Powering the Future: The Long-Term Human Capital Effects of Rural Electrification

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Abstract

This paper examines how exposure to rural electrification during middle childhood affected long-term human capital in 1990s China. Unlike most studies that focus on grid connection, this paper emphasizes electricity affordability. I develop a model of human capital investment where rural electrification is an adult-labor-biased technical change. The model predicts a strong income effect and a negligible substitution effect, resulting in increased schooling for children. I test this empirically using a cohort difference-in-differences design, leveraging variation in electricity price reductions across counties. I find that middle childhood exposure to lower electricity prices significantly increases educational attainment, school completion, and adult cognitive scores. Further analysis identifies increased agricultural productivity as a key mechanism, consistent with the model. The focus on middle childhood reflects children's limited substitutability for adult laborers at this age. At older ages, children provide labor that closely resembles that of adults, and a strong substitution effect may offset the income effect—evidence supports this prediction. China's late-1990s experience offers insights for rural electrification efforts in many developing countries today.

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1 Introduction

Over the past two decades, rural electrification has expanded rapidly across developing countries, bringing electricity to hundreds of millions. In Bangladesh, the share of rural population with access to electricity rose from 17% in 2000 to 99% in 2022; in Kenya, from just 7% to 66%; and in India, from 49% to nearly universal coverage.[1] Despite this remarkable progress, recent evidence shows that simply connecting households to the grid yields only modest or negligible economic benefits (Burlig and Preonas, 2024; Lee, Miguel, and Wolfram, 2020b), raising concerns about the effectiveness of rural electrification.

A possible explanation for this limited impact lies in the distinction between connection and meaningful access. Electrification involves more than simply extending the grid (Lee, Miguel, and Wolfram, 2020a);[2] it also depends on factors such as affordability, reliability, and quality of service (Bhatia and Angelou, 2015). These factors continue to constrain economic activity and daily life in many developing countries (Meeks and Mahadevan, 2025; World Bank, 2024; Kojima and Trimble, 2016; Trimble et al., 2016; Onishi, 2015). Despite these challenges, little is known about whether addressing these broader dimensions of access can generate meaningful economic outcomes.

This paper examines how exposure to rural electrification in middle childhood (ages 6 to 12, or primary school age) affected long-term human capital in 1990s China, focusing on electricity affordability. In late 1998, the central government launched the "Two Reforms and One Price" (TROP) program, which aimed to: (1) upgrade rural power grids and (2) reform rural electricity administration—two essential steps that paved the way for (3) unifying rural and urban electricity pricing.[3] Prior to TROP, rural households faced significantly higher electricity costs than urban residents, along with unstable voltage and inefficient distribution. The program covered China's

[1] Source: World Bank DataBank.

[2] Burgess et al. (2020) shows that unconditional grid connections can produce inefficient outcomes and welfare losses.

[3] TROP was announced in October 1998, so 1999 is designated as the starting point for the treatment period in this paper.

entire rural population, making it the largest rural electrification effort in global history. Its nationwide rollout offers a rare opportunity to study the general equilibrium effects of rural electrification while minimizing spillovers and selection bias—two common challenges in other contexts.

Rural electrification improves irrigation and agricultural productivity (Fried and Lagakos, 2021; Lewis and Severnini, 2020; Assunção et al., 2017; Kitchens and Fishback, 2015), raising household income and potentially affecting children's education through two opposing channels: higher income may increase investment in schooling (income effect), while more profitable farming could raise the opportunity cost of schooling (substitution effect).

I formalize this using a simple model of human capital investment based on two assumptions. First, electrification acts as a technology shock to agriculture. Second, adult (parental) and child labor are imperfect substitutes conditional on human capital, since children are less productive than adults even with similar schooling due to differences in strength, stamina, and task suitability. Adults are more efficient workers, so electrification primarily raises parental wages. The model predicts a strong income effect and a negligible substitution effect, as the opportunity cost of schooling (child labor wages) remains largely unchanged. The net impact on schooling for children is therefore positive.

To test this, I construct a dataset by manually collecting county-level rural electricity prices before and after TROP implementation from local gazetteers and linking them to individual and household data from the 2014 China Family Panel Studies (CFPS). The final sample includes 142 counties across multiple provinces. To explore underlying mechanisms, I also gather prefecture-level economic indicators and county-level public expenditure data.

This paper uses a cohort difference-in-differences (DiD) approach to estimate the human capital effects of middle childhood exposure to TROP. I compare cohorts born between 1988 and 1994 (treatment group) with those born between 1979 and 1984 (control group) within the same county.[4] I then leverage the variation in electricity price reductions across counties to estimate the effects.

[4]Treatment cohorts had at least one year of overlap with TROP during primary school. A three-year buffer reduces concerns about partial exposure and variation in school starting age.

A potential identification concern is the difficulty of isolating the effect of the price change itself from that of simultaneous improvements in infrastructure or management. This paper argues that in 1999 China, as in many low- and middle-income countries today, weak infrastructure, inefficient management, and unaffordable electricity were interconnected.[5] Policies targeting affordability must therefore incorporate infrastructure and management reforms; without them, lower prices are not sustainable. This is why China's central government prioritized the "Two Reforms" before unifying electricity prices under TROP, rather than mandating price cuts alone.

I find that a one standard deviation reduction in rural electricity prices (0.21 CNY/kWh, 1 CNY $\approx$ 0.12 USD in 2000) increases children's educational attainment by 0.605 years. This effect is comparable to the estimate in Lipscomb, Mobarak, and Barham (2013), but more than six times the impact of China's Send-Down Movement during the late 1960s and 1970s (Chen et al., 2020a),[6] and more than twice that of China's 1986 Compulsory Education Law (Chen and Park, 2021). The results remain robust across various settings.

In addition to years of schooling, cognitive outcomes also improve: math test scores increase by 0.164 standard deviations, and Chinese word recognition scores rise by 0.142 standard deviations. School completion rates show consistent gains across levels: primary school completion increases by 3.7 percentage points, junior high by 5.12 points, and senior high by 6.17 points.

While no significant differences are found by gender, income, or sibling status, significantly larger effects are observed in drier regions. Given drought's well-documented impact on agricultural productivity,[7] this pattern suggests that TROP's effects may operate, at least in part, through improvements in agricultural productivity.

Further analysis identifies two channels through which TROP improved human capital. First, it increased agricultural productivity, measured by agricultural GDP per hectare at the prefectural level. I find that a one standard deviation reduction in rural electricity prices leads to an increase

[5] See https://www.worldbank.org/en/topic/energy/publication/making-power-work-for-africa.

[6] The Send-Down Movement (1968–1978) was a campaign during China's Cultural Revolution where over 17 million urban youths were sent to rural areas to work and learn from peasants.

[7] Drought is recognized as the leading cause of agricultural production loss. Source: Food and Agriculture Organization of the United Nations. https://www.fao.org/interactive/disasters-in-agriculture/en/.

in agricultural productivity of 824 CNY per acre ($\approx$ 97 USD in 2000), equivalent to about 12.7% of the average per capita net annual income of rural households in 1999.[8] This finding supports the model's assumption that electrification boosts productivity and aligns with prior literature.[9] Additional evidence, based on comparisons among children born before and after 1999, supports the income channel by showing improvements in health outcomes.

Second, TROP encouraged greater government investment in education. Cheaper and more reliable electricity could support the operation of devices, equipment, and other educational infrastructure. I find that a one standard deviation reduction in rural electricity prices leads to a 0.42 percentage point increase in the public expenditure share on education.

Why does middle childhood exposure matter? The key is the opportunity cost of schooling. Children at this stage are poor substitutes for adult laborers, so the productivity shock from electrification has little impact on the opportunity cost of schooling (child labor wages). In contrast, older children contribute labor similar to adults, so electrification increases returns to both adult and child labor, potentially offsetting income-driven schooling gains through a strong substitution effect. In practice, rigidities in China's education system, particularly high-stakes entrance exams, further limit the effectiveness of later-stage interventions. Consistent with this argument, I find that exposure to TROP during secondary school age has a negative but statistically insignificant effect on educational attainment.

This paper makes three contributions. First, it shifts the focus from grid connection to affordability in rural electrification in developing economies. A large literature examines rural electrification across South and Southeast Asia, Sub-Saharan Africa, and Latin America.[10] However, most of

[8]In 1999, the average per capita net annual income of rural households in China was 2,210 CNY ($\approx$ 265 USD in 2000). Source: The National Bureau of Statistics of China. https://www.stats.gov.cn/sj/ndsj/zgnj/2000/J16c.htm. In the same year, the national average per capita arable land operated by rural households was 2.07 mu (China's metric, where 1 mu is equal to 0.165 acres), equivalent to 0.34 acres. Source: https://www.stats.gov.cn/sj/ndsj/zgnj/2000/L13c.htm.

[9]See Fried and Lagakos (2021), Lewis and Severnini (2020), Assunção et al. (2017), and Kitchens and Fishback (2015).

[10]These include India (Fetter and Usmani, 2024; Burlig and Preonas, 2024; Burgess et al., 2023; Thomas et al., 2020; Van de Walle et al., 2017; Khandker et al., 2014; Rud, 2012), Indonesian (Kassem, 2024), Vietnam (Khandker, Barnes, and Samad, 2013), the Philippines (Barnes et al., 2002), Brazil (Lipscomb, Mobarak, and Barham, 2013), Peru (Dasso Arana, Fernandez, and Ñopo, 2015), South Africa (Dinkelman, 2011), Kenya (Koima, 2024; Lee, Miguel, and

these studies focus on grid connections. A growing literature explores reliability,[11] but evidence on the impacts of electricity affordability, another key dimension of electrification, remains limited.[12] Moreover, evidence from China, home to the world's largest rural population during TROP implementation, is scarce.[13] This paper fills these gaps by providing empirical evidence on the effects of electricity affordability from late-1990s China, when its development indicators were comparable to those of many developing countries today (see Figure 1).[14] As many low- and middle-income countries continue to struggle with effective electricity access despite rising connection rates, this paper shows that targeting affordability can generate substantial educational benefits.

Second, this paper is the first to document the long-term effects of electricity affordability on human capital. While several studies find electrification yields only negligible benefits and modest welfare gains (Burlig and Preonas, 2024; Koima, 2024; Burgess et al., 2023; Lee, Miguel, and Wolfram, 2020b; Lenz et al., 2017; Peters and Sievert, 2016), these authors focus on short-term outcomes, potentially missing longer-term effects. A small but growing body of literature documents long-term impacts, including increased female labor force participation (Vidart, 2024; Greenwood, Seshadri, and Yorukoglu, 2005),[15] improved firm productivity (Fried and Lagakos, 2023; Fiszbein et al., 2020), better infant health and reduced fertility (Lewis, 2018), faster economic growth (Lewis and Severnini, 2020), and higher household consumption (Van de Walle et al., 2017). My paper adds to this literature by documenting long-term human capital effects of

Wolfram, 2020b), Ghana (Akpandjar and Kitchens, 2017), Rwanda (Lenz et al., 2017), Ethiopia (Fried and Lagakos, 2021; Bernard and Torero, 2015), Sub-Saharan Africa (Bernard, 2012), and Africa as a whole (Peters and Sievert, 2016).

[11] These include impacts on firm performance (Abeberese, Ackah, and Asuming, 2021; Hardy and McCasland, 2021; Cole et al., 2018; Allcott, Collard-Wexler, and O'Connell, 2016; Fisher-Vanden, Mansur, and Wang, 2015), employment (Mensah, 2024), and agricultural wages (Nag, 2024) in developing countries. For a comprehensive review of the economics of electricity reliability, see Borenstein, Bushnell, and Mansur (2023).

[12] Exceptions include Lee, Miguel, and Wolfram (2020b) and Burgess et al. (2023) on upfront connection costs, and Abeberese (2017) on electricity prices and firm performance. My paper differs by linking electricity prices to long-term educational outcomes. Related U.S.-based work includes Cong et al. (2022) on energy poverty, and Levinson and Silva (2022) and Borenstein (2012) on the distributional effects of pricing.

[13] Two exceptions are Lin and Xu (2024) and Ding, Qin, and Shi (2018), which examine the impact of China's rural electrification on economic growth. My paper focuses on long-term human capital effects.

[14] Lee, Miguel, and Wolfram (2020a) highlights the importance of understanding cross-country heterogeneity in electrification impacts for effective policymaking.

[15] Vidart (2024) highlights the role of human capital accumulation in linking electrification to female labor force participation, but does not directly examine educational outcomes.

electrification. Unlike Lipscomb, Mobarak, and Barham (2013), which studies how grid expansion due to hydropower dam construction affects the Human Development Index over the long run, I examine the long-term human capital effects of electricity affordability.[16] The findings reveal that lower electricity prices have lasting effects on educational outcomes.

Third, this paper expands the literature on the "missing middle" associated with the fetal origins hypothesis by examining middle childhood exposure to electrification. While extensive literature links fetal and early-life shocks to later-life outcomes,[17] the "missing middle" years, spanning the period between early childhood and adulthood, is not as well understood (Almond, Currie, and Duque, 2018). Studying this interval is crucial for identifying when effective interventions can occur and for evaluating the impact of recent policies within a practical timeframe (Almond, Currie, and Duque, 2018). Prior literature investigates the long-term human capital effects of childhood exposure to various shocks, including welfare cuts (Dustmann, Landersø, and Andersen, 2024), school absences (Cattan et al., 2023), access to home loans (Aaronson et al., 2023), and rainfall variability (Ponnusamy, 2025; Shah and Steinberg, 2017). My paper extends this literature by showing that exposure to rural electrification during middle childhood improves educational outcomes. Most importantly, my findings underscore that timing matters: exposure during primary school age plays a critical role in shaping long-term human capital, in contrast to later interventions.

The remainder of this paper is organized as follows: Section 2 develops the theoretical framework that guides the empirical analysis. Section 3 provides background on China's rural electrification. Section 4 describes the data. Section 5 outlines the empirical strategy. Section 6 presents the main results. Section 7 conducts robustness checks. Section 8 analyzes heterogeneity. Section 9 examines mechanisms. Section 10 discusses the importance of exposure during middle childhood. Section 11 concludes.

[16] The Human Development Index (HDI) is a summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and having a decent standard of living. Source: United Nations Development Programme. https://hdr.undp.org/data-center/human-development-index#/indicies/HDI.

[17] For instance, Bharadwaj, Eberhard, and Neilson (2018); Isen, Rossin-Slater, and Walker (2017); Hoynes, Schanzenbach, and Almond (2016); Deschênes, Greenstone, and Guryan (2009); Schultz and Strauss (2008); Barker (1990) (see Almond and Currie (2011) and Almond, Currie, and Duque (2018) for a more complete review).

2 A Model of Adult-Labor-Biased Technological change and Human Capital Investment

Evidence shows that rural electrification improves irrigation and farm productivity (Fried and Lagakos, 2021; Lewis and Severnini, 2020; Assunção et al., 2017; Kitchens and Fishback, 2015), creating a technology (productivity) shock that raises household income. This can affect children's education through two opposing channels: higher income may increase investment in schooling, while more profitable farming can raise the opportunity cost of schooling. The net effect depends on which force dominates.

To formalize this, I develop a household decision-making model in the spirit of Shah and Steinberg (2017), which assumes adult and child labor are perfect substitutes conditional on human capital. However, children are less productive than adults in agricultural work, even with similar levels of human capital—for example, five years of schooling—due to differences in strength, stamina, and task suitability. My paper therefore assumes that adult and child labor are imperfect substitutes, with adults being more efficient workers.

Rural electrification further amplifies adults' productivity advantage. It enhances tasks requiring adult labor such as irrigation, mechanized processing, and extended work hours enabled by improved lighting.[18] This is consistent with evidence that electrification increases adult work hours (Dinkelman, 2011) and expands opportunities for skilled women (Vidart, 2024). Electrification thus raises adult wages by shifting production technology in an adult-labor-intensive direction.

If adult and child labor are viewed as analogues to skilled and unskilled labor, respectively, the mechanism mentioned above is comparable to skill-biased technological change, as discussed in Acemoglu (1998, 2002), which increases the skill premium and contributes to wage inequality. Consistent with this analogy, Goldin and Katz (1998) show that electrification increased the relative demand for skilled workers.

[18] Children are less likely to operate electrified machinery because these tasks demand physical strength, technical knowledge, and involve higher safety risks. They are also less able to take advantage of extended hours due to safety concerns and physical fatigue.

While electrification displaces some traditional child tasks, such as manual irrigation and grain processing, other forms of child work, including field labor, weeding, and light livestock chores, remain largely unaffected. Consequently, the overall impact on child labor is likely modest.[19]

Together, these patterns support modeling rural electrification as a technological change that primarily benefits adult labor. Unlike the temporary productivity boost from favorable weather in Shah and Steinberg (2017), electrification represents a permanent shift in productivity.

My paper first considers a case in which electrification raises adult productivity (wages) while leaving child labor productivity unchanged. As a result, the substitution effect vanishes, since the opportunity cost of schooling remains constant. However, the income effect persists, leading to increased investments in child schooling and, ultimately, higher long-term human capital. Appendix Section D further investigates whether these results hold when child labor productivity responds to electrification. It shows that, as long as this response is modest, the income effect continues to dominate.

2.1 The Model

The household consists of one parent and one child. The parent maximizes lifetime utility over three periods. In period 1 (early childhood), the child is too young to attend school or work and only consumes. In period 2 (middle childhood, ages 6–12), the child consumes and allocates one unit of time between schooling (or study) and productive (manual) labor. Let s_2 denote time spent in school. In period 3 (adolescence and beyond), the household benefits from the child's accumulated human capital.[20] Borrowing and saving are ruled out throughout the framework.

Let c_t denote household consumption in period $t \in \{1, 2\}$, and $u_t(c_t)$ the corresponding utility, with $\frac{\partial u_t(c_t)}{\partial c_t} > 0$ and $\frac{\partial^2 u_t(c_t)}{\partial c_t^2} < 0$. Let e_t denote the child's human capital in period t, and e_p the parent's human capital (assumed constant). Let $V(e_3)$ represent the utility derived from the child's

[19] The impact depends on the substitutability of child for adult labor. If children are poor substitutes, electrification has little effect on their labor demand. If they are close substitutes, effects could be larger. Section 10 provides further discussion.

[20] Note that individuals aged 12–14 are excluded from the empirical analysis to avoid partial exposure, account for variation in school starting ages, and allow time for policy effects to materialize. Thus, period 3 empirically corresponds to age 15 and above.

human capital in period 3. The household's total utility function is given by:

$$U = u_1(c_1) + \beta u_2(c_2) + \beta^2 V(e_3), \tag{1}$$

where $\beta \in (0, 1)$ is the discount factor.

In period 1, consumption is financed solely through parental income:

$$c_1 \leq w_1 e_p, \tag{2}$$

where w_1 is the wage per unit of parental human capital, with $w_t \in (0, \bar{w})$ and $\bar{w}$ finite.

In period 2, consumption is financed by both the parent and the child. The child's human capital e_2 affects the return to child labor. Let w_2 and $w_{c,2}$ denote adult (or parental) and child wage rates, respectively. The period 2 budget constraint is:

$$c_2 \leq w_2 e_p + w_{c,2}(1 - s_2)e_2, \tag{3}$$

where $1 - s_2$ represents the time allocated to working.

Wages are treated as exogenous and interpreted as shifters of agricultural productivity. In contrast to Shah and Steinberg (2017), where $w_2 = w_{c,2}$ and both increase with favorable rainfall,[21] my paper assumes that child labor is less productive ($w_{c,2} < w_2$), and rural electrification raises only adult wages (w_2).[22] Note that in the empirical analysis, changes in adult wages are proxied by electricity price reductions.

Following Cunha and Heckman (2007), the child's human capital in period t depends on prior human capital and investments made through consumption or schooling. In this three-period model, early-life human capital is normalized to zero ($e_1 = 0$). The human capital evolution is given by:

[21] In Shah and Steinberg (2017), $c_2 = w_2[e_p + (1 - s_2)e_2]$, so if the child works full time ($s_2 = 0$), the marginal returns to child and adult human capital are equal. This implies perfect substitutability between child and adult labor conditional on human capital.

[22] Appendix Table A1 summarizes the key differences in assumptions.

$$e_1 = 0, \quad e_2 = f_2(c_1), \quad e_3 = f_3(e_2, c_2, s_2).$$

The production functions satisfy:

$$\frac{\partial f_2}{\partial c_1} \geq 0, \quad \frac{\partial f_3}{\partial e_2} \geq 0, \quad \frac{\partial f_3}{\partial c_2} \geq 0, \quad \frac{\partial f_3}{\partial s_2} \geq 0,$$

and

$$\frac{\partial^2 f_2}{\partial c_1^2} \leq 0, \quad \frac{\partial^2 f_3}{\partial e_2^2} \leq 0, \quad \frac{\partial^2 f_3}{\partial c_2^2} \leq 0, \quad \frac{\partial^2 f_3}{\partial s_2^2} \leq 0.$$

2.2 Maximization Problem

Following the literature, let $V(e_3) = e_3$ for simplicity. In period 2, when the child is in middle childhood, the parent chooses s_2 to maximize lifetime utility. Since utility is strictly increasing in consumption and intertemporal saving is not allowed, both budget constraints bind. Substituting $c_2 = w_2 e_p + w_{c,2}(1 - s_2)e_2$ into the total utility function and omitting c_1 (as it is predetermined from the perspective of period 2), the household solves:

$$\max_{s_2 \in [0,1]} \; u_2[w_2 e_p + w_{c,2}(1 - s_2)e_2] + \beta f_3(e_2, w_2 e_p + w_{c,2}(1 - s_2)e_2, s_2). \tag{4}$$

Assume the following boundary and curvature conditions for an interior solution:

$$\lim_{s_2 \to 0^+} \frac{\partial f_3}{\partial s_2} = +\infty, \quad \lim_{s_2 \to 1^-} \frac{\partial f_3}{\partial s_2} = 0,$$

$$\left(\frac{\partial^2 u_2}{\partial c_2^2} + \beta \frac{\partial^2 f_3}{\partial c_2^2}\right) \cdot \left(\beta \frac{\partial^2 f_3}{\partial s_2^2}\right) > \left(\beta \frac{\partial^2 f_3}{\partial s_2 \partial c_2}\right)^2.$$

The first-order condition (FOC) is:

$$w_{c,2} e_2 \frac{\partial u_2}{\partial c_2} = \beta \Phi(e_2, c_2^*, w_2, w_{c,2}, s_2^*), \tag{5}$$

where

$$\Phi = \frac{\partial f_3}{\partial s_2} - w_{c,2} e_2 \frac{\partial f_3}{\partial c_2}. \tag{6}$$

Eq. 5 implies that, at an interior optimum, the parent equates the marginal utility gained from consumption with the net long-term benefit of schooling. Given that $\partial u_2/\partial c_2 > 0$, $w_{c,2} > 0$, and $e_2 > 0$, it follows that $\Phi(e_2, c_2^*, w_2, w_{c,2}, s_2^*) > 0$: the human capital return to schooling exceeds the return to working and consuming.

2.3 Effect of Parental Wage on Schooling and Long-Term Human Capital

Effect of Second-Period Wage on Schooling

Differentiating the FOC with respect to w_2, the comparative static result yields:

$$\frac{\partial s_2^*}{\partial w_2} \propto \underbrace{-w_{c,2} e_2 \frac{\partial^2 u_2}{\partial c_2^2}}_{\text{Income effect } (+)} + \underbrace{\beta \frac{\partial \Phi}{\partial c_2}}_{\text{Effect of } c_2 \text{ on net impact of schooling (weakly } +)} . \tag{7}$$

The first term captures the income effect: as w_2 rises, so does c_2, reducing the marginal utility of consumption and thus the value of child labor. The second term reflects the effect of c_2 on net impact of schooling. Following the literature, this paper assumes $\frac{\partial \Phi}{\partial c_2} \geq 0$.[23] That is, when a child is well-nourished and not burdened by basic needs, additional schooling becomes more productive than consumption. Thus, the income effect is likely the main driver in this setting.

Effect of Second-Period Wage on Long-Term Human Capital

$$\frac{de_3}{dw_2} = \frac{\partial f_3}{\partial c_2} e_p + \frac{\partial s_2^*}{\partial w_2} \Phi. \tag{8}$$

This effect is positive because $\partial f_3/\partial c_2 > 0$, $\Phi > 0$, and $\partial s_2^*/\partial w_2 > 0$ as shown above.

[23] Shah and Steinberg (2017) argues that as consumption increases, schooling becomes relatively more effective at converting time into human capital. Nutrition literature shows that improved diet enhances cognitive function (e.g., Gómez-Pinilla, 2008; Bryan et al., 2004), while economic research links better nutrition to improved academic performance (e.g., Chakraborty and Jayaraman, 2019; Anderson, Gallagher, and Ritchie, 2018). Work on dynamic complementarities (e.g., Johnson and Jackson, 2019; Nandi et al., 2017; Aizer and Cunha, 2012; Cunha, Heckman, and Schennach, 2010) further highlights how early health and human capital complement each other in producing later human capital.

2.4 Empirical Goal

The model predicts that an increase in w_2 leads to higher optimal schooling and greater long-term human capital for the child. My paper tests this prediction by estimating $\frac{de_3}{dw_2}$, which captures the effect of middle childhood exposure to higher adult wages, proxied by larger reductions in electricity prices, on children's long-term human capital accumulation.

3 Background

3.1 Rural Electricity Management in China (1979–1999)

Following the launch of China's Reform and Opening-up policy in 1979, the country began transitioning from a centrally planned economy to a market-oriented system. This transformation extended to the electricity sector, where funding constraints posed a major obstacle to reform.

To address the shortage of capital for power infrastructure, the Ministry of Electric Power introduced measures such as joint investment by government departments, local fundraising, and the use of foreign capital. It also shifted from uniform pricing to cost-recovery pricing,[24] moving toward a more market-oriented system (Chen, 2018). As a result, national and local electricity networks operated in parallel until the late 1998 launch of the "Two Reforms and One Price" (TROP) policy.

Before 1998, among more than 2,400 county-level power supply enterprises across China, roughly one-third were directly managed and supplied by the national grid—typically in relatively rich counties (or county-level districts) or suburban areas. The remaining counties were locally managed, either purchasing electricity in bulk from the national grid or running their own independent systems.[25] In most cases, electricity was delivered to rural households via township and village-level substations, with prices marked up at each stage of distribution (Section 5.1 provides an example).

[24] Cost recovery refers to the principle of recouping the costs associated with providing a product or service.

[25] Source: https://finance.sina.com.cn/g/20060110/15592263755.shtml (in Chinese). In the empirical analysis, I include county fixed effects to absorb variation in electricity management systems.

Before 2012, China implemented a categorized electricity pricing system based on usage types (e.g., household lighting, agricultural, industrial). After 2012, there was a shift to a tiered pricing system in which rates vary by consumption level.[26] For rural households, electricity prices for lighting (referring to daily life usage) and agricultural production were typically similar (see Appendix Table A2 for an example from Yangzhou City in 2000). In practice, it is often difficult to distinguish between "household" and "productive uses" of electricity in rural areas, as many residents use electricity to pump water for nearby farmland or to run small home-based businesses.

3.2 Rural Electricity Prices in 1990s China

One of the primary reasons for high rural electricity prices in 1990s China was the aging and fragile condition of rural power infrastructure. Outdated transformers and transmission lines, long delivery distances, and high line losses significantly increased costs—burdens that ultimately fell on rural residents, constraining both household consumption and agricultural production.

In addition, the fee collection process was often disorganized. Township governments and village committees frequently imposed surcharges beyond nationally approved rates. Informal practices such as "power for favors," personal connections, and other non-transparent arrangements further exacerbated the burden on rural consumers.[27] These institutional and infrastructural shortcomings contributed to electricity prices in rural areas that far exceeded those in urban areas.[28]

In contrast, urban (and some suburban) areas benefited from better infrastructure and more efficient management systems, typically charging only the officially approved rates. For instance, in Guangxi Zhuang Autonomous Region, the average rural electricity price before 1999 was 0.85 CNY, more than 50% higher than the urban rate of 0.55 CNY.[29]

[26] Source: National Development and Reform Commission of China. https://www.ndrc.gov.cn/xwdt/xwfb/201206/t20120614_956502.html (in Chinese).

[27] Source: The State Council of China. https://www.gov.cn/gongbao/shuju/1998/gwyb199825.pdf.

[28] See page 423 of Guangxi Zhuang Autonomous Region Electric Power Industry Gazetteer Compilation Commission (2010).

[29] Source: page 426 of Guangxi Zhuang Autonomous Region Electric Power Industry Gazetteer Compilation Commission (2010).

3.3 Two Reforms and One Price (TROP)

In October 1998, the State Council of China launched the TROP program to reduce rural electricity prices, ease the financial burden on farmers, and improve rural living and production conditions. The initiative aimed to: (1) upgrade rural power grids and (2) reform rural electricity administration—two essential steps that paved the way for (3) unifying rural and urban electricity pricing, hence the name "Two Reforms and One Price" (TROP).

It's important to note that TROP did not involve new power generation.The upgrading of electricity infrastructure included the installation of more dependable transmission lines and transformers, which might also improve electricity quality.[30] However, the primary goal was to make lower prices in rural areas sustainable. In many developing countries today, electricity subsidies are common, yet many still struggle with intermittent service and poor power quality (Meeks and Mahadevan, 2025). The "Two Reforms" were essential steps to ensure that affordability could be sustained.

TROP removed administrative intermediaries, streamlined local personnel, curbed corruption, and standardized electricity pricing. Rural households were connected directly to the national grid managed by the State Grid Corporation.[31] Electricity usage was measured by newly installed meters, with prices transparently posted in each village. Retail electricity prices are set by distributors but require government approval. In most cases, pricing reflects long-run marginal supply costs. However, inefficiencies remain in the pricing system (International Energy Agency, 2002).

TROP was implemented in two phases. The first phase (1999–2001) was more intensive, accounting for most infrastructure upgrades and price reductions. For example, in Hubei Province, over 8 billion CNY was invested during the first phase, compared to 3.6 billion CNY in the second phase (2002–2005).[32] Most provinces achieved unified electricity pricing between rural and urban areas by around 2001. The program delivered measurable improvements. In Guangdong Province,

[30] In Section 7, my paper checks whether these time-varying unobservables significantly bias the estimates.

[31] The State Grid Corporation, owned by the central government, was later split into the State Grid and China Southern Power Grid, both managing different regions of the national grid.

[32] See pages 340–341 of Hubei Electric Power Industry Gazetteer Compilation Commission (2012).

low-voltage line losses declined from 25–30% to below 12%, rural electricity prices dropped by 0.49 CNY (a 35.6% reduction), and voltage levels rose from 150–180 volts to the standard 220 volts.[33]

Funding for TROP primarily came from the State Grid Corporation, which is owned by the central government, while rural households were responsible only for wiring below the meter.[34] Although the central government adjusted electricity prices a few times, such as a 0.025 CNY increase in 2006, these changes were relatively small.[35]

3.4 The Structure of Electricity Consumption and Development Indicators in China around 1999

Electricity Consumption Patterns

China's rural household connection rate reached 85% by 1991 and 97% by 1998.[36] Despite this widespread access, per capita electricity consumption in rural areas remained low—just 235 kWh in 1998.[37] For comparison, this was only 5.8% of U.S. per capita electricity consumption in 1960.[38]

Table 1 presents electricity consumption data from Henan Province, a major agricultural region in central China. In 1998, rural electricity consumption per agricultural capita in Henan was 185 kWh. Of this, 16% for lighting (referring to daily life usage), 18% was used for irrigation and drainage, and 22% for agricultural processing, with most of the remainder attributed to rural industry. Note that in China's statistical system, "rural industry" refers to enterprises located within a county, but most of which are situated in the county's urban areas.[39] This classification aligns

[33] See pages 550–551 of Guangdong Electric Power Industry Bureau (Group Corporation) (2004).

[34] Government regulations prohibited additional charges beyond household wiring, except in cases where residents contributed to the cost of electricity meters due to insufficient renovation funds. Source: https://www.gov.cn/gongbao/content/2001/content_61344.htm.

[35] These adjustments reflected rising input costs and pressure to repay the program's funding. Source: https://www.gov.cn/banshi/2006-06/30/content_324013.htm.

[36] Source: https://kjpj.bit.edu.cn/docs/20150119212311371518.pdf and https://ncdqh.com.cn/interpretation/200109/132007.html (in Chinese).

[37] Author's calculation based on National Bureau of Statistics of China (1999). This figure includes industrial usage within a county.

[38] The earliest year with available data. Source: World Bank DataBank.

[39] Starting in January 1985, the National Bureau of Statistics of China began distinguishing between "urban" and "rural" areas, with county seats (towns) being classified as part of the rural category. Source: https://www.stats.gov.cn

with China's administrative hierarchy, in which a city (prefecture) governs multiple counties.

In 1999, annual per capita expenditure in rural China was approximately 2,390 CNY.[40] In the same year, rural electricity consumption per agricultural capita in Henan was 194 kWh. At a unit price of 0.85 CNY per kWh, this translates to an annual electricity cost of 164.9 CNY, which accounted for about 6.9% of total per capita expenditure. This share closely matches the 6.8% of household spending that U.S. consumers allocated to utilities, fuels, and public services in 2020.[41]

Table 1: Annual Rural Electricity Use Per Agricultural Capita in Henan Province

Year	Total use (kWh/agri[a] capita) (1)	Irrigation and drainage[b] (kWh/agri[a] capita) (2)	Lighting (referring to daily life use (kWh/agri[a] capita) (3)	Agri[a] processing (kWh/agri[a] capita) (4)	Irrigation and drainage[b] (kWh/acre) (5)
1990	85	21	9	22	348
1991	92	24	11	22	324
1992	104	27	14	24	359
1993	114	25	16	26	297
1994	130	27	18	29	274
1995	156	31	22	33	309
1996	164	30	25	36	302
1997	188	40	28	39	398
1998	185	34	30	40	319
1999	194	37	35	39	350
2000	184	30	36	33	291
2001	195	29	43	31	276
2002	221	30	55	29	254

Note: This table presents annual electricity consumption in rural areas of Henan Province. Data after 2002 are unavailable. The average rural electricity price in Henan in 1998 was 0.85 CNY ($\approx$ 0.10 USD in 2000), which fell to 0.53 CNY in 2001 following TROP implementation. Source: page 312 of Henan Electric Power Industry Gazetteer Compilation Commission (2010).

[a] "agri" refers to "agricultural."

[b] Although the category includes both drainage and irrigation, it primarily reflects irrigation, as most areas in Henan—located in northern China with limited water resources—rely heavily on irrigation.

/hd/lyzx/zxgk/202412/t20241206_1957664.html.

[40]Source: National Bureau of Statistics of China. https://www.stats.gov.cn/zt_18555/ztsj/hjtjzl/1999/202303/t20230302_1923300.html.

[41]Source: U.S. Bureau of Labor Statistics. https://www.bls.gov/opub/reports/consumer-expenditures/2023/.

Development Indicators: China 1998 vs. the World in 2022

In 1998, China had the world's largest rural population—820 million—and key development indicators comparable to many low- and middle-income countries today. Figure 1 plots rural population share against GDP per capita (in constant 2015 USD). The cross marks China in 1998, while the circles represent 61 low- and lower-middle-income countries with rural population shares exceeding 40% in 2022. Circle sizes are in proportion to rural population.

These countries (excluding China) had a combined rural population of 2.2 billion. Among them, 40 countries (66%) had per capita GDP levels below China's 1998 level, while 12 countries (20%) had per capita GDP within 80–120% of China's 1998 value. These 12 countries alone accounted for 1.25 billion rural residents, with an average rural electrification rate of 80.4%, comparable to rural China in the 1990s. China's late-1990s experience may thus offer insights for rural electrification in many low- and middle-income countries today.

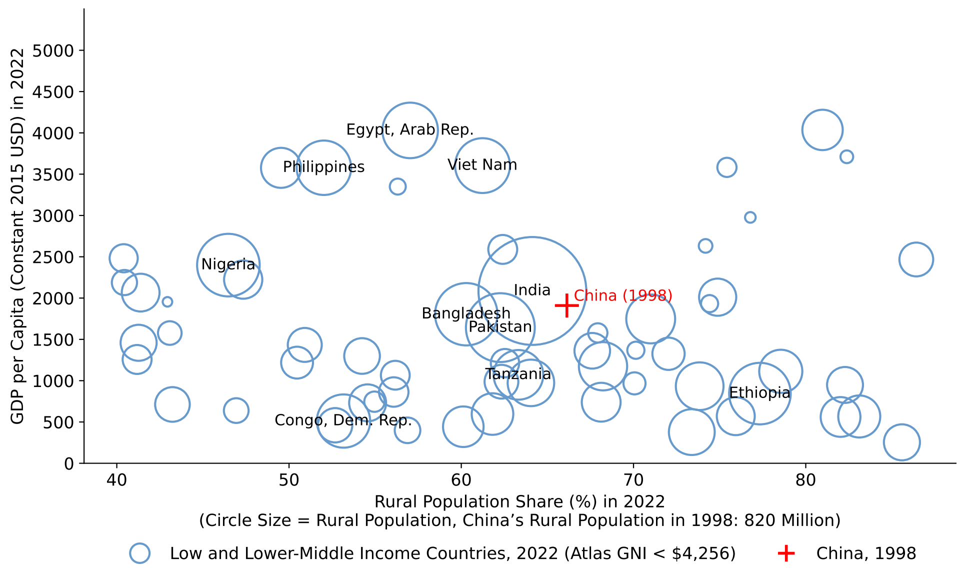

Figure 1: GDP per Capita and Rural Population Share: China 1998 vs. the World in 2022. *Note*: This figure plots GDP per capita (constant 2015 USD) against rural population share. The cross represents China in 1998. Each circle corresponds to one of 61 low- and lower-middle-income countries with a rural population share above 40% in 2022. Circle sizes are proportional to each country's rural population. The 10 countries with the largest rural populations are labeled. A total of 12 countries had per capita GDP between 80 and 120% of China's 1998 value. These countries alone accounted for 57% of the total rural population across the 61 countries and had an average rural electrification rate of 80.4%, comparable to rural China in the 1990s. Data are from World Bank DataBank.

4 Data

My paper draws data from three sources: (1) individual-level data from the 2014 wave of the China Family Panel Studies (CFPS), with missing outcome variables supplemented using the 2010 wave; (2) county-level electricity prices from local gazetteers and newspapers; and (3) regional economic indicators from various statistical yearbooks.

4.1 Individual and Household Survey Data

This paper uses individual and household data from the 2014 wave of the China Family Panel Studies (CFPS), a nationally representative longitudinal survey launched in 2010 by the Institute of Social Science Survey at Peking University. The baseline survey includes 14,797 households across 162 counties in 25 provinces.[42] After excluding 20 county-level districts in Beijing, Shanghai, and Tianjin (due to limited rural representation), this paper covers 142 counties.[43]

My paper uses years of education completed in 2014 as the primary outcome variable, supplemented by cognitive test scores.[44] The sample is restricted to individuals aged 20 or older in 2014, as their years of education are less likely to vary. To reduce the influence of major national reforms (including the Cultural Revolution from 1966 to 1976, the Reform and Opening-up in 1978, and the Compulsory Education Law in 1986), I exclude individuals born before 1979. My paper focuses on cohorts born between 1979 and 1994. Appendix Figure B1 shows the average years of education by cohort (birth year) in my sample.

Approximately 24% of individuals surveyed in 2010 are missing from the 2014 wave.[45] Following Bianchi, Lu, and Song (2022), I use 2010 wave data to impute missing outcome variables for these individuals.[46] Section 7 shows that including these imputed individuals does not substantially affect the main results and improves estimation precision.

Because TROP targeted rural areas, I restrict the analysis to individuals with agricultural Hukou at both ages 3 and 12,[47] assuming they resided in rural areas during the treatment period. The CFPS provides Hukou status at ages 3, 12, and the survey year. In Section 7, I test for potential migration bias using CFPS data on birthplace, location at age 12, and both Hukou status and residence at the time of the survey.

[42] See https://opendata.pku.edu.cn/dataverse/CFPS?language=en.

[43] The analysis of county-level data in this paper was conducted in the restricted data laboratory of the Institute of Social Science Survey at Peking University.

[44] China's education system temporarily shifted to a 5-2-2 structure during the Cultural Revolution (1966–1976), and later returned to the standardized 6-3-3 system: six years of primary school, followed by three years each of junior and senior high school (Chen, Jiang, and Zhou, 2020).

[45] Appendix Figure B2 compares the birth year distributions (1979–1994) for individuals present in both waves and those missing in 2014. While the latter group skews slightly younger, the overall distribution remains balanced. Appendix Figure B3 shows that the distributions of years of education are also similar across groups.

[46] To mitigate concerns about migration, my analysis includes only individuals from the 2010 baseline, excluding new respondents added in 2014. This approach also avoids potential bias from post-2012 Hukou (China's household registration system) reform, which relaxed rural-to-urban migration restrictions. Control variables such as gender, ethnicity, and parental education are taken from the 2010 baseline, as they are unlikely to change over time. Source: https://www.ndrc.gov.cn/wsdwhfz/202206/t20220628_1328962.html.

[47] Hukou is China's household registration system that historically restricted rural-to-urban migration; these restrictions began easing after 1993 (Chan and Zhang, 1999).

4.2 Electricity Prices

I manually collect county-level rural electricity prices before and after TROP primarily from local gazetteers. In China's administrative hierarchy, counties fall under prefectures. Local gazetteers (Di Fang Zhi, in Chinese) serve as encyclopedic records, documenting a region's history, economy, governance, and infrastructure. Gazetteers are compiled at the provincial, prefectural, and county levels and are a key source for historical and institutional research. While traditional gazetteers were typically produced through collaboration between local officials and elites, modern versions are compiled by government agencies.

The gazetteers I use were published in the 2000s and 2010s, as TROP was announced at the end of 1998 and its first phase ran through approximately 2001. I focus on records describing the implementation and consequences of TROP. Some counties provide detailed documentation that facilitates data collection. For example, the electricity gazetteer of Luoding City (a county-level city in Guangdong Province) reports: "... the optimization of the rural grid layout reduced line losses significantly, with the overall loss rate dropping from 36% to 11%... supply reliability and voltage compliance improved from 75% to 99.5%, with a voltage increase of 30 volts.[48] By 2002, rural electricity prices fell from 1.19 CNY per kWh before the 'Two Reforms and One Price' initiative to 0.99 CNY, and then further to 0.79 CNY (the ultimately unified price)."(Luoding City Gazetteer Compilation Commission, 2003) In this case, I use 1.19 CNY and 0.99 CNY as the pre- and post-TROP prices, respectively, as this window aligns with the most intensive phase of implementation (see Section 3.3).[49]

Some counties may not have specific records of TROP, while more information could be found in the prefectural gazetteers. For instance, the electricity prices of Jiangdu City (a county-level city) of Yangzhou Prefecture in Jiangsu Province are collected from the gazetteer of Yangzhou electric power industry, in which page 227 notes that "in July 1998, the average electricity price for rural

[48] China's standard household voltage is 220V. Most gazetteers, however, do not include electricity quality data.

[49] According to local records, some counties completed price unification slightly earlier or later than the planned 2001 endpoint. For instance, Qiyang County implemented unified rural-urban pricing in 2002. My robustness checks account for variation in timing across counties.

household lighting in the entire prefecture of Yangzhou was around 1 CNY per kWh. Starting from March 1, 2001, the first batch of three rural power grid renovation counties in Yangzhou, i.e., Jiangdu City, Yizheng City, and Hanjiang County, implemented the same electricity rate for both urban and rural residents, with a price of 0.52 CNY per kWh."(Yangzhou Power Supply Company, 2012) In such cases, 1 and 0.52 are collected as the pre- and post-TROP prices of Jiangdu City.

If county and prefecture records are unavailable, I use information from local newspapers or provincial-level sources.[50] In total, I collect electricity price data for 142 counties matched to CFPS survey sites. Of these, 80 counties (56.3%) have data from county or prefectural records, while the remainder use provincial-level sources. Additionally, price data for 3 counties come from county or prefectural newspapers, and for 5 counties from provincial newspapers. Note that my price data has within-province variation, as at least one county in each province in my sample uses county- or prefectural-level prices. This is important because my regression model includes province $\times$ year fixed effects, which require sufficient within-province variation. Appendix Table A3 summarizes data sources.

Appendix Table A4 presents correlations between pre-TROP electricity prices and county-level characteristics in 1999.[51] It shows that counties with higher pre-TROP electricity prices tend to have higher rural transmission losses at the provincial level, higher agricultural GDP shares, and larger rural populations. These patterns imply that high prices were concentrated in more underdeveloped counties with weaker infrastructure.

4.3 Regional Data

To check the robustness of my results and explore the economic impact of electrification, I collect prefecture-level indicators—including GDP, foreign direct investment, sectoral output, population composition, and arable land—from the China City Statistical Yearbook (1995–2008).[52] Note that

[50] Potential bias from measurement error is addressed in the robustness checks.

[51] Data on transmission loss is draw from local gazetteers. Most counties don't have these records. In these cases, I use provincial level records instead. Other county-level indicators are draw from 1999 National City and County Financial Statistics (Quanguo Di Shi Xian Caizheng Tongji Ziliao, in Chinese). Note that most of these indicators are missing for the pre-treatment period. I use 1999 data as it is closest to TROP implementation and most complete.

[52] Due to data limitations, county-level variables are often unavailable or incomplete. The yearbooks report data from 1994–2007. Source: National Bureau of Statistics of China, Urban Social and Economic Survey and Statistical

in these yearbooks, "cities" are administratively equivalent to prefectures, each covering several counties. I also gather county-level data on public expenditure and agricultural vs. industrial GDP shares from the National Finance Statistics of Cities, Counties, and Districts (1993–2007).[53]

4.4 Summary Statistics

Appendix Table A5 reports summary statistics for electricity prices before and after TROP. On average, rural prices declined by 0.24 CNY, a 29% reduction. The standard deviation of post-TROP prices is half that of pre-TROP prices.[54]

Three counties experienced small price increases after TROP. Located in Liaoning Province near prefectural centers with high industrial output, these counties had among the lowest pre-TROP prices in the sample. Price increases in these counties may reflect local efforts to recoup infrastructure investments.

Table 2 shows summary statistics for key variables from the 2014 CFPS. Columns (1) and (2) compare counties with small (bottom 25th percentile) and large (top 25th percentile) price reductions. Counties with larger reductions tend to have lower average education levels and a higher share of minority populations.[55] These patterns, consistent with Appendix Table A6, suggest that larger price reductions were concentrated in poorer regions. This reinforces the notion that electricity price changes were not random but correlated with local conditions. However, as discussed in the next section, my identification strategy relies on the parallel trends assumption rather than exogenous price reductions. Columns (3) and (4) compare control and treatment cohorts, showing that the latter has higher average years of schooling.

Division (1995–2008).

[53] Source: Ministry of Finance of the People's Republic of China, Budget Department (1993–2007).

[54] Additional details on price data are omitted to comply with CFPS confidentiality rules.

[55] Minority populations refer to non-Han ethnic groups, often residing in remote or underdeveloped areas.

Table 2: Summary Statistics for Key Variables

Sample (rural residents)	Counties: small vs. large price reductions		All counties	
	Bottom 25th percentile (1)	Top 25th percentile (2)	Control group (1980–1984) (3)	Treatment group (1988–1994) (4)
Years of education	10.39	8.56	8.38	10.35
	(3.24)	(4.36)	(4.03)	(3.72)
Gender (male = 1)	0.49	0.47	0.47	0.48
	(0.50)	(0.50)	(0.50)	(0.50)
Ethnic (Han = 1)	0.98	0.82	0.88	0.90
	(0.15)	(0.38)	(0.33)	(0.30)
Number of siblings	1.30	1.87	1.87	1.41
	(0.94)	(1.40)	(1.29)	(1.03)
Father's years of education	7.19	5.29	5.82	6.69
	(3.61)	(4.31)	(4.20)	(3.94)
Mother's years of education	5.18	3.34	3.35	4.44
	(4.09)	(3.96)	(3.96)	(4.12)
Observations	1057	845	1742	2408

Note: This table includes only rural residents, defined as those with an agricultural Hukou at ages 3 and 12. Columns (1) and (2) represent counties that experienced small (bottom 25th percentile) and large (top 25th percentile) price reductions in electricity prices after TROP, respectively. Standard deviations are in parentheses.

5 Treatment Intensity and Empirical Strategy

5.1 Treatment Intensity

This paper uses the reduction in rural electricity prices following TROP as a measure of treatment intensity.[56] A potential concern is that TROP combined price reform with infrastructure upgrades and management improvements, making it difficult to isolate the effect of price changes alone. This paper argues that in 1999 China, as in many low- and middle-income countries today, weak infrastructure, inefficient management, and unaffordable electricity were deeply intercon-

[56] The goal of TROP was to eliminate the rural-urban electricity price gap. Therefore, the observed price reduction is an outcome of the program's implementation. See Appendix Table A5 for summary statistics and Section 4.4 for a discussion of counties with negative price reductions.

nected.[57] Policies targeting affordability must therefore address infrastructure and management reforms; without such reforms, lower prices are not sustainable. This is why China's central government prioritized the "Two Reforms" before unifying electricity prices under TROP, rather than mandating price cuts alone.

Appendix Tables A4 and A6 provide suggestive evidence of the interconnection between weak infrastructure and unaffordable electricity. They show that both electricity prices before TROP and the subsequent reductions are negatively correlated with GDP per capita and the industrial share of GDP, and positively correlated with low-voltage transmission losses (provincial level), the agricultural share of GDP, and the rural population share. These patterns suggest that areas with larger price reductions tended to have weaker infrastructure and more underdeveloped economies. In addition to the correlations, a newspaper report from a village in Jiangxi Province by Li (2009) further illustrates this connection:

"Before 1998, the household electricity price in Sanlian Village, Ruichang City (a county-level city under Jiujiang Prefecture) was 3.5 CNY per kWh. The pricing structure involved multiple layers: the Jiujiang Bureau of Power Supply sold electricity to the Ruichang Bureau at 0.37 CNY per kWh; the Hongling Township Electric Station then sold to the 3rd group of Sanlian Village at 0.86 CNY (including losses);[58] the 3rd group resold to the 1st and 2nd groups at 1.6 CNY (including equipment and labor costs); and finally, each group charged households 3.5 CNY per kWh, accounting for leakage, technical losses, and theft."[59]

However, infrastructure upgrades, such as the installation of more dependable transmission lines and transformers, also improve electricity quality by reducing outages and stabilizing voltage. These quality improvements are unobserved and may confound the effect of price changes, although evidence from Berkouwer et al. (2024) suggests that voltage quality improvements have

[57] See https://www.worldbank.org/en/topic/energy/publication/making-power-work-for-africa. Source: World Bank.

[58] In China, each village is typically divided into several groups.

[59] This example also highlights electricity theft, a common issue in many developing countries (Wong et al., 2021). TROP likely reduced theft through infrastructure upgrades such as improved wiring and meters, potentially affecting electricity prices. Theft is typically reflected in transmission losses, but Appendix Table A6 shows no significant correlation between price reductions and these losses.

limited economic impact. To further mitigate this concern, my paper checks whether these time-varying unobservables significantly bias the estimates in Section 7.

5.2 Empirical Strategy

This paper examines the long-term human capital effects of exposure to rural electrification during middle childhood (ages 6–12). This period is emphasized because the opportunity cost of schooling is lower than during adolescence, making electrification's productivity gains more likely to significantly impact schooling outcomes. Section 10 offers further discussion on the importance of exposure during middle childhood.

To assess the impact of rural electrification on human capital, this paper uses a cohort difference-in-differences (DiD) approach with continuous treatment.[60] I compare cohorts who were of primary school age or younger (under 12) at the time of TROP implementation in 1999 to those who were older than middle school age (aged 15 or above) in the same county. To mitigate concerns related to partial exposure, variation in school starting ages, and to allow time for the policy's effects to materialize, I introduce a three-year gap between the groups. The treatment group includes individuals born between 1988 and 1994, all of whom had at least one year of overlap with TROP during their primary school years. The control group includes those born between 1979 and 1984. Figure 2 illustrates the cohort definitions.

Because TROP was implemented nationwide,[61] there is no clean untreated group. Instead, I exploit variation in pre- and post-TROP electricity prices across counties, which led to heterogeneous price reductions after implementation.[62] I compare counties that experienced larger price drops to those with smaller reductions. Pre-TROP electricity prices may be correlated with factors such as transmission line length, local characteristics, and contractor attributes, in addition to the factors listed in Appendix Table A4. These factors are less likely to be exogenous, making treatment intensity (price reduction) plausibly endogenous. However, my identification strategy

[60] This methodology follows Duflo (2001), Chen et al. (2020a), and Chen (2025), and aligns with the continuous treatment framework discussed in Callaway, Goodman-Bacon, and Sant'Anna (2024).

[61] Although implementation timing may have varied slightly across regions, the program was broadly simultaneous.

[62] Post-TROP prices show significantly less variation than pre-TROP prices. See Appendix Table A5.

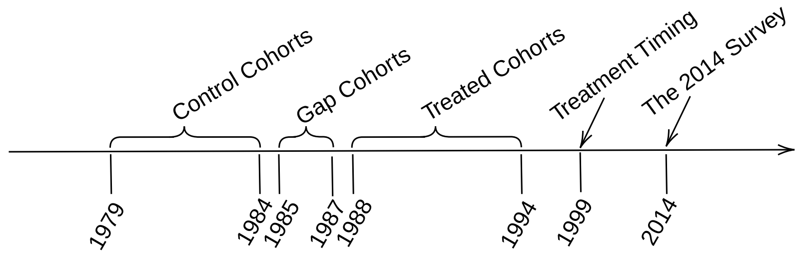

Figure 2: Definition of Cohorts. *Note*: Cohorts born between 1985 and 1987 are classified as "gap cohorts." They are included in the event study but excluded from the baseline regression. To ensure at least one year of overlap with TROP, the oldest cohort in the treatment group is those born in 1988, who were 11 years old in 1999.

does not require the exogeneity of treatment; it relies on the assumption that, in the absence of TROP, counties with larger and smaller price reductions would have followed similar trends in the post-treatment period.

The identification relies on two sources of variation: first, cohorts born before 1984 and after 1988 differed in their exposure to TROP during primary school age; second, counties experienced varying magnitudes of electricity price reductions.

5.3 Setup for Event Study

Although the parallel trends assumption cannot be tested directly because it involves a counterfactual: what treated counties would have looked like in the absence of treatment, one can assess its empirical plausibility by studying the pre-treatment period using an event study framework. Eq. 9 presents the event study specification. As noted earlier, cohorts born between 1985 and 1987 are classified as "gap cohorts" due to concerns such as variation in school starting ages. These cohorts are included in the event study to assess trends but are excluded from the baseline regression. The 1984 birth cohort serves as the reference group in Eq. 9.

$$
\begin{aligned}
Y_{i,t,c} = & \alpha + \sum_{\lambda=1979}^{1983} \beta_\lambda \times Reduction_c \times \mathbf{1}\{t=\lambda\} \\
& + \sum_{\lambda=1985}^{1994} \beta_\lambda \times Reduction_c \times \mathbf{1}\{t=\lambda\} + \varphi X_{i,t,c} \\
& + \gamma_c + \mu_{prov} \times \tau_t + \varepsilon_{i,t,c}
\end{aligned} \tag{9}
$$

$Y_{i,t,c}$ denotes an outcome of interest, such as years of education, for an individual i born in year t and residing in county c. $Reduction_c$ represents the reduction in electricity prices following TROP implementation. The function $\mathbf{1}\{t = \lambda\}$ is an indicator that equals 1 when an individual's birth year t matches the specified parameter λ. X includes individual-level controls: ethnicity, gender, number of siblings, and parental education. γ_c captures county fixed effects.

To address potential policy confounders during the study period—such as the staggered implementation of the 1986 Compulsory Education Law across provinces (Chen and Park, 2021)–I incorporate province × birth year fixed effects ($\mu_{prov} \times \tau_t$) in the model.[63] As previously noted, 44% of the counties in my sample use provincial-level price data, and adding these interaction terms takes away all provincial-level variation. Despite this, my paper opts to include these terms for two reasons: first, my price reduction data have within-province variation, as not all counties in a province use provincial-level data; second, these terms effectively control for potential time-varying confounding factors at the provincial level. While this paper makes efforts to control for varying trends, some unobservables may still confound the results. To address this concern, I conduct a series of robustness checks in Section 7. The error term is denoted as ε, with standard errors clustered at the county level.

5.4 Baseline Model

To estimate the causal effect of rural electrification on human capital, I adopt a cohort-DiD approach. I compare cohorts who were of primary school age (ages 6–12) when TROP was implemented to those who were of senior high school age or older (15+) in the same county. I exploit

[63] Another policy concern is the provincial-level rural tax and fee reform pilot, launched in 2002 to ease farmers' financial burdens and improve the rural economy.

variation from county-level differences in electricity price reductions to identify the effects. The baseline estimation equation is given by:

$$
\begin{aligned}
Y_{i,t,c} = & \alpha + \beta \times Reduction_c \times \mathbf{1}\{1988 \leq t \leq 1994\} + \varphi X_{i,t,c} \\
& + \gamma_c + \mu_{prov} \times \tau_t + \varepsilon_{i,t,c}
\end{aligned} \tag{10}
$$

All notation in Equation 10 is consistent with that in Equation 9. The coefficient of interest, β, captures the differential effect of a 1 CNY reduction in electricity prices on the outcomes of the treated cohorts relative to the control group. As mentioned earlier, the gap cohorts born between 1985 and 1987 are excluded from the baseline regression.

6 Empirical results

6.1 Results of Event Study

This paper uses the 2014 wave of the CFPS as the primary dataset. Since the electrification program targeted rural areas, the analysis is restricted to individuals classified as rural residents. I further limit the sample to individuals aged 20 or older in 2014 to ensure their educational attainment is largely complete.

Figure 3 presents the event study results, with the 1984 cohort serving as the reference. Cohorts born before 1984 show similar pre-treatment trends, supporting the parallel trends assumption. However, as Roth (2022) cautions, event studies may lack sufficient power to detect violations of parallel trends, even when pre-trends appear statistically insignificant. Following the author's recommended procedure, I conduct a power analysis for my setting. Assuming 50% power (the probability of detecting a significant pre-trend under a hypothesized trend), the analysis yields a Bayes factor of 0.61 and a likelihood ratio of 0.03, both well below 1.[64] These results indicate that the observed insignificant pre-trend in Figure 3 provides strong support for the parallel trends

[64] The Bayes factor is the ratio of the probability of "passing" the pretest under the hypothesized trend relative to under parallel trends. The likelihood ratio compares the likelihood of the observed coefficients under the hypothesized trend versus under parallel trends. See https://github.com/mcaceresb/stata-pretrends?tab=readme-ov-file#pretrends for implementation details.

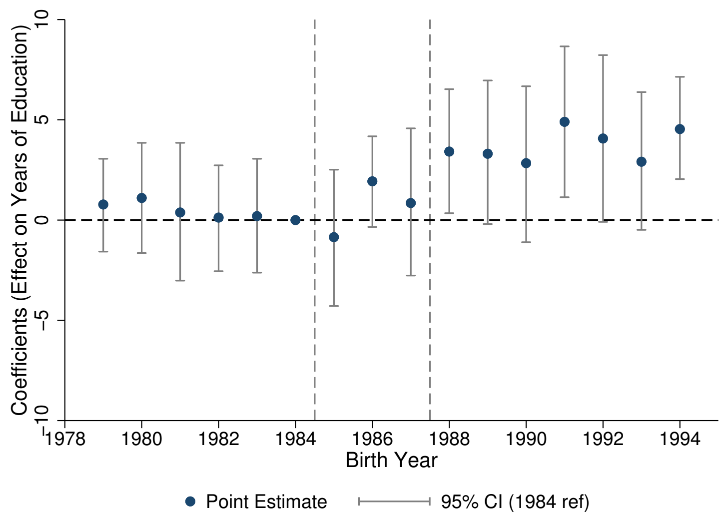

Figure 3: Event Study Results. *Note*: The y-axis represents the coefficients estimated from Eq. 9. The "gap cohorts," shown between the two dashed lines, are included in the event study but excluded from the baseline regression.

assumption.

6.2 Results of Baseline Specification

In the baseline specification, I compare cohorts born between 1988 and 1994 with those who were born between 1979 and 1984. Column (1) of Table 3 reports the baseline results: a one standard deviation reduction in rural electricity prices (0.21 CNY) increases educational attainment by 0.605 years (0.21×2.879).[65] This effect is large—more than six times the impact of China's Send-Down Movement in the 1960s–70s (Chen et al., 2020a),[66] and more than twice the effect of China's 1986 Compulsory Education Law (Chen and Park, 2021).[67]

Note again that the results should be interpreted in the context of broader reforms. Note that the results should be interpreted in the context of broader reforms. As discussed in Section 5.1, observed price reductions coincided with infrastructure upgrades and administrative reforms. Low-

[65]This effect size is comparable to Lipscomb, Mobarak, and Barham (2013), which shows that a one standard deviation increase in treatment intensity due to grid expansion raises educational attainment by 0.667 years (0.33×2.022).

[66]Effect sizes correspond to a one-standard-deviation change. Calculations are based on data from Chen et al. (2020b). The Send-Down Movement (1968–1978) was a campaign during China's Cultural Revolution where over 17 million urban youths were sent to rural areas to work and learn from peasants.

[67]Treatment in Chen and Park (2021) is binary.

ering electricity prices in isolation would have been unsustainable.

Columns (2) and (3) of Table 3 examine the effects on cognitive ability, measured by standardized math and Chinese word recognition test scores from the 2014 CFPS.[68] To ensure comparability, I standardize the original scores into z-scores.[69] The results indicate that a one standard deviation reduction in rural electricity prices raises math and word test scores by 0.164 (0.21×0.78) and 0.142 (0.21×0.676) standard deviations, respectively.

Columns (4)–(6) of Table 3 use primary and secondary school completion as alternative educational outcomes. The results show that a one standard deviation decrease in electricity prices increases primary school graduation rates by 3.7 percentage points (0.21×0.176). The same price reduction raises junior high and senior high school graduation rates by 5.12 (0.21×0.244) and 6.17 (0.21×0.294) percentage points, respectively.

The final two columns of Table 3 present falsification tests, based on the premise that TROP primarily targeted rural areas and had limited direct impact on urban households.[70] If this holds, TROP should not significantly affect urban counterparts of the treated rural cohorts. Column (7) of Table 4 tests this by including individuals with urban Hukou at both ages 3 and 12. The estimated effect is statistically insignificant, though the sample size is relatively small. Column (8) focuses on individuals residing in the urban area of their birth county at the time of the survey, including those with longstanding urban Hukou and those who acquired it later—typically from reclassified suburban areas. These individuals likely had consistent access to urban electricity infrastructure. The estimated effect is again small and statistically insignificant.

To further explore how completion outcomes vary across schooling levels, Figure 4 plots the estimated effects of TROP exposure on completion rates by grade. The results show that the largest gains occur between Grades 7 and 12, corresponding to junior and senior high school. This pattern

[68] The CFPS math and word tests are based on the Guttman Scale in psychometrics (Guttman, 1944). More details are available on the CFPS website: https://www.isss.pku.edu.cn/cfps/cjwt/cfpsxkt/1295348.htm.

[69] z-score=(x-μ)/δ, where x represents the value being evaluated, μ is the mean, and δ is the standard deviation.

[70] Anecdotal evidence suggests that urban electricity prices might have risen slightly in some regions to offset rural price reductions, but such instances appear limited and economically insignificant—widespread increases would likely have prompted public complaints from urban residents.

Table 3: Results of Baseline Specification and Falsification Tests (2014 CFPS)

Dependent var:	(1) Years of education	(2) Math test (z-score)	(3) Word test (z-score)	(4) Complete primary (edu≥6)[a]	(5) Complete junior (edu≥9)[a]	(6) Complete senior (edu≥12)[a]	(7) Falsification (urban Hukou at ages 3 and 12)	(8) Falsification (urban residence at survey)
Reduction × affected cohorts (1988–1994)	2.879*** (0.716)	0.780*** (0.175)	0.676*** (0.142)	0.176*** (0.041)	0.244*** (0.083)	0.294** (0.135)	-0.149 (0.913)	-0.034 (1.164)
Observations	4,145	4,144	4,144	4,145	4,145	4,145	647	1,510
R-squared	0.438	0.384	0.395	0.388	0.329	0.304	0.442	0.404
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province × birth year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep var	9.525	0	0	0.913	0.742	0.399	13.07	11.54

Note: Columns (1) present the baseline results. Columns (2) and (3) use cognitive test scores from the 2014 CFPS as dependent variables. "Word test" refers to Chinese word test. Columns (4)–(6) examine the completion of primary and secondary school as alternative outcome variables. College completion is excluded, as many in the treatment group were still of college age in 2014. Columns (7) and (8) present falsification tests: Column (7) includes individuals with urban Hukou at both ages 3 and 12, while Column (8) includes those residing in the urban area of their birth county at the time of the survey. Standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

[a] "edu" represents years of education.

suggests that children exposed to rural electrification during middle childhood were more likely to remain in school through later stages, consistent with the model's prediction that early exposure increases educational investment and persistence. The effects on earlier grades are smaller, likely because most children complete primary school regardless of treatment, while effects on college (Grade 13) are imprecisely estimated due to low baseline enrollment and high opportunity costs.

Note that control cohorts were also exposed to TROP, but only from senior high school age onward. This paper shows that such late exposure has little effect on human capital, as discussed in Section 10. Section 7 also examines whether variation in exposure length during primary school among treatment cohorts biases the estimates.

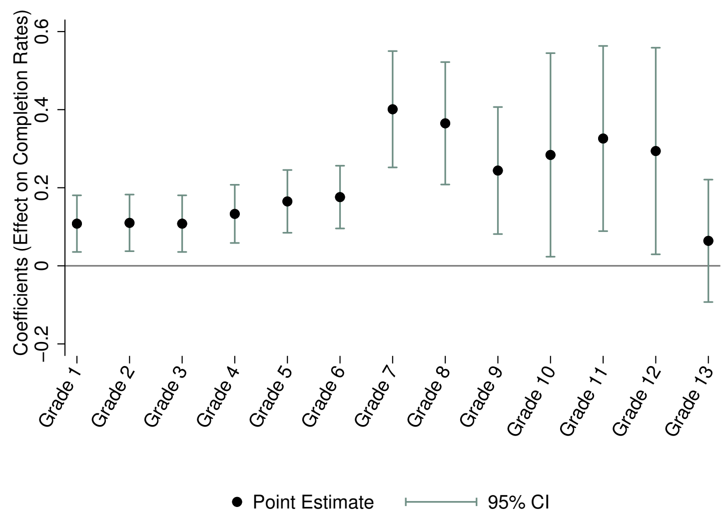

Figure 4: Effect of Electricity Price Reduction on Completion Rates by Grade. *Note*: This figure shows point estimates and 95% confidence intervals of the effect of electricity price reduction on the probability of completing each grade. Estimates are from regressions analogous to the baseline specification but using binary indicators for each grade level as outcomes. China follows a 6-3-3 education structure—six years of primary, three years of junior high, and three years of senior high education.

7 Robustness

This section demonstrates the robustness of the key result in column (1) of Table 3 through a series of checks. These include: (1) rural school consolidation around 2000; (2) China's accession to the WTO in 2001; (3) heterogeneous trends across counties; and (4) migration. It also addresses potential biases related to electricity price data availability, exposure duration, treatment timing, and missing observations.

7.1 School Consolidation

Starting in the early 2000s, China launched a rural school consolidation initiative, which primarily merged small village primary schools into larger, centralized ones.[71] The impacts of consolidation on education are mixed (Hannum, Liu, and Wang, 2021; Hannum and Wang, 2022), and treated

[71]In the 1980s and 1990s, village-run schools played a key role in expanding access to basic education. However, as quality concerns grew and rural enrollment declined, the government began consolidating schools. Between 2000 and 2005, the number of primary schools dropped by about 34%, and junior high schools by about 1.3%. Source: China Youth Daily. https://zqb.cyol.com/html/2015-09/14/nw.D110000zgqnb_20150914_1-10.htm.

cohorts in my sample might be affected.

I measure consolidation intensity using the ratio of primary schools in 2000 to 2007 at the prefectural level (from the China City Statistical Yearbook). I interact this measure with the treatment cohort dummy and add it to the baseline model. Column (1) of Table 4 shows that this adjustment does not substantially change the coefficient of interest.

Additionally, CFPS asks whether a primary school exists near an individual's village (community). If school consolidation confounded the impact of TROP, controlling for this variable should significantly affect the results. Column (2) of Table 4 shows that the coefficient of interest remains consistent, further suggesting that my findings are not driven by school consolidation.

7.2 WTO Accession

China's WTO accession in 2001 spurred export growth and foreign direct investment (FDI), which may influence household education decisions (Erten and Leight, 2021). To account for this, I measure FDI intensity as the ratio of prefecture-level FDI in 2007 to that in 2000 and interact it with the treatment indicator. Column (3) of Table 4 shows that controlling for this factor does not affect the main result.

7.3 Heterogeneous Trends across Counties

The baseline model includes county fixed effects and province $\times$ birth year fixed effects. However, unobserved time-varying potential determinants of outcomes, such as outages or voltage quality, could be correlated with price changes and bias the estimates. To mitigate this concern, I introduce county base education $\times$ birth year fixed effects to the model. Base education is defined as the average years of education among rural cohorts born between 1970 and 1978 in each county, using data from the 2000 China Census.[72] This variable serves as a proxy for local human capital stock. As shown earlier, local economic conditions were correlated with pre-TROP electricity prices. Column (4) of Table 4 reports the results. The coefficient of interest remains nearly identical to

[72]The 2000 China census data is obtained from the Integrated Public Use Microdata Series (IPUMS) (Minnesota Population Center, 2020).

the baseline estimate in column (1) of Table 3.[73] Nevertheless, if there are additional time-varying unobservables correlated with price reductions but not captured by the interaction terms—or if such trends are nonlinear—the estimates may still be subject to some bias.

Table 4: Robustness to Confounding Factors

Dependent var:	Years of education			
	(1)	(2)	(3)	(4)
Robustness check:	School consolidation	School nearby	WTO accession	County-level trends
Reduction ×	2.869***	2.925***	2.8820***	2.862***
affected cohorts (1988–1994)	(0.711)	(0.737)	(0.719)	(0.698)
Consolidation intensity	0.004			
× affected cohorts (1988–1994)	(0.010)			
FDI intensity ×			-0.0007	
affected cohorts (1988–1994)			(0.0064)	
Observations	4,145	4,061	4,145	3,738
R-squared	0.438	0.439	0.438	0.447
County FE	Yes	Yes	Yes	Yes
Province × birth year FE	Yes	Yes	Yes	Yes
Base education[a] × birth year FE				Yes
Mean of dep var	9.525	9.539	10.33	9.442

Note: Column (1) addresses China's rural school consolidation initiative around 2000, which primarily involved merging primary schools in rural and remote areas. Column (2) indirectly controls for the impact of this initiative by including a control for whether a primary school was located near the respondent's village (or community). Column (3) accounts for China's WTO accession by controlling for changes in foreign direct investment. Column (4) controls for county-level heterogeneous trends by adding base education × birth year fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

[a] Base education is measured as the county-level average years of education among individuals born between 1970 and 1978, calculated using the 2000 census.

7.4 Migration

Migration presents another potential concern. The substantial urban-rural divide in China creates strong incentives for labor migration from rural to urban areas, particularly among more educated

[73] Appendix Figure B4 presents the corresponding event study results, which remain consistent after accounting for heterogeneous trends across counties.

individuals (Zhao, 1997). Such migration could result in selective attrition, creating a rural brain drain. To alleviate this concern, the baseline sample includes only individuals with agricultural Hukou during middle childhood, rather than relying on their current Hukou status. However, some individuals may have moved after TROP implementation or lived elsewhere at the time of the survey. To mitigate these concerns, I use additional information on residence at age 12, residence at the time of the survey, and Hukou status at the time of the survey to test whether stricter sample restrictions affect the results.

Columns (1) to (3) of Table 5 implement incremental restrictions. In addition to the baseline requirement of agricultural Hukou at ages 3 and 12,[74] column (1) restricts the sample to those who also lived in their birthplace at age 12. Column (2) further limits the sample to those still living in their birthplace at the time of the survey. Column (3) adds a third condition: holding agricultural Hukou at the time of the survey. Across these increasingly restrictive samples, the estimated effects remain consistent, suggesting that migration does not substantially bias the main results.

Since 2000, an increasing number of suburban counties in China have been reclassified as districts. Compared to regular counties, districts generally exhibit higher urbanization and stronger economic development. Agricultural Hukou holders at ages 3 and 12 in these areas—many of which were formerly suburban counties—may be more likely to migrate to urban centers. To address this concern, column (4) of Table 5 drops all county-level districts, regardless of when they were designated. The estimated coefficient is somewhat smaller than in the baseline specification, likely due to reduced sample size, but the change is not substantial. The findings remain robust.

7.5 Additional Robustness Checks

In addition to the checks discussed above, this paper further examines: (1) potential bias from measurement error due to the use of prefectural or provincial electricity prices when county-level data are unavailable; (2) variation in lengths of exposure; (3) the choice of timing for post-TROP electricity prices; (4) alternative treatment measures, including price reductions using the unified price as the post-TROP benchmark and the price reduction ratio; and (5) the impact of missing

[74] In the baseline regression, my sample includes only individuals with agricultural Hukou at both ages 3 and 12.

Table 5: Migration

Dependent var:	Years of education			
	(1)	(2)	(3)	(4)
Robustness check:	Live in birthplace at age 12	(1) + live in birthplace at survey	(2) + agricultural Hukou at survey	Drop county-level districts
Reduction ×	2.932***	2.925***	3.154***	2.701***
affected cohorts (1988–1994)	(0.722)	(0.654)	(0.745)	(0.714)
Observations	4,011	3,469	3,228	3,116
R-squared	0.442	0.457	0.485	0.467
County FE	Yes	Yes	Yes	Yes
Province × birth year FE	Yes	Yes	Yes	Yes
Mean of dep var	9.513	9.519	9.295	9.217

Note: In addition to the Hukou restriction at ages 3 and 12 used in the baseline regression, columns (1) to (3) apply increasingly strict sample restrictions. Column (1) limits the sample to individuals who lived in their birthplace at age 12. Column (2) further restricts the sample to those still living in their birthplace at the time of the survey. Column (3) adds an additional condition, keeping only individuals who also held agricultural Hukou at the time of the survey. Column (4) drops all county-level districts. Standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

observations in the 2014 survey. Appendix Table C1 presents the results. My findings remain robust across these alternative specifications. Further details are provided in Appendix Section C.

8 Heterogeneity

The impact of electrification may differ by gender. In developed countries, electrification is shown to reduce the burden of household chores for women (Greenwood, Seshadri, and Yorukoglu, 2005), enabling them to invest in human capital earlier in life (Vidart, 2024). In developing countries, however, the evidence on gender-specific impacts remains mixed.[75]

Column (1) of Table 6 includes an interaction term between gender (1 for male, 0 for female) and the price reduction. The results show that price reductions significantly improved educational attainment for both genders, with a larger (but statistically insignificant) effect for males. This

[75] Some studies suggest girls benefit more (Van de Walle et al., 2017; Dasso Arana, Fernandez, and Ñopo, 2015; Khandker, Barnes, and Samad, 2013), while others find no significant effects on girls (Burlig and Preonas, 2024; Lee, Miguel, and Wolfram, 2020b). Khandker et al. (2014) and Lipscomb, Mobarak, and Barham (2013) find positive impacts on both boys' and girls' education. See Lee, Miguel, and Wolfram (2020a) for a comprehensive review.

may reflect the reality that in rural China, boys and girls alike often helped with farm work during childhood. Given the low household income, few families could afford appliances that would meaningfully reduce girls' domestic workload. Instead, both genders likely benefited similarly from productivity gains in agriculture.

Column (2) examines heterogeneity by regional income. It includes an interaction with a binary variable equal to 1 if the province belongs to the bottom 25th percentile of rural per capita income in 1999.[76] The effect of price reductions is larger in these poorer provinces, though not statistically significant.

Column (3) examines heterogeneity by family size, using a binary variable equal to 1 if the individual has siblings. Consistent with theories on the quantity-quality tradeoff in child-rearing (Becker, 1960; Becker and Lewis, 1973; Becker and Tomes, 1976), the results suggest a smaller effect for individuals with siblings, though again the difference is statistically insignificant.

As a large share of rural electricity consumption is used for irrigation,[77] rural electrification is expected to have a larger impact in areas more dependent on precipitation, particularly drier regions. In such areas, access to cheaper and more reliable electricity can support water pumping for irrigation, potentially boosting agricultural income. To test this, I collect annual county-level precipitation data from 1999 to 2007 using the ERA5-Land reanalysis dataset via Google Earth Engine.[78] Based on average annual precipitation, I classify counties as non-humid (binary variable = 1) or humid (binary variable = 0), following the classification of the central government of China.[79] Column (4) of Table 6 reports the results, showing that reductions in rural electricity prices have a larger impact on educational attainment in non-humid areas. This effect is statistically significant.

Column (5) uses an alternative measure of drought: the total number of moderate or worse

[76] 1736.63 CNY, approximately 208 USD in 2000. Source: National Bureau of Statistics of China. https://www.stats.gov.cn/sj/ndsj/zgnj/2000/J16c.htm.

[77] Section 3 provides an example of rural electricity consumption patterns in China.

[78] Source: https://developers.google.com/earth-engine/datasets/catalog/ECMWF_ERA5_LAND_MONTHLY_AGGR.Monthly data are aggregated to annual values. The period 1999–2007 aligns with the primary school years of the treatment cohorts.

[79] See https://www.gov.cn/test/2005-06/24/content_9220.htm.

drought months from 1999 to 2007, based on the Standardized Precipitation Evapotranspiration Index (SPEI).[80] The results show that the educational gains from electrification are significantly larger in counties that experienced more drought months during this period. The final column includes all interaction terms except drought months, as the latter is correlated with precipitation in column (4). Most of the above conclusions remain unchanged.

Taken together, the analysis of heterogeneity suggests that the educational benefits of rural electrification in my setting are closely linked to agricultural production—particularly irrigation. In drier areas, the opportunity cost of schooling is typically lower than in wetter regions. As a result, the agricultural gains from electrification in these areas are more likely to encourage children to remain in school. This finding motivates a closer examination of the agricultural income channel as a potential mechanism in the next section.

[80] Source: Beguería, Vicente-Serrano, and Angulo-Martínez (2010), Vicente-Serrano et al. (2010), and https://spei.csic.es/spei_database_2_10/#map_name=spei01. I use the SPEI at the nearest grid point to each county center. The timescale is one month.

Table 6: Heterogeneity

Dependent var:	Years of education					
Heterogeneity:	(1) Gender difference (male=1)	(2) Income per capita (bottom 25th percentile=1)	(3) Siblings (have siblings=1)	(4) Annual precipitation (non-humid area=1)	(5) Drought months	(6) All but drought
Reduction × affected cohorts	2.133***	2.500***	3.578***	2.521***	-0.129	2.122**
(1988–1994)	(0.749)	(0.625)	(1.050)	(0.625)	(1.929)	(1.045)
Reduction × affected cohorts	1.491					1.560*
(1988–1994) × gender	(0.947)					(0.940)
Reduction × affected cohorts		4.274				0.749
(1988–1994) × low income		(2.887)				(3.041)
Reduction × affected cohorts			-1.272			-0.586
(1988–1994) × siblings			(1.099)			(1.145)
Reduction × affected cohorts				5.494**		4.881*
(1988–1994) × non-humid area				(2.606)		(2.717)
Reduction × affected cohorts					0.681*	
× (1988–1994) × drought months					(0.376)	
Observations	4,145	4,145	4,145	4,145	4,008	4,145
R-squared	0.441	0.439	0.432	0.439	0.442	0.442
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Province × birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep var	9.525	9.525	9.525	9.525	9.544	9.525

Note: Column (1) includes interaction terms between gender (0 for female, 1 for male) and the electricity price reduction. Column (2) incorporates an indicator variable equal to 1 if the province falls within the lowest 25th percentile of rural per capita net income in 1999. Column (3) adds a binary variable indicating whether the individual has siblings (1 if yes, 0 otherwise). Column (4) classifies counties as either humid or non-humid based on annual precipitation. Column (5) interacts the number of moderate or severe drought months—calculated using the Standardized Precipitation Evapotranspiration Index (SPEI)–with the treatment intensity. The final column includes all interaction terms except drought months, as the latter is correlated with precipitation in column (4). Standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

9 Mechanisms

The analysis of heterogeneity indicates that TROP's impact on human capital is greater in areas with greater irrigation needs. This section presents evidence supporting one potential mechanism: increased agricultural productivity. I first show direct evidence of improvements in agricultural productivity at the prefectural level, followed by suggestive evidence of gains in child nutrition and health. Given that electricity is a necessary input for education infrastructure, I also explore whether reductions in electricity prices lead to increased public investment in education.

9.1 Rural Electrification Enhances Agricultural Productivity

Direct Evidence

As mentioned earlier, existing literature suggests that rural electrification increases crop yields, improves productivity, and supports agricultural expansion. These changes likely translate into higher agricultural income for rural households. Meanwhile, household income is widely recognized as a key determinant of children's educational attainment (e.g., Taubman, 1989; Acemoglu and Pischke, 2001; Dahl and Lochner, 2012; Page, 2024).

To examine TROP's impact on agricultural productivity, I collect data on electricity prices, agricultural GDP,[81] industrial GDP, and arable land area at the prefectural level for the period 1994–2007.[82] Columns (1) and (2) of Table 7 show the impact of rural electricity price reductions on agricultural productivity, measured by agricultural GDP per unit of arable land.[83] Column (2) includes weather controls; column (1) does not. As shown in column (2), lower rural electricity prices significantly increase agricultural productivity (measured by agricultural GDP per hectare). A one standard deviation reduction in electricity prices raises agricultural productivity by 2,037 CNY per hectare ($0.21 \times 0.97 \times 10^7$/1,000), or approximately 240 USD in 2000. This is equivalent to 824 CNY—or about 97 USD—per acre. The effect size is substantial: it represents a 12.7% increase (or 280 CNY) in the annual per capita net income of rural households in 1999.[84] For context, annual tuition in 2000 was about 200 CNY for primary school and 400 CNY for middle school. (Liu, 2000).

[81] Note that in the statistical classification in China, the broader definition of agriculture refers to the primary industry, including sectors such as agriculture, forestry, fishing, and animal husbandry.

[82] For prefectures where electricity price data are unavailable, I use provincial-level data instead.

[83] GDP is reported in 10 million CNY, and one unit of arable land equals 1,000 hectares.

[84] In 1999, the average annual per capita net income of rural households in China was 2,210 CNY ($\approx$ 265 USD in 2000). Source: The National Bureau of Statistics of China. https://www.stats.gov.cn/sj/ndsj/zgnj/2000/J16c.htm. In the same year, the national average per capita arable land operated by rural households was 2.07 mu (China's metric, where 1 mu is equal to 0.165 acres), equivalent to 0.34 acres. Source: https://www.stats.gov.cn/sj/ndsj/zgnj/2000/L13c.htm.

A valid concern is that the observed increase in agricultural productivity may be driven by a decline in arable land rather than a rise in agricultural output. Columns (3) and (4) of Table 7 report the effects of TROP on agricultural GDP and arable land area, respectively. The results indicate that the productivity gains are driven by higher agricultural output, not by reductions in cultivated land.

Column (5) presents TROP's impact on the agricultural share of GDP. The results show that reductions in rural electricity prices significantly increase the agricultural GDP share. For comparison, column (6) reports the corresponding effect on the industrial GDP share, which is statistically insignificant—as expected, given that TROP was designed specifically to target rural areas.

Taken together, this evidence provides strong support for the mechanism that TROP enhances children's human capital by improving agricultural productivity and, in turn, raising rural household income. As emphasized earlier in this section, household income is a key determinant of children's educational attainment.

Table 7: TROP's Impact on Agricultural Productivity at the Prefectural Level

Mechanism	Boost agricultural productivity and agricultural output					
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var:	Agricultural GDP per unit arable land	Agricultural GDP per unit arable land	Agricultural GDP	Areas of arable land	Agricultural GDP share	Industrial GDP share
Reduction	1.103**	0.970**	470.380***	89.872	0.093*	-0.040
× after TROP	(0.431)	(0.435)	(169.562)	(106.535)	(0.054)	(0.043)
Observations	1,475	1,461	1,627	1,463	1,502	1,502
R-squared	0.87	0.871	0.852	0.888	0.806	0.849
Controls	No	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep var	2.592	2.592	600.3	341.1	0.194	0.456

Note: Sample period: 1994–2007. GDP is in 10 million CNY, and one unit of arable land equals 1,000 hectares or 2,471 acres. In addition to fixed effects, columns (2) – (6) control for prefectural annual precipitation and average temperature. Standard errors are clustered at the prefectural level. *** p<0.01, ** p<0.05, * p<0.1.

Suggestive Evidence

It's well established that household income is positively correlated with children's health (e.g., Case, Lubotsky, and Paxson, 2002; Currie and Stabile, 2003; Condliffe and Link, 2008). If rural electrification raises agricultural income, we should also expect improvements in children's nutrition and health, at least in the short term. While direct data on short-run nutrition and health status for individuals in my main sample are unavailable, the 2010 CFPS includes information on birth weight and hospital visits in the previous year for children under age 16.[85] I use this child sample to examine whether TROP improved birth weight and reduced hospital visits, providing suggestive evidence of an income effect.[86]

Specifically, I compare children born between 1999 and 2005 to those born between 1995 and 1998. Columns (1) and (2) of Table 8 present the results. TROP significantly increased birth weight and reduced hospital visits during the year prior to the 2010 survey. A one standard deviation of reduction in electricity prices lead to an increase in birth weight by 39 grams ($0.21 \times 0.187 \times 1000$), and a decrease in the probability of visiting hospital at least once last year by 3.8 (0.21×-0.18) percentage points. These results are consistent with an income-driven improvement in child health, lending support to the mechanism that TROP raised agricultural income.

9.2 Rural Electrification Encourages Public Educational Investment

Electricity is essential for operating schools effectively, yet unreliable or unavailable electricity is a common issue in developing countries (Sovacool and Vera, 2014).TROP might enable use of lighting, fans, and educational equipment, potentially encouraging local governments to allocate more resources to education.

To investigate this mechanism, I collect county-level fiscal data from 1993 to 2007. Note that the available data on educational expenditure covers both urban and rural schools; separate figures for rural schools are unavailable. Columns (3) and (4) of Table 8 present the results. Column (3)

[85] Note that the baseline analysis in this paper focuses on adults, defined by CFPS as individuals aged 16 or older.

[86] Higher household income may enhance maternal health and parental care, both of which are important determinants of child health (Currie and Cole, 1993; Warner, 1995).

Table 8: TROP's Impact on Birth Weight, Hospital Visits, and Public Expenditure on Education

Mechanism	Improve nutrition	Improve health	Encourage public educational expenditure	Encourage public educational expenditure
	(1)	(2)	(3)	(4)
Dependent var:	Birth weight (kg)	Hospital visits (at least once=1)	Public educational expenditure share	Public educational expenditure share (drop districts)
Reduction × affected children (1999–2005)	0.187*** (0.068)	-0.180*** (0.054)		
Reduction × after TROP			0.019* (0.010)	0.020** (0.010)
Observations	2,221	2,815	1,472	1,287
R-squared	0.256	0.283	0.83	0.811
County FE	Yes	Yes	Yes	Yes
Year FE	-	-	Yes	Yes
Province × birth year FE	Yes	Yes	No	No
Mean of dep var	3.169	0.434	0.266	0.270

Note: Columns (1) and (2) report the impact on birth weight and hospital visits for cohorts born between 1995 and 2005 from the 2010 wave children sample, which differs from the baseline. Discrepancy in sample size between columns (1) and (2) is due to missing values. Columns (3) and (4) present the results of the impact on public expenditure share on education. The first two columns control for gender, parents' ethnicity, parents' ages, and parents' education. Column (3) includes all counties in my sample, while column (4) drops all county-level districts as they have larger portion of urban schools. Both columns (3) and (4) don't include province × birth year fixed effects but control for rural population and the ratio of agricultural GDP and industrial GDP. Standard errors in columns (1) and (2) are clustered at the county level. Standard errors in columns (3) and (4) are clustered at the provincial level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

includes all counties in the sample, while column (4) excludes county-level districts, which typically have a higher concentration of urban schools.[87] The results indicate that TROP significantly increases the share of public expenditure allocated to education. In column (4), a one standard deviation reduction in rural electricity prices leads to a 0.42 percentage point increase (0.21×0.02) in the education share of public spending. Since the expenditure data include urban schools, the actual effect on rural schools may be even larger.

[87]Since the education expenditure data are aggregated across urban and rural schools, excluding districts likely improves the precision of the estimate. Additionally, columns (3) and (4) do not include province × birth year fixed effects but instead control for rural population and the ratios of agricultural and industrial GDP.

10 Discussion: Why Middle Childhood Exposure Matters

The theoretical model in Section 2 assumes imperfect substitution between adult and child labor, implying that only the income effect operates. If children provide labor nearly equivalent to that of adults, however, both income and substitution effects may arise, with the latter potentially offsetting the former. This paper argues that such a scenario arises when exposure occurs during secondary school age or later, as adolescents at that stage become close substitutes for adult labor. In this case, rural electrification boosts productivity for both age groups, and the substitution effect may negate the income-driven gains in human capital. In practice, rigidities in the education system, such as high-stakes entrance exams, further limit the effectiveness of late-stage interventions.[88]

To support the argument that middle childhood is a key period for human capital investment, I conduct an event study and a cohort-DiD regression analogous to the baseline specification, focusing on cohorts who were in secondary school age or older when TROP was implemented in 1999. The treatment group includes cohorts born between 1982 and 1987 (secondary school age), and the control group includes those born between 1975 and 1979 (older than secondary school age). Note that a two-year cohort gap, rather than the three-year gap used in Section 6, is used here to include more control cohorts.

Figure 5 presents the event study results, using the 1979 birth cohort as the reference. The treatment year remains 1999. The figure shows no significant pre- or post-trends, reinforcing the claim that middle childhood is the critical window for long-term human capital formation. Appendix Table A7 reports DiD regression results. The coefficient of interest is small (-0.391) and statistically insignificant, indicating that exposure during secondary school age has little impact on educational attainment. This finding is consistent with Shah and Steinberg (2017), which shows that a higher opportunity cost of schooling reduces human capital.

[88] Statistics from the Ministry of Education of China show that the gross enrollment rate for the 15–17 age group (high school) was 41% in 1999, while for the 18–22 age group (higher education) it was only 10.5%. These numbers include both urban and rural areas; rural rates were likely lower. Source: http://www.moe.gov.cn/jyb_sjzl/moe_560/moe_566/moe_588/201002/t20100226_7844.html.

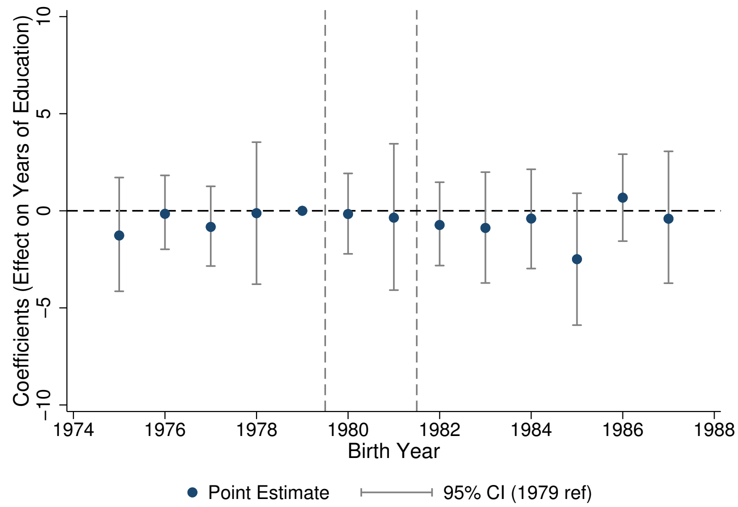

Figure 5: Event Study Results of Secondary School Age Exposure to TROP. *Note*: This figure presents event study estimates of secondary school age exposure to TROP. The treatment year is 1999. Estimates follow the baseline specification. The "gap cohorts," shown between the dashed lines, are included in the event study but excluded from the DiD regression reported in Appendix Table A7.

11 Conclusions

Recent empirical evidence suggests that rural electrification programs focus solely on expanding grid connections often generate negligible economic benefits, at least in the medium term. Electrification involves more than just grid connection—it encompasses affordability, reliability, and quality. In many developing countries, aging and inadequate infrastructure limits the effectiveness of electrification efforts. Despite these challenges, little is known about whether rural electrification programs that improve access beyond grid connection can generate meaningful economics outcomes. This paper addresses this gap by examining the long-term human capital effects of China's 1999 "Two Reforms and One Price" (TROP) program, focusing on affordability in a context where most households were already connected to the grid.

I use a cohort difference-in-differences (DiD) approach to compare cohorts who were of primary school age (middle childhood) during the implementation of TROP with those who had already passed junior high school age. By leveraging regional variation in electricity price reductions, I identify the effects of TROP. My paper focuses on middle childhood (primary school age) because, at this age, children are less substitutable for adult labor. In contrast, at older ages, children become closer substitutes for adults, and electrification may raise productivity for both groups, potentially offsetting income-driven gains through a stronger substitution effect.

The findings reveal that middle childhood exposure to electricity price reductions significantly increases educational attainment, school completion, and adult cognitive performance. Two channels are identified that drive these gains: (1) increased agricultural productivity at the prefectural level, likely from improved irrigation efficiency enabled by cheaper and more reliable electricity; and (2) greater government investment in education, reflecting electricity's role in enabling effective school infrastructure.

This paper provides empirical evidence on the long-term effects of rural electrification in China, which, during the TROP implementation, had the world's largest rural population and socio-economic indicators comparable to many developing countries today.

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Appendix

Appendix A: Tables

Table A1: Key Differences: Electrification Versus Rainfall

	This paper	Shah and Steinberg (2017)
Shock	Electrification	Rainfall
Affected wage	Adults only	Adults and children
Child labor productivity	Unchanged	Increased
Empirical proxy for wage change	Electricity price reduction	Rainfall change

Table A2: Rural Electricity Sales Prices in Yangzhou, 2000 (Unit: CNY/kWh)

Region (county)	Residential Lighting	Other Non-standard Lighting	Industrial Use	Agricultural Use
Gaoyou	0.60	0.98	0.90	0.64
Baoying	0.64	0.99	0.89	0.66
Jiangdu	0.60	0.99	0.86	0.64
Hanjiang	0.61	0.98	0.86	0.62
Yizheng	0.64	0.99	0.89	0.65
Suburbs	0.59	0.99	0.89	0.60

Note: This table reports rural electricity prices in Yangzhou, Jiangsu Province, in 2000. At the time, 1 CNY was approximately equal to 0.12 USD. Data source: page 227 of Yangzhou Power Supply Company (2012).

Table A3: Sources of Electricity Prices

Administrative level of price	Number	Source
county	30	local gazetteer
	2	local newspaper
prefecture (city)	47	local gazetteer
	1	local newspaper
province	57	local gazetteer
	5	local newspaper
In total	142	

Note: This table provides a summary of the price data sources. Note that in China, the county is a administrative level below the prefecture (or city), which differs from the structure in the United States.

Table A4: Correlation between Electricity Price pre-TROP and County-Level Characteristics in 1999

Dependent var:	Pre-TROP price				
	(1)	(2)	(3)	(4)	(5)
Rural transmission loss	0.822***				
	(0.291)				
GDP per capita		-0.001			
		(0.002)			
Agricultural GDP share[a]			0.152**		
			(0.073)		
Industrial GDP share[a]				-0.028	
				(0.028)	
Rural population share					0.214***
					(0.068)
Observations	136	123	120	123	119
R-squared	0.033	0.001	0.024	0.004	0.036
Mean of indep var	0.275	5.326	0.475	0.999	0.734

Note: Data on transmission loss is draw from local gazetteers. Most counties don't have these records. In these cases, I use provincial level records instead. Other county-level indicators are draw from 1999 National City and County Financial Statistics (Quanguo Di Shi Xian Caizheng Tongji Ziliao, in Chinese). Most of these indicators are missing for the pre-treatment period. I use 1999 data as it is closest to TROP implementation and most complete. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[a] Since industrial/agricultural GDP is unavailable, GDP share here is measured as the ratio of gross industrial/agricultural output to GDP. This measure is imprecise because gross output includes intermediate goods, while GDP reflects only value added. This also explains why the mean of the independent variable in column (4)—industrial GDP share—is close to 1.

Table A5: Summary Statistics for Electricity Price before and after TROP

	Mean	Std. dev.	Obs
Pre-TROP price	0.83	0.29	142
Post-TROP price	0.59	0.14	142
Price Reduction	0.24	0.21	142

Note:This table presents statistics on rural electricity prices before and after the implementation of TROP. Prices are measured in CNY (Chinese yuan, where 1 CNY $\approx$ 0.12 USD in 2000). A positive price reduction indicates that TROP led to a decrease in electricity prices. Three counties in my sample show a negative price reduction, meaning their electricity prices increased slightly due to TROP.

Table A6: Correlation between Electricity Price Reduction and County-Level Characteristics in 1999

Dependent var:	Price reduction				
	(1)	(2)	(3)	(4)	(5)
Rural transmission loss	0.172				
	(0.264)				
GDP per capita		-0.002*			
		(0.001)			
Agricultural GDP share[a]			0.097*		
			(0.057)		
Industrial GDP share[a]				-0.052**	
				(0.021)	
Rural population share					0.169***
					(0.043)
Observations[b]	136	123	120	123	119
R-squared	0.002	0.006	0.019	0.028	0.043
Mean of indep var	0.143	5.326	0.475	0.999	0.734

Note: Data on transmission loss is draw from local gazetteers. Most counties don't have these records. In these cases, I use provincial level records instead. Other county-level indicators are draw from 1999 National City and County Financial Statistics (Quanguo Di Shi Xian Caizheng Tongji Ziliao, in Chinese). Most of these indicators are missing for the pre-treatment period. I use 1999 data as it is closest to TROP implementation and most complete. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

[a] Since industrial/agricultural GDP is unavailable, GDP share here is measured as the ratio of gross industrial/agricultural output to GDP. This measure is imprecise because gross output includes intermediate goods, while GDP reflects only value added. This also explains why the mean of the independent variable in column (4)—industrial GDP share—is close to 1.

[b] Observation counts vary due to missing data for some counties.

Table A7: Results of Secondary School Age Exposure

Dependent var:	Years of education
Reduction ×	-0.391
affected cohorts (1982–1987)	(0.811)
Observations	3,582
R-squared	0.446
County FE	Yes
Province × birth year FE	Yes
Mean of dep var	8.396

Note: This table reports the impact of secondary school age exposure to electricity price reductions on years of education, using cohorts born 1982–1987 as the treatment group and those born 1975–1979 as the control group. The treatment year is 1999. The oldest treatment cohort had at least one year of overlap with TROP during senior high school, while the youngest control cohorts were already 20 years old in 1999. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix B: Figures

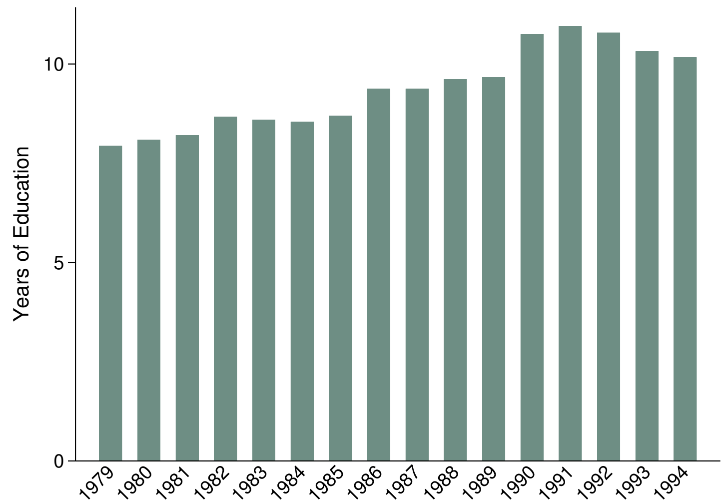
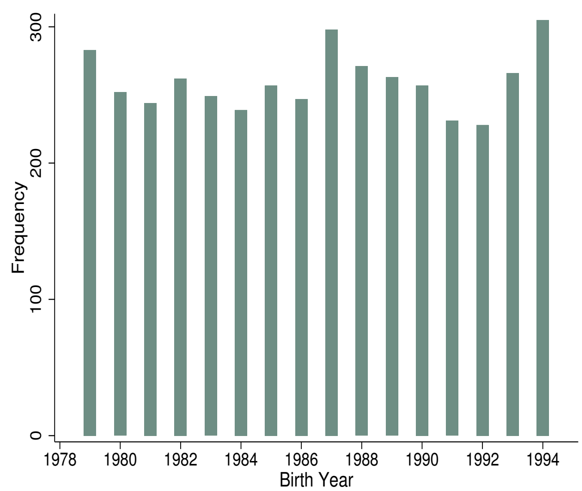
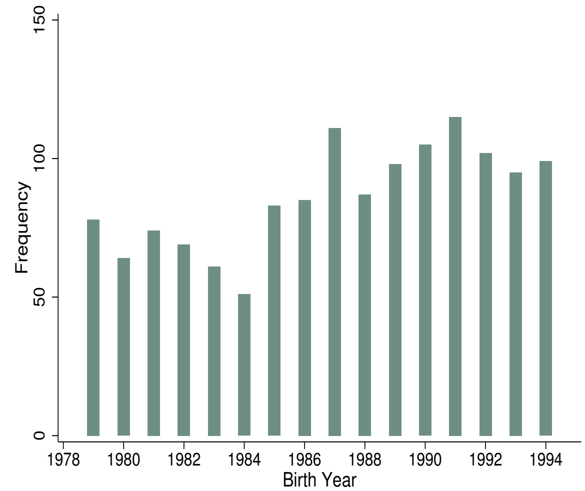


Figure B1: Years of Education by Birth Year. *Note*: This figures illustrates the average years of education by birth year in my sample.

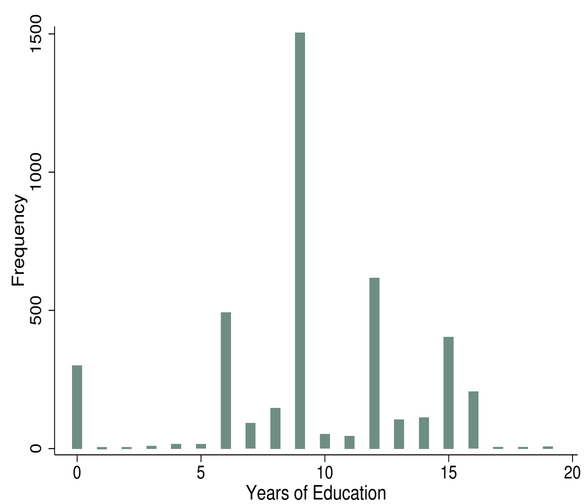


(a) Distribution of Birth Year in the 2014 Wave Matched to the 2010 Wave (n = 4,152)

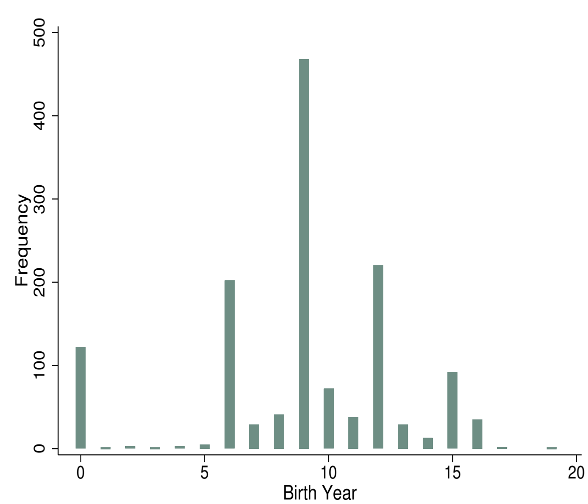


(b) Distribution of Birth Year for the Missing Sample in the 2014 Wave (n = 1,377)

Figure B2: Sample Distribution of Birth Year. *Note*: Panel (a) shows the distribution of birth year for individuals present in both 2010 and 2014 waves, while panel (b) displays the distribution of birth year for individuals surveyed in the 2010 wave but missing in the 2014 wave. Both panels include cohorts born between 1979 and 1994 with an agricultural Hukou at ages 3 and 12.



(a) Distribution of Years of Education in the 2014 Wave Matched to the 2010 Wave (n = 4,152)



(b) Distribution of Years of Education for the Missing Sample in the 2014 Wave (n = 1,377)

Figure B3: Sample Distribution of Years of Education. *Note*: Panel (a) shows the sample distribution of years of education in 2014 for individuals present in both the 2010 and 2014 surveys, while panel (b) displays the sample distribution of years of education in 2010 for individuals surveyed in the 2010 wave but missing in the 2014 wave. Both panels include cohorts born between 1979 and 1994 with an agricultural Hukou at ages 3 and 12.

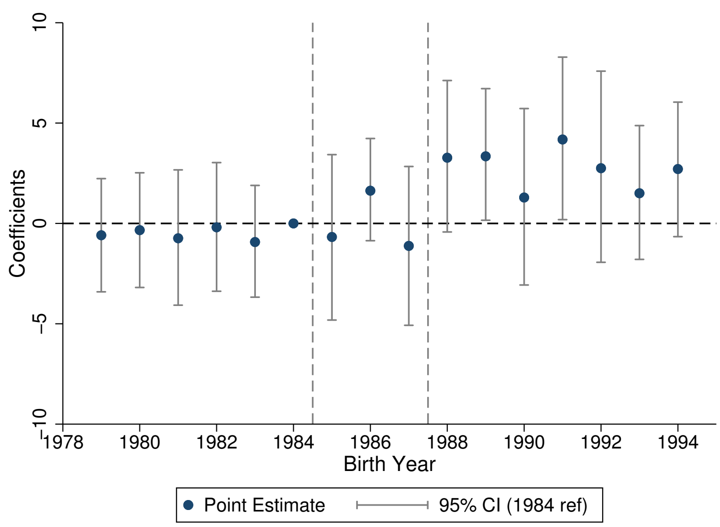


Figure B4: Event Study Results—Controlling for Heterogeneous Trends across Counties. *Note*: The y-axis represents the coefficients estimated from Eq. 9. "Gap cohorts," which lie between the two dashed lines, are included in event study but excluded from the baseline regression.

Appendix C: Additional Robustness Checks

Measurement Error. One potential concern with the data collection strategy is the use of prefectural or provincial electricity prices when county-level data are unavailable. Variation at higher administrative levels may not fully capture county-level heterogeneity in electricity prices, leading to mismeasurement of the true treatment intensity. This could bias the estimated effect toward zero.

To assess the robustness of my results to potential measurement error in treatment intensity, I conduct two additional checks. First, I include interaction terms between the administrative level of the price data (county, prefecture, or province) and birth year dummies to allow for heterogeneous trends by data source. As shown in column (1) of Appendix Table C1, the coefficient of interest increases slightly to 3.036, compared to the baseline estimate of 2.879. Second, I drop all counties where treatment is based on province-level prices, which are more prone to measurement error. Column (2) of Appendix Table C1 shows the coefficient rises to 3.293, though the difference remains modest. These results suggest that bias from measurement error is limited, and that the baseline estimate can be interpreted as a conservative lower bound.

Lengths of Exposure. Treatment cohorts experienced varying lengths of exposure to TROP during primary school. For example, children born in 1988 were exposed for only one year, while those born in 1994 had six years of exposure. To assess whether this variation affects the precision of the estimated effect, I calculate the share of primary school years each cohort was exposed to TROP. The 1988 cohort, for instance, had 1/6 exposure, while cohorts born in 1994 and later were fully exposed. Cohorts born before 1988 had zero exposure. I then construct a new treatment intensity measure by multiplying this exposure share by the electricity price reduction and re-estimate the model using the baseline specification. Column (3) of Appendix Table C1 shows that the coefficient remains highly comparable to the baseline estimate.

Price Selection. As discussed in Section 4, there are two key considerations in selecting post-TROP electricity prices. First, in some regions, rural electricity prices were lowered soon after

TROP implementation (post-TROP price 1), and later, rural-urban price unification was completed (post-TROP price 2, or the unified price). This paper uses post-TROP price 1, which aligns with the most intensive phase of TROP. Second, although full price unification did not occur uniformly in 2001, most regions completed this change around that time, with some doing so earlier or later. To test the robustness of price selection, I introduce the following two regressions:

$$\begin{aligned} Y_{i,t,c} =& \alpha + \beta_1 \times Reduction_c \times \mathbf{1}\{Age \leq 12\} + \beta_2 \times \mathbf{1}\{Age \leq 12\} \\ &+ \varphi X_{i,t,c} + \gamma_c + \mu_{prov} \times \tau_t + \varepsilon_{i,t,c} \end{aligned} \tag{11}$$

where the indicator function equals 1 if individual i in county c was 12 or younger in the year the post-TROP price is chosen. All other notations follow the baseline specification (Eq. 10).

$$\begin{aligned} Y_{i,t,c} =& \alpha + \beta_1' \times Reduction'_c \times \mathbf{1}\{Age \leq 12\} + \beta_2' \times \mathbf{1}\{Age \leq 12\} \\ &+ \varphi X_{i,t,c} + \gamma_c + \mu_{prov} \times \tau_t + \varepsilon_{i,t,c} \end{aligned} \tag{12}$$

In Eq. 12, $Reduction'_c$ represents the difference between the pre-TROP price and the unified price, regardless of the year the unification occurred. The indicator function equals 1 if individual i in county c was 12 or younger when the price was unified. All other notations follow the baseline specification (Eq. 10).

Eq. 11 and Eq. 12 are both based on a staggered DiD framework,[1] though a full econometric discussion is beyond the scope of this paper. The coefficients β_1 and β_1' capture the treatment effects. As in the baseline, I exclude cohorts aged 13 to 15 in the year the post-TROP price is selected.[2]

Column (4) of Appendix Table C1 reports results from Eq. 11, and column (5) shows results from Eq. 12. Both estimates are statistically significant and close to the baseline. These findings confirm that the core results are robust to variation in the timing of post-TROP prices. The baseline

[1] If $\beta_1 \times Reduction_c \times \mathbf{1}\{Age \leq 12\}$ is omitted from Eq. 11, the model becomes a binary-treatment staggered DiD setup. However, my data lacks sufficient variation in the timing of post-TROP prices to identify the effects under this setup.

[2] In practice, the indicator $\mathbf{1}\text{Age} \leq 12$ is absorbed by birth year fixed effects, since the variation stems from dropped cohorts aged 13–15 in the relevant year. This underscores the limited timing variation in the data.

specification remains preferred because Eq. 11 and Eq. 12 rely on additional assumptions and involve more complex econometric frameworks.

Alternative Treatment Measure. To check the robustness of my results with respect to alternative treatment measures, I first use the unified price as the post-TROP price, regardless of timing, to calculate price reductions and run the baseline regression. The effect in column (6) of Appendix Table C1 is statistically significant and comparable to the baseline.

In column (7) of Appendix Table C1, I use the price reduction ratio as another alternative treatment measure. The results remain statistically significant. A one standard deviation increase in the price reduction ratio (17%) leads to an increase in children's educational attainment by 0.747 years, which is comparable to the baseline effect of 0.605 years.

Missing Observations. Section 4 indicates that about 24% of individuals in the 2010 wave are missing from the 2014 wave. In the baseline, I use data from the 2010 wave to impute missing outcome variables for individuals absent in the 2014 wave. To check if my results are robust to missing observations, I first add a dummy variable indicating whether an individual in the 2010 wave is missing from the 2014 wave to the baseline regression. Column (8) of Appendix Table C1 reports the results, where the coefficient of interest remains statistically significant and close to the baseline. In column (9), I further interact the dummy variable with birth year fixed effects and add them to the baseline regression. The coefficient remains consistent with the baseline.

Additionally, I restrict the sample to individuals present in both the 2010 and 2014 waves. Column (10) of Appendix Table C1 shows that the coefficient is slightly smaller than in the baseline but still statistically significant. The smaller effect size may be due to a smaller sample size and the fact that many treatment cohorts had not yet completed schooling in 2010.

Table C1: Price Selection, Alternative Treatment Measure, and Missing Observations in the 2014 Survey

Dependent var:	Years of education									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Robustness check:	Control price administrative level	Drop province-level price counties	Years of exposure	Varying timing of post-TROP price	Varying timing of unified price	Unified price as post-TROP price	Reduction ratio as treatment	Control missing obs I	Control missing obs II	Matched sample in 2010 and 2014
Reduction × affected cohorts (1988–1994)	3.036***	3.293***	2.740***			2.534***		3.018***	3.037***	2.794**
	(0.703)	(0.687)	(0.752)			(0.571)		(0.692)	(0.626)	(1.220)
Reduction × affected cohorts (age≤12 when price chosen)				2.924***						
				(0.781)						
Reduction × affected cohorts (age≤12 when price unified)					2.677***					
					(0.707)					
Reduction ratio × affected cohorts (1988–1994)							4.396***			
							(1.366)			
Observations	4,145	2,511	4,145	4,136	4,196	4,145	4,145	4,145	4,145	3,154
R-squared	0.441	0.493	0.436	0.446	0.443	0.437	0.438	0.448	0.456	0.474
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province × birth year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep var	9.438	9.438	9.438	9.405	9.328	9.438	9.525	9.525	9.525	9.709

Note: This table reports the results of additional robustness checks. Column (1) includes interaction terms between the administrative level of the price data and birth year dummies. Column (2) drops counties where treatment is based on province-level price changes. Column (3) accounts for variation in lengths of exposure. Column (4) defines treated cohorts as those age $\leq$ 12 when post-TROP electricity prices were chosen. Column (5) uses the unified price to calculate treatment intensity and defines treated cohorts as those age $\leq$ 12 when the unified price was implemented. Column (6) simply redefines treatment intensity using the unified price as the post-TROP price. Column (7) uses the price reduction ratio as an alternative measure. Column (8) adds a dummy for individuals in the 2010 wave who are missing in 2014, and column (9) interacts this dummy with birth year fixed effects. Column (10) restricts the sample to individuals observed in both 2010 and 2014. Standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix D: Child Wages Respond Weakly to Electrification

The results in Section 2 rely on the assumption that child wages are unaffected by electrification. While this is arguably reasonable, a more realistic case may be one where child wages respond weakly to electrification, i.e., $\frac{\partial w_{c,2}}{\partial w_2}$ is small. This section shows that as long as this condition holds, the income effect continues to dominate, and the previous results remain valid. The simplified version in Section 2 is therefore retained without loss of generality.

Formally, let the child wage $w_{c,2}$ depend on the adult wage w_2, such that $\frac{\partial w_{c,2}}{\partial w_2} > 0$.[1] The household's maximization problem and the first-order condition (FOC) remain as defined in Eq. 4 and Eq. 5, respectively. In line with Section 2, this section also assumes $\frac{\partial \Phi}{\partial c_2} \geq 0$.

Effect of Second-Period Wage on Schooling

Differentiating the FOC with respect to w_2 and applying the assumptions yields the following comparative static:

$$\frac{\partial s_2^*}{\partial w_2} \propto \underbrace{-e_2 \frac{\partial w_{c,2}}{\partial w_2}\left(\frac{\partial u_2}{\partial c_2} + \beta \frac{\partial f_3}{\partial c_2}\right)}_{\text{Substitution effect}(-)} \underbrace{- \left[e_p + e_2(1 - s_2^*)\frac{\partial w_{c,2}}{\partial w_2}\right] w_{c,2} e_2 \frac{\partial^2 u_2}{\partial c_2^2}}_{\text{Income effect }(+)}$$
$$\underbrace{+\beta \left[e_p + e_2(1 - s_2^*)\frac{\partial w_{c,2}}{\partial w_2}\right] \frac{\partial \Phi}{\partial c_2}}_{\text{Effect of } c_2 \text{ on net impact of schooling (weakly } +)} . \tag{D1}$$

As shown in Eq. D1, when $\frac{\partial w_{c,2}}{\partial w_2}$ is small, the substitution effect becomes negligible. The income effect remains strictly positive, and the third term is weakly positive under the assumption. Therefore, the overall positive effect of electrification, proxied by an increase in w_2, on schooling is primarily driven by the income effect. Note that if child wages are completely unaffected by electrification, then Eq. D1 collapses to Eq. 7.

[1] If $\frac{\partial w_{c,2}}{\partial w_2} < 0$, the substitution effect is positive, and the overall effect on education is unambiguously positive.

Effect of Second-Period Wage on Long-Term Human Capital

$$\frac{de_3}{dw_2} = \frac{\partial f_3}{\partial c_2}\left[e_p + e_2(1-s_2^*)\frac{\partial w_{c,2}}{\partial w_2}\right] + \frac{\partial s_2^*}{\partial w_2}\Phi. \tag{D2}$$

Given that $\frac{\partial w_{c,2}}{\partial w_2} > 0$ and $\frac{\partial s_2^*}{\partial w_2} > 0$, the overall effect of electrification on long-term human capital e_3 remains positive.

Maximum Value of $\frac{\partial w_{c,2}}{\partial w_2}$

First, define $A = \frac{\partial u_2}{\partial c_2} + \beta\frac{\partial f_3}{\partial c_2} > 0$, $B = w_{c,2}e_2\frac{\partial^2 u_2}{\partial c_2^2} < 0$, $C = \frac{\partial \Phi}{\partial c_2} \geq 0$. To determine the threshold value of $\frac{\partial w_{c,2}}{\partial w_2} = \epsilon$ at which $\frac{\partial s_2^*}{\partial w_2} > 0$ still holds, set:

$$-e_2\epsilon A - [e_p + e_2(1-s_2^*)\epsilon]\, B + \beta\, [e_p + e_2(1-s_2^*)\epsilon]\, C = 0. \tag{D3}$$

Solving Eq. D3 gives the boundary condition:

$$\epsilon < \bar{\epsilon} = \frac{e_p}{e_2} \cdot \frac{-B + \beta C}{A + (1-s_2^*)(B - \beta C)}, \tag{D4}$$

which defines the largest permissible value of ϵ that ensures $\frac{\partial s_2^*}{\partial w_2} > 0$ continues to hold.

Since C is assumed to be weakly positive, setting $C = 0$ provides a conservative estimate of the threshold. Under this simplification, Eq. D4 reduces to:

$$\epsilon < \bar{\epsilon} = \frac{e_p}{e_2} \cdot \frac{-B}{A + (1-s_2^*)B}. \tag{D5}$$

This defines the maximum value of ϵ such that the income effect continues to dominate the substitution effect.