblings, years of schooling of fathers and mothers, age of fathers and mothers, non-agricultural hukou, parents are married, kindergarten experience, and household asset index. In the model, we include fixed effects for birth village, township-by-cohort, the availability of ECE service before the OVOP establishment-by-cohort and village specific linear cohort trends. Standard errors clustered at the village level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

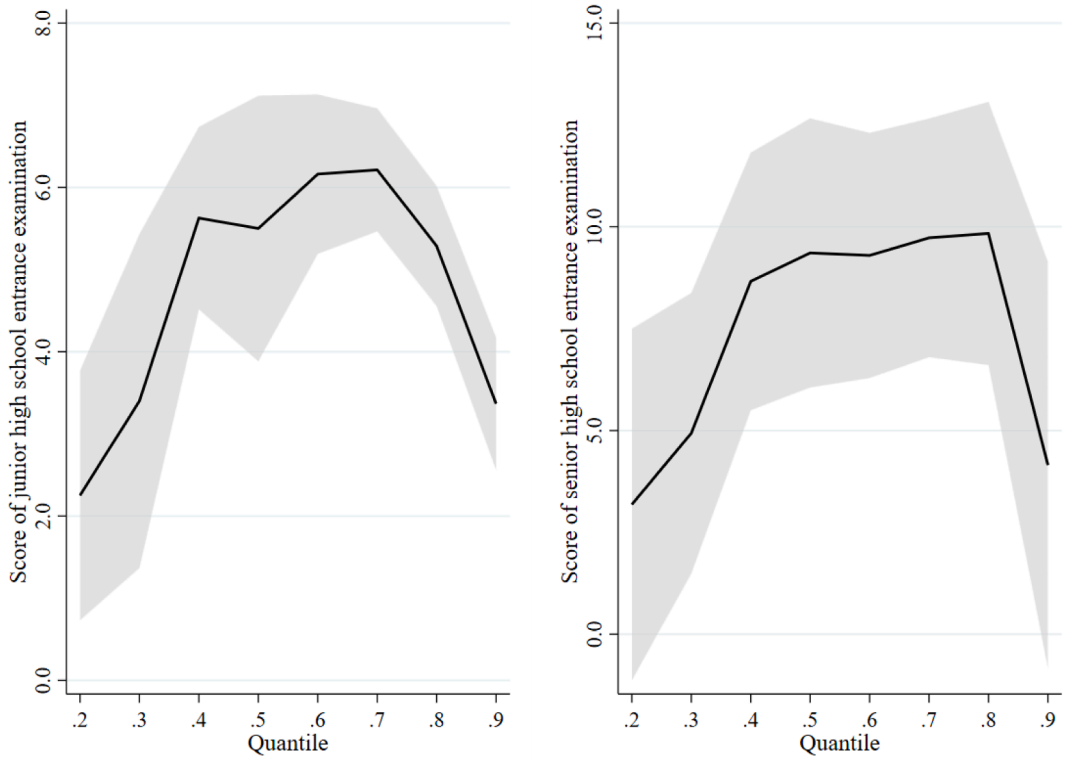

Fig. 6. QTE estimates on scores of junior (senior) high school entrance exams.
Notes: This figure presents the quantile treatment effect (QTE) estimates for sample students' academic performance, including scores on junior and senior high school entrance examinations. It displays the point estimates for students at different score percentiles (black solid line) along with the 90 percent confidence intervals (gray areas). The set of covariates includes female, ethnic minority, number of siblings, years of schooling of fathers and mothers, age of fathers and mothers, non-agricultural hukou, married parents, kindergarten experience, and a household asset index. The model also incorporates fixed effects for birth village, township-by-cohort, the availability of ECE services before the OVOP establishment interacted with cohort, and village-specific linear cohort trends. Standard errors are clustered at the village level.

families/caregivers was not strong enough, and teachers mainly drew on two home visits on average per year to provide care givers with limited parenting knowledge. Moreover, intervention in family parenting behaviors starting from the preschool-age may be too late to reverse the inadequate or inappropriate parenting behaviors (Emmers et al., 2021). Therefore, whether the OVOPs in later years with improved family-preschool connections can promote better family parenting behaviors remains an important research topic in the future.

5.4.4. Effects on parental educational investment and behaviors during high school age

In Table A.21, we find that OVOP fails to further improve educational investment in students and parental involvement during the high school years. The only exception is that children more exposed to OVOP had fewer younger siblings, suggesting that parents did not increase their fertility due to the availability of free preschool education.

5.5. Heterogenous analyses

So far, we have demonstrated the long-term human capital benefits of years of OVOP exposure for high school-aged students. Do these impacts vary across different sub-groups of students? To answer this, we conduct heterogenous analyses by children's gender (girl=1), ethnicity (ethnic minorities=1) and age (continuous), together with parental migration status (any parent has migrated to other counties more than six months=1), parental education (any parent has finished senior high school=1) and household socio-economic status (ever classified as poverty-registered households=1). We introduce these dummy variables into Eq. (1) and interact them with the variable indicating students' years of OVOP exposure before re-running the regressions. Heterogeneous effects on educational attainment are shown in Table 9.

The results reveal two notable patterns. First, the human capital benefits of OVOP exhibit little demographic variation (Table 9), suggesting age/gender differences between surveyed and non-surveyed students are unlikely to bias our findings. Second, family background matters significantly. Students with migrant parents (lack parental care and companionship) and those from poverty-registered households show greater gains in academic high school enrollment (Panel A and B, Table 10). Given the high prevalence

Table 9
Effect of OVOP exposure to the human capital outcomes of high school-aged children, by students' personal characteristics.

	Attend academic high school (1)	Attend selective high school (2)	Grade retention (3)
Panel A:			
Years of exposure	0.014	0.045**	−0.039**
	(0.017)	(0.022)	(0.017)
Girl	0.067***	0.031*	−0.063***
	(0.016)	(0.018)	(0.016)
Years of exposure × Girl	−0.007	0.002	0.003
	(0.011)	(0.011)	(0.009)
N	4660	4660	4660
R^2	0.142	0.120	0.184
Panel B:			
Years of exposure	0.009	0.052**	−0.040**
	(0.016)	(0.022)	(0.016)
Ethnic minorities	0.001	0.036	−0.021
	(0.025)	(0.026)	(0.025)
Years of exposure × Ethnic minorities	0.008	−0.029*	0.010
	(0.014)	(0.015)	(0.011)
N	4660	4660	4660
R^2	0.142	0.121	0.184
Panel C:			
Years of exposure	0.064	−0.147	0.187
	(0.183)	(0.228)	(0.165)
Years of exposure × Age	−0.003	0.012	−0.013
	(0.011)	(0.014)	(0.010)
N	4660	4660	4660
R^2	0.142	0.120	0.184
Covariates	Yes	Yes	Yes
Village FE	Yes	Yes	Yes
Township-by-cohort FE	Yes	Yes	Yes
ECE before 2009-cohort FE	Yes	Yes	Yes
Village specific linear cohort trend	Yes	Yes	Yes

Notes: This table shows the DID estimates of the heterogenous effects of OVOP exposure by personal characteristics. We introduce these dummy variables into Eq. (1) and interact them with the variable indicating students' exposure to OVOP before re-running the regressions. The sample consists of individuals who: (1) graduated from primary school in Ledu County between 2016 and 2018; (2) were born in rural areas of Ledu, as verified by their registered birth address; and (3) were successfully tracked and interviewed in the 2022 survey. Covariates include girls, ethnic minorities, number of siblings, years of schooling of fathers and mothers, age of fathers and mothers, non-agricultural hukou, parents are married, kindergarten experience, and household asset index. In the model, we include fixed effects for birth village, township-by-cohort, the availability of ECE service before the OVOP establishment-by-cohort and village specific linear cohort trends. Standard errors clustered at the village level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of left-behind rural students in China (Bai et al., 2022), our results highlight the importance of providing quality ECE services for these students. Our findings also align with the literature that ECE programs are more beneficial to those from disadvantaged families (Blanden et al., 2016; Cascio and Schanzenbach, 2013; Fort et al., 2020; Brinkman et al., 2017). Meanwhile, benefits of years of OVOP exposure differ little by parental education (Panel C, Table 10). Robustness checks using alternative measures of family background confirm these patterns (Table A.22).

6. Cost-benefit analyses and marginal value of public funds

To gain a deeper understanding of the economic significance of our findings, we assessed whether the benefits of establishing OVOPs in rural China exceed the costs. For this, we drew on two frameworks to calculate the returns of the OVOP pilot: cost-benefit analyses (Heckman et al., 2010) and the Marginal Value of Public Funds (MVPF) approach (Hendren and Sprung-Keyser, 2020; Hendren, 2016).

The cost-benefit analyses were conducted in a three-step procedure. First, we calculated the costs using the method of Levin et al. (2018).[43] To be specific, we divided costs into the following six categories: personnel salary, training, school building, facilities, management and user input. As shown in Table A.23, the rental and renovation fee of school buildings account for the highest proportion, followed by the cost of teacher salaries. Overall, the costs of the program were around CNY 1700 (equivalent to USD 239) per participant child per year. Due to data constraints, we employed the years of exposure to OVOP (1.6 years) for OVOP attendees as the

[43] In this section, all costs and benefits are measured in 2010 yuan, and a three percent discount rate is used for the analyses. We assume that the depreciation period of the school building investment tends to be 10 years, and that of the equipment investment such as tables and chairs is five years.

Table 10
Effect of OVOP exposure to the human capital outcomes of high school-aged children, by parental and household characteristics.

	Attend academic high school (1)	Attend selective high school (2)	Grade retention (3)
Panel A:			
Years of exposure	−0.027	0.042*	−0.039**
	(0.019)	(0.025)	(0.018)
At least one parent migration	−0.038**	0.037	−0.022
	(0.017)	(0.024)	(0.018)
Years of exposure ×	0.050***	0.006	0.002
At least one parent migration	(0.013)	(0.016)	(0.010)
N	4660	4660	4660
R^2	0.146	0.122	0.184
Panel B:			
Years of exposure	0.004	0.049**	−0.035**
	(0.017)	(0.022)	(0.016)
Poverty-registered household	−0.143***	−0.020	0.052**
	(0.028)	(0.028)	(0.021)
Years of exposure ×	0.033**	−0.013	−0.011
Poverty-registered household	(0.016)	(0.016)	(0.012)
N	4660	4660	4660
R^2	0.153	0.121	0.185
Panel C:			
Years of exposure	0.011	0.049**	−0.039**
	(0.016)	(0.022)	(0.017)
Neither parent attended senior	−0.071***	−0.074***	0.012
high school (yes=1)	(0.025)	(0.025)	(0.025)
Years of exposure × Neither parent	0.008	−0.006	0.008
attended senior high school (yes=1)	(0.015)	(0.015)	(0.013)
N	4660	4660	4660
R^2	0.139	0.115	0.183
Covariates	Yes	Yes	Yes
Village FE	Yes	Yes	Yes
Township-by-cohort FE	Yes	Yes	Yes
ECE before 2009-cohort FE	Yes	Yes	Yes
Village specific linear cohort trend	Yes	Yes	Yes

Notes: This table shows the DID estimates of the heterogenous effects of OVOP exposure by parental and household characteristics. We introduce these dummy variables into Eq. (1) and interact them with the variable indicating students' exposure to OVOP before re-running the regressions. The sample consists of individuals who: (1) graduated from primary school in Ledu County between 2016 and 2018; (2) were born in rural areas of Ledu, as verified by their registered birth address; and (3) were successfully tracked and interviewed in the 2022 survey. Covariates include girls, ethnic minorities, number of siblings, years of schooling of fathers and mothers, age of fathers and mothers, non-agricultural hukou, parents are married, kindergarten experience, and household asset index. In the model, we include fixed effects for birth village, township-by-cohort, the availability of ECE service before the OVOP establishment-by-cohort and village specific linear cohort trends. Standard errors clustered at the village level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

expected average OVOP duration. We also assumed a 20 percent deadweight tax loss rate, following Auriol and Warlters (2012). In this case, the cost of OVOP is estimated at CNY 3264 per child.

We then estimated the economic returns related to selective high school attendance. Given our main estimates, students with one extra year of exposure to OVOP are 4.6 pp more likely to attend selective high school, and a one-year exposure of OVOP leads to an 8.9 pp increase in the probability of attending OVOPs. Meanwhile, we used data from the China Household Income Project (CHIP) to calculate the labor market returns of selective high school attendance, and our results show that selective high schools graduates in China earn 5.7 percent more annual income than their counterparts. Thus, it is calculated that students attending OVOP would earn 1.8 percent more annually than their peers.

Regarding the costs associated with grade retention, the labor market impacts of this phenomenon remain a subject of debate in the literature. Studies in rural China suggest that grade retention has an insignificant effect on students' academic performance in primary school (Chen et al., 2010). Following Reynolds et al. (2011), we argue that avoiding grade retention prevents students from delayed entry into the labor market, effectively enabling them to earn an additional year of wages. As such, OVOP attendance is associated with an extra 0.3 years of income relative to peers, owing to its reduction in the likelihood of grade retention. Furthermore, reducing the probability of grade retention also results in savings on the social costs of public education spending. Following Reynolds et al. (2011), this study uses the average public education expenditure (CNY 16,646) per student in 2022, from primary school through high school in China, as a proxy for the social cost of grade retention.

Finally, we converted the annual income benefits into the present value (PV) of lifetime income and calculate the benefit-cost ratio. Assuming that students work 40 years in the labor market, the lifetime income benefits from selective high school attendance are CNY 11,685 in present value. Including the additional income from avoided grade retention (CNY 4907), we estimate the total present value of OVOP's returns at CNY 16,592, yielding a benefit-cost ratio of 5.1:1. When compared to similar projects in other countries, primarily

in developed nations (due to limited data from developing countries), we find that OVOP's returns are at least comparable to those of well-known universal ECE programs, such as Head Start, and universal ECE programs in Spain and Uruguay (Berlinski et al., 2008; Ludwig and Miller, 2007) (summarized in Table A.24). However, the returns to OVOP still do not match those of targeted preschool programs, such as the Perry Preschool Project (Heckman et al., 2010). One potential explanation is that targeted programs often focus on the most disadvantaged groups, who stand to benefit the most from preschool education (Bailey et al., 2021; Thompson, 2018). In contrast, OVOP primarily targets rural populations in relatively impoverished areas without imposing further restrictions on access. Nevertheless, by focusing specifically on rural students, OVOP has achieved a higher return rate than most universal preschool programs.

Following Hendren and Sprung-Keyser (2020), we then conducted an MVPF analysis to calculate the social benefits of OVOP.[44] Considering only the social benefits from wage increases, our estimated MVPF tends to be 9.3. Moreover, when factoring in the savings from reduced educational expenditures, the MVPF of OVOP becomes infinite. In comparison to 133 public policies in the United States (Hendren and Sprung-Keyser, 2020), the MVPF of OVOP, even under the most conservative estimate, outperforms more than half of the policies.

Our cost-benefit analyses came with a potential concern: urban students may be crowded out of selective high schools when rural students gain more access, although empirical evidence shows that they have an advantage in the competition for selective high schools in Ledu.[45] Considering that most of our sample students are still in school in 2025, the potential general equilibrium effects are ex ante unclear and rely on whether senior high schools would admit more students if OVOP makes rural students more qualified (Sorrenti et al., 2025). We thus examined the year-to-year variation in the number of students admitted to senior high schools in Ledu, which shows that academic high schools in Ledu expanded enrollment by an average of 2.64 pp annually from 2017 to 2022 (Fig. A.7).[46] Other counties in Qinghai province exhibit a similar variation, with provincial high school enrollment growing at 2.10 pp annually (Figs. A.8 and A.9).

We then calculated to what extent the crowding-out effects may reduce the social benefits of OVOP. Moreover, given similar expansion rate and assuming a zero-sum competition for selective high school admission, we demonstrated that OVOP yields net social benefits overall. Under current expansion, OVOP has crowded 42 urban students from selective high schools per year.[47] Incorporating their labor market losses reduces the benefit-cost ratio to 4.1:1 and the MVPF to 6.2, as shown in Panel A of Table 11.[48] Notably, China's ongoing efforts to expand academic high school enrollment, particularly in rural areas, may mitigate this zero-sum dynamic in further.[49] Other sensitivity analyses consistent with previous studies (Cascio and Schanzenbach, 2013; Heckman et al., 2010), including adjusting the labor market returns, time spent in the labor market and so on, further confirm the robustness of our cost-benefit analyses (Panel B-G, Table 11).

Last but not least, in the long term, quality ECE for disadvantaged groups generates significant spillovers, which will deliver meaningful societal gains. At the household level, evidence suggests positive spillovers from older Head Start participants to younger siblings (Garces et al., 2002). In classrooms, peers with ECE experience improve learning environments, boosting academic performance for all the students, and ignoring such spillovers underestimates the returns to ECE by 16–30% (Neidell et al., 2010). For the whole society, quality ECE is associated with reductions in prison costs, welfare savings, and so on (Garces et al., 2002; Heckman et al., 2013). Furthermore, if OVOP were targeted only at sub-groups that benefit the most, such as students from poverty-registered households, the return would be higher. Overall, our findings reinforce that the OVOP polit is highly cost beneficial.

[44] A brief formula for calculating MVPF is $MVPF = \frac{WTP}{Cost-FE}$. First, we only consider the social benefits induced by income increases. It can be shown that the present value of lifetime income return to children full exposure to OVOP is CNY 16,592. Assuming that the personal income tax rate is 10%, each beneficiary child can bring in an additional tax income of CNY 1,659, which is equivalent to the revenue externality (FE). Thus, their willing to pay price (WTP) for the OVOP is CNY 14,933, and the average cost per child tends to be CNY 3,264.

[45] Such empirical evidence includes: (1) Urban students in Ledu graduated from primary school in 2016-2018 (N = 1,961) maintained significantly higher enrollment rates in selective high schools than their rural peers (+9.6 pp) (N = 4,681), despite the introduction of OVOP; (2) Urban families can secure alternative selective educational opportunities (e.g., 2.4% urban students attended selective high schools outside Ledu vs. 0.4% for rural students).

[46] Since the available administrative county-level data aggregate all academic high schools without distinguishing selective from non-selective schools, we assume parallel enrollment growth rates between selective and non-selective high schools.

[47] Among the 4,681 rural students (70%) and 1,961 urban children (30%) who took the 2016-2018 junior high school entrance exams in Ledu, their selective high school enrollment rates were 28% and 37%, respectively, resulting in 1,311 rural and 726 urban admissions in selective schools. One year exposure of OVOP increased rural children's enrollment in selective schools by 4.6 pp, adding 215 rural admissions. Meanwhile, the overall admission rate expanded by 2.64 pp, raising total enrollment to 2,210. Consequently, urban admissions fell to 684, implying 42 urban children were displaced due to the OVOP expansion.

[48] Our evaluation shows that OVOP has resulted in 215 rural students gaining access to selective high schools while crowding out 42 urban students annually. This crowding-out effect represents a net reduction of approximately 20% in potential labor market gains, leading to the adjusted benefit-cost ratio to decline from 5.1:1 to 4.1:1.

[49] The State Council of China has proposed to establish or renovate over 1,000 high-quality academic high schools, prioritizing improvements to basic teaching conditions in county-level institutions in 2025. The policy has further mandated accelerated expansion of direct enrollment quotas allocated to junior high schools within each district, with allocations weighted by student population size and explicitly favoring rural schools. Source: https://www.gov.cn/zhengce/202506/content_7027015.htm.

Table 11
Sensitivity analyses.

	NPV (1)	Benefit-cost ratio (2)	MVPF (3)
Panel A: Considering potential crowding-out effects on urban students			
Include the labor market loss of displaced urban students	13,273	4.1:1	6.2-+∞
Panel B: Adjust the estimates for the labor market return to human capital			
	23,844	7.3:1	24.4-+∞
Panel C: Adjust the time spent in the labor market			
Enter labor market in 22 years old	16,958	5.2:1	9.7-+∞
Leave labor market in 65 years old	17,534	5.4:1	10.4-+∞
Panel D: Adjust the salaries			
Use the average salary in the northwest provinces of China in the CHIP survey	19,042	5.8:1	12.6-+∞
Use the minimum wage in Beijing, one of the most developed areas in China	28,152	8.6:1	56.5-+∞
Panel E: Considering economic fluctuations in future			
Decrease the lifetime returns by 30%	14,465	4.4:1	7.2-+∞
Raise the lifetime income 30%	26,864	8.2:1	41.9-+∞
Panel F: Adjust the deadweight loss rate of tax revenue			
Use the VAT rate	16,592	5.2:1	9.8-+∞
Panel G: Adjust the discount rate			
3%	20,645	6.3:1	15.5-+∞
4%	18,393	5.6:1	11.6-+∞
6%	15,140	4.6:1	7.8-+∞
7%	13,959	4.3:1	6.7-+∞

Notes: This table presents the results of various sensitivity analyses conducted for the cost-benefit assessment. Panel A considers potential crowding-out effects on urban students. Panel B draws on estimates of labor market returns to human capital from other countries to project the lifetime returns to OVOP. For instance, the estimates of the labor market return from attending a selective high school are sourced from Allensworth et al. (2017), while those associated with avoiding grade retention are based on Goos et al. (2021). Panels C-G incorporate adjustments to other elements in the cost-benefit analyses, such as the deadweight loss rate of tax revenue. All values are denominated in 2022 CNY and assume a 5% annual real discount rate (Except for Panel G). NPV denotes net present value.

7. Conclusions

Early childhood education (ECE) is widely recognized as a cost-effective intervention to address developmental deficits among disadvantaged children (Heckman et al., 2010). However, developing countries have long been hindered by insufficient access to quality ECE programs. This paper evaluates the One Village One Preschool (OVOP) initiative, a teacher-supported rural ECE pilot in northwestern China, as a natural experiment to estimate its long-term human capital benefits on high-school-aged students.

Drawing on a unique dataset that integrates survey data collected by the authors with novel administrative data, our results demonstrate OVOP's lasting human capital benefits. Specifically, an additional year of exposure raises selective high school enrollment by 4.6 pp and reduces the likelihood of grade retention by 3.8 pp, though with null effects on academic high school enrollment. Moreover, the quality of OVOP is crucial in promoting the long-term benefits. OVOPs with higher qualified teachers, indicated by the presence of certification, preschool education specialization, and working experience, have a greater impact on students' educational attainments. In terms of potential mechanisms, OVOP helps boost early childhood development, together with subsequent academic performance in compulsory education. In particular, the benefits are more pronounced among students in the upper-middle ability distribution, which may explain its stronger positive effects on selective high school enrollment. Meanwhile, those with migrant parents and from poverty-stricken households benefit more from years of OVOP exposure. To conclude, the benefit-cost ratio of OVOP investment is estimated to be at least 4.1:1, demonstrating that the polit is highly cost-efficient.

Overall, our results support Heckman and Masterov's (2007) argument that investing in preschool education for disadvantaged children is highly beneficial, without any equity-efficiency tradeoff. Our findings also offer important policy implications in four ways. First, given the positive impacts of OVOP on students' long-term human capital development, efforts should be made to ensure that rural students in developing countries have access to high-quality ECE services. Second, more attention should be paid to improving the quality of rural ECE, focusing not only on facilities but also on teacher qualifications. Additionally, practical measures should be taken to improve the family care environment and parental involvement for rural students with the support of preschools. Finally, rural ECE programs in developing countries should be more targeted, providing additional support to vulnerable groups, such as those performing in the bottom achievement distribution and from disadvantaged backgrounds.

We also acknowledge some limitations of our study. First, the external validity of this study is limited. Our sample consists of students from Qinghai, a relatively underdeveloped region in western China. Therefore, the conclusions of this paper are more applicable to rural areas with similarly underdeveloped economies. Moreover, our calculation of the cost-benefit ratio is preliminary. For instance, we fail to include other potential social returns, such as reductions in crime, which could lead to an underestimation of OVOP's social benefits.

Declaration of competing interest

The author(s) declare that there are no conflicts of interest related to this article.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2025.107377.

Data availability

The authors do not have permission to share data.

References

Allensworth, E.M., Moore, P.T., Sartain, L., De La Torre, M., 2017. The educational benefits of attending higher performing schools: evidence from Chicago high schools. Educ. Eval. Policy Anal. 39 (2), 175–197. https://doi.org/10.3102/0162373716672039.

Amadon, S., Gormley, W.T., Claessens, A., Magnuson, K., Hummel-Price, D., Romm, K., 2022. Does early childhood education help to improve high school outcomes? Results from Tulsa. Child Dev. 93 (4). https://doi.org/10.1111/cdev.13752.

Anderson, K., Gong, X., Hong, K., Zhang, X., 2016. Do selective high schools improve student achievement? Effects of exam schools in China. China Econ. Rev. 40, 121–134. https://doi.org/10.1016/j.chieco.2016.06.002.

Angrist, J., Lavy, V., 2009. The effects of high stakes high school achievement awards: evidence from a randomized trial. Am. Econ. Rev. 99 (4), 1384–1414. https://doi.org/10.1257/aer.99.4.1384.

Arapa, B., Sánchez, E., Hurtado-Mazeyra, A., Sánchez, A., 2021. The relationship between access to pre-school education and the development of social-emotional competencies: longitudinal evidence from Peru. Int. J. Educ. Dev. 87, 102482. https://doi.org/10.1016/j.ijedudev.2021.102482.

Auriol, E., Warlters, M., 2012. The marginal cost of public funds and tax reform in Africa. J. Dev. Econ. 97, 58–72. https://doi.org/10.1016/j.jdeveco.2011.01.003.

Bai, Y., Yang, N., Wang, L., Zhang, S., 2022. The impacts of maternal migration on the cognitive development of preschool-aged children left behind in rural China. World Dev. 158, 106007. https://doi.org/10.1016/j.worlddev.2022.106007.

Bailey, M.J., Sun, S., Timpe, B., 2021. Prep school for poor kids: the long-run impacts of head start on human capital and economic self-sufficiency. Am. Econ. Rev. 111 (12), 3963–4001. https://doi.org/10.1257/aer.20181801.

Barnett, W.S., Jung, K., 2021. Effects of New Jersey's Abbott preschool program on children's achievement, grade retention, and special education through tenth grade. Early Child. Res. Q. 56, 248–259. https://doi.org/10.1016/j.ecresq.2021.04.001.

Belfield, C.R., Nores, M., Barnett, S., et al., 2006. The high/scope Perry Preschool Program: cost-benefit analysis using data from the age-40 follow-up. J. Hum. Resour. 1, 162–190.

Berlinski, S., Galiani, S., Manacorda, M., 2008. Giving children a better start: preschool attendance and school-age profiles. J. Public Econ. 92 (5), 1416–1440. https://doi.org/10.1016/j.jpubeco.2007.10.007.

Berlinski, S., Galiani, S., Gertler, P., 2009. The effect of pre-primary education on primary school performance. J. Public Econ. 93 (1), 219–234. https://doi.org/10.1016/j.jpubeco.2008.09.002.

Bietenbeck, J., Ericsson, S., Wamalwa, F.M., 2019. Preschool attendance, schooling, and cognitive skills in East Africa. Econ. Educ. Rev. 73, 101909. https://doi.org/10.1016/j.econedurev.2019.101909.

Birkelund, J.F., Capsada-Munsech, Q., Boliver, V., Karlson, K.B., 2021. Lives on track? Long-term earnings return to selective school placement in England and Denmark. Br. J. Sociol. 72 (3), 672–692. https://doi.org/10.1111/1468-4446.12856.

Blanden, J., Del Bono, E., McNally, S., Rabe, B., 2016. Universal pre-school education: the case of public funding with private provision. Econ. J. 126 (592), 682–723. https://doi.org/10.1111/ecoj.12374.

Blanden, J., Del Bono, E., Hansen, K., Rabe, B., 2021. Quantity and quality of childcare and children's educational outcomes. J. Popul. Econ. https://doi.org/10.1007/s00148-021-00835-4.

Bouguen, A., Filmer, D., Macours, K., Naudeau, S., 2018. Preschool and parental response in a second-best world evidence from a school construction experiment. J. Hum. Resour. 53 (2), 474–512. https://doi.org/10.3368/jhr.53.2.1215-7581R1.

Brinkman, S.A., Hasan, A., Jung, H., Kinnell, A., Pradhan, M., 2017. The impact of expanding access to early childhood education services in rural Indonesia. J. Labor Econ. https://doi.org/10.1086/691278.

Callaway, B., Sant'Anna, P.H.C., 2021. Difference-in-differences with multiple time periods. J. Econom. 225 (2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001.

Cascio, E.U., Schanzenbach, D.W., 2013. The impacts of expanding access to high-quality preschool education. Brook. Pap. Econ. Act. 2013 (2), 127–192. https://doi.org/10.1353/eca.2013.0012.
Chen, X., Liu, C., Zhang, L., Shi, Y., Rozelle, S., 2010. Does taking one step back get you two steps forward? Grade retention and school performance in poor areas in rural China. Int. J. Educ. Dev. 30 (6), 544–559. https://doi.org/10.1016/j.ijedudev.2009.12.002.
Chen, S., Zhao, C., Cao, Y., Chen, C., Snow, C.E., Lu, M., 2019. Long-term effects of China's One Village One Preschool program on elementary academic achievement. Early Child. Res. Q. 49, 218–228. https://doi.org/10.1016/j.ecresq.2019.06.010.
Chen, S., Zhao, C., Chen, C., Wu, Z., Snow, C.E., Lu, M., 2022. Does one more year matter? Dosage effect of the one-village-one-preschool intervention in rural China. J. Res. Educ. Eff. https://www.tandfonline.com/doi/abs/10.1080/19345747.2021.2006383.
Chen, S., Liu, Y., Yang, J., Yang, Y., Ye, X., 2023. Impacts of village preschools on student enrollment and longer-term outcomes: new evidence from the poorest regions in China. Int. J. Educ. Dev. 102, 102852. https://doi.org/10.1016/j.ijedudev.2023.102852.
Chetty, R., Friedman, J.N., Hilger, N., Saez, E., Schanzenbach, D.W., Yagan, D., 2011. How does your kindergarten classroom affect your earnings? Evidence from project star. Quart. J. Econ. 126 (4), 1593–1660. https://doi.org/10.1093/qje/qjr041.
Cunha, F., Heckman, J.J., 2008. Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. J. Hum. Resour. 43 (4), 738–782. https://doi.org/10.3368/jhr.43.4.738.
Cunha, F., Heckman, J.J., Schennach, S.M., 2010. Estimating the technology of cognitive and noncognitive skill formation. Econometrica 78 (3), 883–931. https://doi.org/10.3982/ECTA6551.
Démurger, S., Hanushek, E.A., Zhang, L., 2024. Employer learning and the dynamics of returns to universities: evidence from Chinese elite education during university expansion. Econ. Dev. Cult. Chang. 73 (1), 339–379. https://doi.org/10.1086/727519.
de Chaisemartin, C., D'Haultfœuille, X., 2023. Two-way fixed effects and differences-in-differences estimators with several treatments. J. Econom. 236 (2), 105480. https://doi.org/10.1016/j.jeconom.2023.105480.
De Haan, M., Leuven, E., 2020. Head start and the distribution of long-term education and labor market outcomes. J. Labor Econ. 38 (3), 727–765. https://doi.org/10.1086/706090.
Dietrichson, J., Lykke Kristiansen, I., Viinholt, B.A., 2020. Universal preschool programs and long-term child outcomes: a systematic review. J. Econ. Surv. 34 (5), 1007–1043. https://doi.org/10.1111/joes.12382.
Duflo, E., 2001. Schooling and labor market consequences of school construction in Indonesia: evidence from an unusual policy experiment. Am. Econ. Rev. 91 (4), 19.
Duncan, G., Kalil, A., Mogstad, M., Rege, M., 2023. Chapter 1-investing in early childhood development in preschool and at home. In: Handbook of the Economics of Education, 6. Elsevier, pp. 1–91. https://doi.org/10.1016/bs.hesedu.2022.11.005. Volpp.
Emmers, D., Jiang, Q., Xue, H., Zhang, Y., Zhang, Y., Zhao, Y., Liu, B., Dill, S.E., Qian, Y., Warrinnier, N., Johnstone, H., Cai, J., Wang, X., Wang, L., Luo, R., Li, G., Xu, J., Liu, M., Huang, Y., Rozelle, S., 2021. Early childhood development and parental training interventions in rural China: a systematic review and meta-analysis. BMJ Glob. Health 6 (8), e005578. https://doi.org/10.1136/bmjgh-2021-005578.
Evans, M., Shaw, D., Bell, M., 2000. Home literacy activities and their influence on early literacy skills. Can. J. Exp. Psychol. 54, 65–75. https://doi.org/10.1037/h0087330.
Felfe, C., Nollenberger, N., Rodríguez-Planas, N., 2015. Can't buy mommy's love? Universal childcare and children's long-term cognitive development. J. Popul. Econ. 28 (2), 393–422. https://doi.org/10.1007/s00148-014-0532-x.
Fort, M., Ichino, A., Zanella, G., 2020. Cognitive and noncognitive costs of day care at age 0-2 for children in advantaged families. J. Political Econ. 128 (1), 158–205. https://doi.org/10.1086/704075.
García, J.L., Heckman, J.J., Ronda, V., 2023. The lasting effects of early-childhood education on promoting the skills and social mobility of disadvantaged African Americans and their children. J. Political Econ. 131 (6), 1477–1506. https://doi.org/10.1086/722936.
Garces, E., Thomas, D., Currie, J., 2002. Longer-term effects of head start. Am. Econ. Rev. 15.
Gelber, A., Isen, A., 2013. Children's schooling and parents' behavior: evidence from the head start impact study. J. Public Econ. 101, 25–38. https://doi.org/10.1016/j.jpubeco.2013.02.005.
Gertler, P., Heckman, J., Pinto, R., Zanolini, A., Vermeersch, C., Walker, S., Chang, S.M., Grantham-McGregor, S., 2014. Labor market returns to an early childhood stimulation intervention in Jamaica. Science 344 (6187), 998–1001. https://doi.org/10.1126/science.1251178.
Goos, M., Pipa, J., Peixoto, F., 2021. Effectiveness of grade retention: a systematic review and meta-analysis. Educ. Res. Rev. 34, 100401. https://doi.org/10.1016/j.edurev.2021.100401.
Gray-Lobe, G., Pathak, P.A., Walters, C.R., 2023. The long-term effects of universal preschool in Boston. Q. J. Econ. 138 (1), 363–411. https://doi.org/10.1093/qje/qjac036.
Hayes, M.S., Gershenson, S., 2016. What differences a day can make: quantile regression estimates of the distribution of daily learning gains. Econ. Lett. 141, 48–51. https://doi.org/10.1016/j.econlet.2016.01.023.
Heckman, J.J., Masterov, D.V., 2007. The productivity argument for investing in young children. Rev. Agric. Econ. 29 (3), 446–493. https://doi.org/10.1111/j.1467-9353.2007.00359.x.
Heckman, J.J., Moon, S.H., Pinto, R., Savelyev, P.A., Yavitz, A., 2010. The rate of return to the HighScope Perry Preschool Program. J. Public Econ. 94 (1–2), 114–128. https://doi.org/10.1016/j.jpubeco.2009.11.001.
Heckman, J., Pinto, R., Savelyev, P., 2013. Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. Am. Econ. Rev. 103 (6), 2052–2086. https://doi.org/10.1257/aer.103.6.2052.
Hendren, N., Sprung-Keyser, B., 2020. A unified welfare analysis of government policies. Q. J. Econ. 135, 1209–1318. https://doi.org/10.1093/qje/qjaa006.
Hendren, N., 2016. The policy elasticity. Tax Policy Econ. 30 (1), 51–89. https://doi.org/10.1086/685593.
Hojman, A., Lopez Boo, F., 2022. Public childcare benefits children and mothers: evidence from a nationwide experiment in a developing country. J. Public Econ. 212, 104686. https://doi.org/10.1016/j.jpubeco.2022.104686.
Hu, F., 2012. Migration, remittances, and children's high school attendance: the case of rural China. Int. J. Educ. Dev. 32 (3), 401–411. https://doi.org/10.1016/j.ijedudev.2011.08.001.
Huang, W., Liu, H., 2023. Early childhood exposure to health insurance and adolescent outcomes: evidence from rural China. J. Dev. Econ. 160, 102925. https://doi.org/10.1016/j.jdeveco.2022.102925.
Jackson, C.K., 2013. Can higher-achieving peers explain the benefits to attending selective schools? Evidence from Trinidad and Tobago. J. Public Econ. 108, 63–77. https://doi.org/10.1016/j.jpubeco.2013.09.007.
Jensen, R., Miller, N.H., 2018. Market integration, demand, and the growth of firms: evidence from a natural experiment in India. Am. Econ. Rev. 108 (12), 3583–3625.
Kim, J.H., 2022. Preschool participation and students' learning outcomes in primary school: evidence from national reform of pre-primary education in Ethiopia. Int. J. Educ. Dev. 94, 102659. https://doi.org/10.1016/j.ijedudev.2022.102659.
Krafft, C., 2015. Increasing educational attainment in Egypt: the impact of early childhood care and education. Econ. Educ. Rev. 46, 127–143. https://doi.org/10.1016/j.econedurev.2015.03.006.
Lassassi, M., 2021. Does preschool improve child development and affect the quality of parent-child interaction? Evidence from Algeria. Int. J. Educ. Dev. 82, 102354. https://doi.org/10.1016/j.ijedudev.2021.102354.
Levin, H., McEwan, P.J., Belfield, C., Bowden, A.B., Shand, R., 2018. Economic Evaluation in Education: Cost-Effectiveness and Benefit-Cost Analysis. SAGE Publications, Inc. https://doi.org/10.4135/9781483396514.
Li, P., Lu, Y., Wang, J., 2016. Does flattening government improve economic performance? Evidence from China. J. Dev. Econ. 123, 18–37. https://doi.org/10.1016/j.jdeveco.2016.07.002.

Li, H., Meng, L., Mu, K., Wang, S., 2024. English language requirement and educational inequality: evidence from 16 million college applicants in China. J. Dev. Econ. 168, 103271. https://doi.org/10.1016/j.jdeveco.2024.103271.
Liu, C., Zhang, L., Luo, R., Rozelle, S., Sharbono, B., Shi, Y., 2009. Development challenges, tuition barriers, and high school education in China. Asia Pac. J. Educ. 29 (4), 503–520. https://doi.org/10.1080/02188790903312698.
Ludwig, J., Miller, D.L., 2007. Does Head Start Improve Children's Life Chances? Evidence from a Regression Discontinuity Design. Quart. J. Econ. 122 (1), 159–208. https://doi.org/10.1162/qjec.122.1.159.
Luo, R., Zhang, L., Liu, C., Zhao, Q., Shi, Y., Rozelle, S., Sharbono, B., 2012. Behind before they begin: the challenge of early childhood education in rural China. Australas. J. Early Child. 37 (1), 55–64. https://doi.org/10.1177/183693911203700107.
Meadows, P. (2011). National evaluation of Sure Start local programmes: an economic perspective. Department for https://www.gov.uk/government/publications/Education. Retrieved from national-evaluation-of-sure-start-local-programmes-an-economic-perspective.
Miguel, E., Kremer, M., 2004. Worms: identifying impacts on education and health in the presence of treatment externalities. Econometrica 72 (1), 159–217.
Ministry of Education of the People's Republic of China. (2013). Preschool staff staffing standards (Interim). Retrieved from http://www.moe.gov.cn/srcsite/A10/s7151/201301/t20130115_147148.html (In Chinese).
Morabito, C., Van de gaer, D., Figueroa, J.L., Vandenbroeck, M., 2018. Effects of high versus low-quality preschool education: a longitudinal study in Mauritius. Econ. Educ. Rev. 65, 126–137. https://doi.org/10.1016/j.econedurev.2018.06.006.
Neidell, M., Waldfogel, J., 2010. Cognitive and noncognitive peer effects in early education. Rev. Econ. Stat. 92 (3), 562–576.
Özler, B., Fernald, L.C.H., Kariger, P., McConnell, C., Neuman, M., Fraga, E., 2018. Combining pre-school teacher training with parenting education: a cluster-randomized controlled trial. J. Dev. Econ. 133, 448–467. https://doi.org/10.1016/j.jdeveco.2018.04.004.
Pilařová, T., Kandakov, A., 2017. The impact of remittances on school attendance: the evidence from the republic of Moldova. Int. J. Educ. Dev. 55, 11–16. https://doi.org/10.1016/j.ijedudev.2017.04.003.
Rao, N., Zhou, J., Sun, J., 2017. Early Childhood Education in Chinese Societies, 19. Springer, Netherlands. https://doi.org/10.1007/978-94-024-1004-4. Vol.
Reynolds, A.J., Temple, J.A., White, B.A.B., Ou, S.R., Robertson, D.L., 2011. Age 26 cost–benefit analysis of the Child-Parent Center early education program. Child Dev. 82 (1), 379–404. https://doi.org/10.1111/j.1467-8624.2010.01563.x.
Rozelle, S., Hell, N., 2020. Invisible China: How the Urban-Rural Divide Threatens China's Rise. University of Chicago Press. https://doi.org/10.1111/apel.12325.
Sorrenti, G., Zölitz, U., Ribeaud, D., Eisner, M., 2025. The causal impact of socio-emotional skills training on educational success. Rev. Econ. Stud. 92 (1), 506–552. https://doi.org/10.1093/restud/rdae018.
State Council Census Office, National Bureau of Statistics Department of Population and Employment Statistics, 2022. 2020 National Census Data of China. China Statistics Press. In Chinese.
Sun, L., Abraham, S., 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. J. Econom. 225 (2), 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006.
The United Nations. (2024). The sustainable development goals report, Retrieved from https://unstats.un.org/sdgs/report/2024/.
Thompson, O., 2018. Head start's long-run impact: evidence from the program's introduction. J. Hum. Resour. 53 (4), 1100–1139.
Wang, L., Dang, R., Bai, Y., Zhang, S., Liu, B., Zheng, L., Yang, N., Song, C., 2020. Teacher qualifications and development outcomes of preschool children in rural China. Early Child. Res. Q. 53, 355–369. https://doi.org/10.1016/j.ecresq.2020.05.015.
Wolf, S., Aber, J.L., Behrman, J.R., Tsinigo, E., 2019. Experimental impacts of the "quality preschool for Ghana" interventions on teacher professional well-being, classroom quality, and children's school readiness. J. Res. Educ. Eff. 12 (1), 10–37. https://doi.org/10.1080/19345747.2018.1517199.
Wong, H.L., Luo, R., Zhang, L., Rozelle, S., 2013. The impact of vouchers on preschool attendance and elementary school readiness: a randomized controlled trial in rural China. Econ. Educ. Rev. 35, 53–65. https://doi.org/10.1016/j.econedurev.2013.03.004.
World Bank. (2018). Fair progress? Economic mobility across generations around the world. 10.1596/978-1-4648-1145-1.
Yang, J., Sicular, T., Lai, D., 2014. The changing determinants of high school attainment in rural China. China Econ. Rev. 30, 551–566. https://doi.org/10.1016/j.chieco.2013.10.001.
Yi, H., Song, Y., Liu, C., Huang, X., Zhang, L., Bai, Y., Ren, B., Shi, Y., Loyalka, P., Chu, J., Rozelle, S., 2015. Giving kids a head start: the impact and mechanisms of early commitment of financial aid on poor students in rural China. J. Dev. Econ. 113, 1–15. https://doi.org/10.1016/j.jdeveco.2014.11.002.
Yi, H., Li, G., Li, L., Loyalka, P., Zhang, L., Xu, J., Kardanova, E., Shi, H., Chu, J., 2018. Assessing the quality of upper-secondary vocational education and training: evidence from China. Comp. Educ. Rev. 62 (2), 199–230. https://doi.org/10.1086/696920.
Zhao, C., Chen, S., Cao, Y., Snow, C., Lu, M., 2020. Targeted poverty alleviation through education: long-term effect of China's "one Village one preschool" project on Rural children's academic achievements. J. East China Norm. Univ. Educ. Sci. 38 (2), 114–125. https://doi.org/10.16382/j.cnki.1000-5560.2020.02.011. In Chinese.