

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, my paper emphasizes electricity affordability. I develop a model of human capital investment in which electrification acts as an adult-labor-biased technical change in agriculture. The model predicts a strong income effect and a negligible substitution effect, leading to higher 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 lower electricity prices in middle childhood significantly increase educational attainment and later adult cognitive scores. Further analysis identifies increased agricultural productivity as one mechanism, consistent with the model. Greater public investment in education may be another mechanism, as cheaper electricity likely supports school infrastructure. This paper also highlights why middle childhood is critical. 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. 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 (Lee, Miguel, and Wolfram, 2020b; Burlig and Preonas, 2024), 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 is not binary: beyond being connected or unconnected, it also involves affordability, reliability, and other aspects (Bhatia and Angelou, 2015; Lee, Miguel, and Wolfram, 2020a).² These broader dimensions continue to constrain economic activity and daily life in many developing countries (Onishi, 2015; World Bank, 2024). The central question is whether improving these dimensions can generate meaningful economic outcomes. While reliability has received growing attention (e.g., Allcott, Collard-Wexler, and O’Connell, 2016; Cole et al., 2018; Carranza and Meeks, 2021; Jha, Preonas, and Burlig, 2022; Mensah, 2024), little is known about affordability.

This paper examines how electricity affordability in middle childhood (primary school age) affects long-term human capital. Affordability is a distinct dimension of electrification, and its effects may differ substantially from those of other aspects. China in the 1990s provides a compelling setting: it had the world’s largest rural population, widespread grid coverage, and development indicators comparable to many developing economies today.³ Yet rural electricity was costly and poorly managed—conditions common in many developing countries today. In late 1998, China’s 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

¹Source: World Bank DataBank.

²Burgess et al. (2020) shows that unconditional grid expansion can lead to inefficient outcomes and welfare losses.

³China’s rural household connection rate reached 85% by 1991 and 97% by 1998. Source: <https://kjpj.bit.edu.cn/docs/20150119212311371518.pdf> and <https://ncdqh.com.cn/interpretation/200109/132007.html> (in Chinese).

that paved the way for (3) equalizing rural and urban electricity pricing.⁴ Prior to TROP, rural households faced much higher electricity costs than urban residents. The program covered China’s entire rural population, making it the largest electrification effort in global history. Its nationwide rollout offers a rare opportunity to study the general equilibrium effects of rural electrification while mitigating concerns about spillovers and selection bias.

Prior literature suggests that electrification improves irrigation and agricultural productivity (Kitchens and Fishback, 2015; Assunção et al., 2017; Lewis and Severnini, 2020; Fried and Lagakos, 2021). This may increase household income and affect children’s education through two opposing channels: higher income can boost investment in schooling (income effect), while more profitable farming may raise the opportunity cost of education (substitution effect).

I formalize this using a simple model of human capital investment based on two assumptions. First, adult (parental) and child labor are imperfect substitutes conditional on human capital: children are less productive than adults even with similar schooling because of differences in strength, stamina, and task suitability. Second, electrification acts as a technical change in agriculture, amplifying adults’ productivity advantage by enabling more effective irrigation, mechanized processing, and longer work hours under better lighting—tasks that primarily require adult labor. Under these assumptions, adult labor gains more than child labor, leaving child wages (which reflect productivity) largely unchanged. As a result, the income effect dominates, and the model predicts a positive impact on children’s schooling.

To test this prediction, 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

⁴“Two Reforms and One Price” (TROP), known in Chinese as *Liang Gai Yi Tong Jia*, was announced in October 1998. Accordingly, 1999 is designated as the starting point of the treatment period in this paper.

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.⁵ I then leverage cross-county variation in the absolute level of electricity price reductions to estimate the effects.

Interpreting the effects of price reductions requires caution. It’s difficult to distinguish the effect of price changes from that of concurrent improvements in infrastructure or management. My paper argues that in 1999 China, as in many low- and middle-income countries today, weak infrastructure, inefficient management, and unaffordable electricity were interconnected ([Kojima and Trimble, 2016](#); [World Bank, 2024](#)). Without robust infrastructure and efficient management systems, lowering prices alone may not be sustainable ([McRae, 2015](#); [Trimble et al., 2016](#); [World Bank, 2024](#); [Meeks and Mahadevan, 2025](#)). This is why China’s central government prioritized the “Two Reforms” before equalizing electricity prices under TROP, rather than mandating price cuts alone. Accordingly, the coefficient on price reduction is best interpreted as capturing both affordability gains and the accompanying reforms.⁶

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](#)),⁷ and more than twice that of China’s 1986 Compulsory Education Law ([Chen and Park, 2021](#)). The results remain robust across various settings. At the aggregate level, about 74 million rural children were of primary school age when TROP began in 1999. A one standard deviation price reduction implies roughly 45 (74×0.605) million additional person-years of schooling. Because TROP was permanent, this corresponds to a sustained annual gain of about 7 (12×0.605) million

⁵Treatment 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.

⁶Infrastructure upgrades (e.g., better transmission lines, transformers) may improve electricity quality by reducing outages and stabilizing voltage—factors not directly observed. If correlated with price changes and not fully controlled for, they could bias the estimates. However, [Berkouwer et al. \(2024\)](#) finds voltage quality has limited economic effects. Section 7 further examines whether such unobserved, time-varying factors bias the results.

⁷The 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.

person-years of schooling in rural areas after 1999.

In addition to years of schooling, later adult 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,⁸ this pattern suggests that agricultural productivity may be one channel through which TROP operated.

Further analysis identifies two mechanisms through which TROP improved human capital. First, it increased agricultural productivity. I find that a one standard deviation reduction in rural electricity prices leads to an increase 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 1999.⁹ This finding is consistent with the model's assumption that electrification boosts productivity and aligns with prior literature.¹⁰ Additional evidence, based on comparisons among children born before and after 1999, supports the agricultural income channel by showing improvements in health outcomes.

Second, TROP encouraged greater government investment in education. Cheaper electricity likely facilitated the use of devices, equipment, and other school 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 focus on middle childhood (primary school age)? Children at this stage are more likely

⁸Drought 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/>.

⁹In 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>.

¹⁰See Kitchens and Fishback (2015), Assunção et al. (2017), Lewis and Severnini (2020), and Fried and Lagakos (2021).

to benefit because the opportunity cost of schooling remains low. If electrification represents an adult-labor-biased technical change in agriculture, cheaper electricity has little effect on the opportunity cost of schooling for middle childhood children, since they are poor substitutes for adult laborers. In this case, the income effect dominates. By contrast, older children contribute labor similar to adults, so electrification raises 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. Gender differences align as well: secondary school age boys, as closer substitutes for adult laborers, experience a more negative effect, though the estimate remains imprecise.

This paper makes three contributions to the literature. First, it contributes to the literature on rural electrification in developing economies. A large literature examines rural electrification across South and Southeast Asia, Sub-Saharan Africa, and Latin America.¹¹ However, most of these studies focus on grid connections. A growing literature explores the reliability of electricity supply,¹² yet affordability, another central dimension of electrification, has received far less attention.¹³ Evidence from China—the world’s largest rural population at the time of TROP—is particularly scarce.¹⁴ This paper fills these gaps by studying electricity affordability, an overlooked

¹¹These include India (Rud, 2012; Khandker et al., 2014; Van de Walle et al., 2017; Thomas et al., 2020; Burgess et al., 2023; Fetter and Usmani, 2024; Burlig and Preonas, 2024), 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 (Lee, Miguel, and Wolfram, 2020b; Koima, 2024), Ghana (Akpandjar and Kitchens, 2017), Rwanda (Lenz et al., 2017), Ethiopia (Bernard and Torero, 2015; Fried and Lagakos, 2021), Sub-Saharan Africa (Bernard, 2012), and Africa as a whole (Peters and Sievert, 2016).

¹²These include impacts on firm performance (Steinbuks and Foster, 2010; Fisher-Vanden, Mansur, and Wang, 2015; Allcott, Collard-Wexler, and O’Connell, 2016; Cole et al., 2018; Hardy and McCasland, 2021; Abeberese, Ackah, and Asuming, 2021), employment (Mensah, 2024), agricultural wages (Nag, 2024), and household income (Burlando, 2014) in developing countries. For a comprehensive review of the economics of electricity reliability, see Borenstein, Bushnell, and Mansur (2023).

¹³Exceptions 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 Borenstein (2012) and Levinson and Silva (2022) on the distributional effects of pricing.

¹⁴Three exceptions are Ding, Qin, and Shi (2018), Lin and Xu (2024), and Jiao (2024), which focus on grid access or agricultural income. My paper instead examines the long-term human capital effects of affordability.

but critical dimension, in late-1990s China, when its development indicators were comparable to those of many developing economies today (see Figure 1).¹⁵ China’s experience can offer insights for ongoing rural electrification efforts in many low- and middle-income countries.

Second, this paper contributes to the literature on the broader socioeconomic impacts of electrification. While several studies find electrification yields only negligible benefits and modest welfare gains (Peters and Sievert, 2016; Lenz et al., 2017; Lee, Miguel, and Wolfram, 2020b; Burgess et al., 2023; Burlig and Preonas, 2024; Koima, 2024), 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 (Greenwood, Se-shadri, and Yorukoglu, 2005; Vidart, 2024),¹⁶ improved firm productivity (Fiszbein et al., 2020; Fried and Lagakos, 2023), 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 the long-term human capital effects. Unlike Lipscomb, Mobarak, and Barham (2013), which studies the impact of electrification from hydropower dam construction on human capital development, my paper examines a nationally implemented program using individual-level data in a highly generalizable context, strengthening both identification and external validity.

Third, this paper contributes to the literature on the “missing middle” associated with the fetal origins hypothesis. 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

¹⁵Lee, Miguel, and Wolfram (2020a) highlights the importance of understanding cross-country heterogeneity in electrification impacts for effective policymaking.

¹⁶Vidart (2024) highlights the role of human capital accumulation in linking electrification to female labor force participation, but does not directly examine educational outcomes.

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

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), rainfall variability (Shah and Steinberg, 2017; Ponnusamy, 2025), and social protection programs (Adhvaryu et al., 2024). My paper extends this literature by showing that exposure to rural electrification during middle childhood improves educational outcomes. Most importantly, it shows that children in middle childhood are more affected than older cohorts.

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 possible mechanisms. Section 10 discusses the focus on middle childhood. Section 11 concludes.

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

Evidence shows that rural electrification improves irrigation and agricultural productivity (Kitchens and Fishback, 2015; Assunção et al., 2017; Lewis and Severnini, 2020; Fried and Lagakos, 2021). If true, this can raise household income and 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 may further amplify adults’ productivity advantage. It enables more ef-

fective irrigation, mechanized processing, and longer work hours under better lighting—tasks that largely require adult labor.¹⁸ This is consistent with evidence that electrification increases adult work hours (Dinkelman, 2011) and expands opportunities for skilled women (Vidart, 2024). Historical evidence further shows that electrification increased the relative demand for skilled workers (Goldin and Katz, 1998). These findings suggest that electrification may raise 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, this adult-biased productivity effect of electrification is comparable to skill-biased technological change, as discussed in Acemoglu (1998, 2002), which increases the skill premium and contributes to wage inequality.

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 motivate modeling rural electrification as a technological change in agriculture that primarily benefits adult labor. My paper first considers a case in which electrification raises adult wages (which reflect productivity) while leaving child labor wages unchanged. As a result, the substitution effect vanishes, since the opportunity cost of schooling remains constant. However, the income effect persists, leading households to invest more in child education and raising 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.

¹⁸Children 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.

¹⁹The 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.

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 6–11), 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 human capital in period 3. The household's total utility function is given by:

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

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

In period 1, consumption is financed solely through parental (or adult) income:

$$c_1 \leq w_1 e_p, \quad (2)$$

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 and child wage rates, respectively.

The period 2 budget constraint is:

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

²⁰Note 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.

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:

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

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

²¹In [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.

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

from the perspective of period 2), the household solves:

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

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

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

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

The first-order condition (FOC) is:

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

where

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

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:

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

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

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

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.

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

²³Shah 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., Bryan et al., 2004; Gómez-Pinilla, 2008), while economic research links better nutrition to improved academic performance (e.g., Anderson, Gallagher, and Ritchie, 2018; Chakraborty and Jayaraman, 2019). Work on dynamic complementarities (e.g., Cunha, Heckman, and Schennach, 2010; Aizer and Cunha, 2012; Nandi et al., 2017; Johnson and Jackson, 2019) further highlights how early health and human capital complement each other in producing later human capital.

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

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).

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

²⁵Source: <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.

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

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

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

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

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) equalizing 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. Experience from many developing countries shows that subsidies alone are not enough: even with low tariffs, households often face intermittent service and poor power quality due to weak infrastructure (Meeks and Mahadevan, 2025). The “Two Reforms” were essential because they combined affordability with the institutional and infrastructure upgrades needed to make provision both sustainable and reliable.

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.³⁰ 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, ac-

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

³⁰The 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.

counting 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).³¹ Most provinces achieved unified electricity pricing between rural and urban areas by around 2001. The program delivered measurable improvements. In Guangdong Province, 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.³²

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 behind the meter.³³ Although the central government adjusted electricity prices a few times, such as a 0.025 CNY increase in 2006, these changes were relatively small.³⁴

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

Electricity Consumption

China's rural household connection rate reached 85% by 1991 and 97% by 1998.³⁵ Despite this widespread access, per capita electricity consumption in rural areas remained low—just 235 kWh in 1998.³⁶ For comparison, this was only 5.8% of U.S. per capita electricity consumption in 1960.³⁷

Appendix Figure B1 shows the breakdown of rural electricity consumption in Henan Province, a major agricultural region in central China, in 1997. Use is divided into three categories: irri-

³¹See pages 340–341 of [Hubei Electric Power Industry Gazetteer Compilation Commission \(2012\)](#).

³²See pages 550–551 of [Guangdong Electric Power Industry Bureau \(Group Corporation\) \(2004\)](#).

³³Government 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.

³⁴These 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.

³⁵Source: <https://kjpj.bit.edu.cn/docs/20150119212311371518.pdf> and <https://ncdqh.com.cn/interpretation/200109/132007.html> (in Chinese).

³⁶Author's calculation based on [National Bureau of Statistics of China \(1999\)](#). This figure includes industrial usage within a county.

³⁷The earliest year with available data. Source: World Bank DataBank.

gation and drainage (37.3%), daily life (26.4%), and agricultural processing (36.2%). In practice, however, daily life and agricultural uses are hard to distinguish, as households live near farmland and often process crops at home.

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 circles (except China) 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.

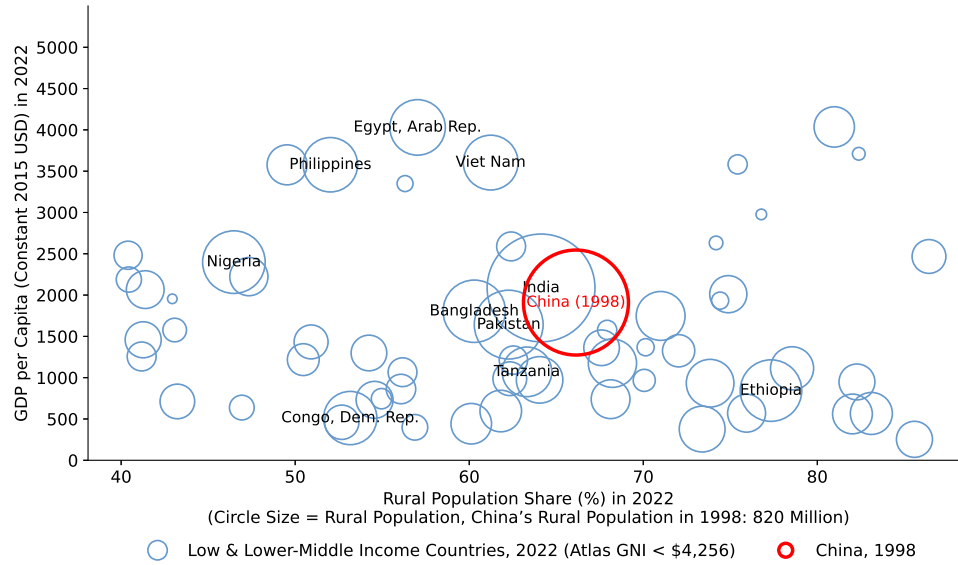


Figure 1: GDP per Capita and Rural Population Share: China 1998 vs. the World in 2022. *Note:* This figure plots GDP per capita (constant 2015 USD) against rural population share. Each circle (except China) corresponds to one of 61 low- and lower-middle-income countries with a rural population share 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.³⁸ After excluding 20 county-level districts in Beijing, Shanghai, and Tianjin (due to limited rural representation), this paper covers 142 counties.³⁹

My paper uses years of education completed in 2014 as the primary outcome variable, supplemented by cognitive test scores.⁴⁰ 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 B2 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.⁴¹ Following Bianchi, Lu, and Song (2022), I use observations from the 2010 wave to fill in missing outcome variables for these individuals.⁴² 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 rural Hukou at both ages 3 and 12,⁴³ 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.

³⁸See <https://opendata.pku.edu.cn/dataverse/CFPS?language=en>.

³⁹The 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.

⁴⁰During the Cultural Revolution (1966–1976), China’s education system temporarily adopted a 5-2-2 structure before reverting to the standard 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). Leveraging this policy shift, Chen, Jiang, and Zhou (2020) estimates a 12.7% return to education, while Giles, Park, and Wang (2019) uses the Cultural Revolution as an exogenous shock to estimate a 37.1% return to college education.

⁴¹Appendix Figure B3 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 B4 shows that the distributions of years of education are also similar across groups.

⁴²To 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.

⁴³Hukou 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.⁴⁴ 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 period aligns with the most intensive phase of implementation (see Section 3.3).⁴⁵

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

⁴⁴China's standard household voltage is 220V. Most gazetteers, however, do not include electricity quality data.

⁴⁵According 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. 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.⁴⁶ Additionally, price data for 3 counties come from county or prefectural newspapers, and for 5 counties from provincial newspapers. Although the price data are not ideal, they exhibit within-province variation, since 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 1999.⁴⁷ 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).⁴⁸ Note that

⁴⁶Potential bias from measurement error is addressed in the robustness checks.

⁴⁷Data on transmission loss is drawn from local gazetteers. Most counties don’t have these records. In these cases, I use provincial level records instead. Other county-level indicators are drawn 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.

⁴⁸Due 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).⁴⁹

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.⁵⁰ To illustrate provincial variation while adhering to CFPS restrictions, Appendix Figure B5 shows a dumbbell plot of pre- and post-TROP prices using data from provincial gazetteers and newspapers.

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 1 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.⁵¹ 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).

⁴⁹Source: Ministry of Finance of the People’s Republic of China, Budget Department (1993–2007).

⁵⁰Additional details on price data are omitted to comply with CFPS confidentiality rules.

⁵¹Minority populations refer to non-Han ethnic groups, often residing in remote or underdeveloped areas.

Table 1: 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 (3.24)	8.56 (4.36)	8.38 (4.03)	10.35 (3.72)
Gender (male = 1)	0.49 (0.50)	0.47 (0.50)	0.47 (0.50)	0.48 (0.50)
Ethnic (Han = 1)	0.98 (0.15)	0.82 (0.38)	0.88 (0.33)	0.90 (0.30)
Number of siblings	1.30 (0.94)	1.87 (1.40)	1.87 (1.29)	1.41 (1.03)
Father's years of education	7.19 (3.61)	5.29 (4.31)	5.82 (4.20)	6.69 (3.94)
Mother's years of education	5.18 (4.09)	3.34 (3.96)	3.35 (3.96)	4.44 (4.12)
Observations	1057	845	1742	2408

Note: This table includes only rural residents, defined as those with a rural 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 absolute reduction in rural electricity prices following TROP as a measure of treatment intensity.⁵² Because these reductions were program-induced and bundled with other changes, interpreting the coefficient on price reduction requires caution: 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

⁵²The 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.

were deeply interconnected.⁵³ 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 equalizing electricity prices under TROP, rather than mandating price cuts alone. Accordingly, the coefficient on price reduction is best interpreted as reflecting both affordability gains and the accompanying reforms.

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);⁵⁴ 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.”⁵⁵

Infrastructure upgrades, including more reliable transmission lines and transformers, also improved electricity quality by reducing outages and stabilizing voltage. These quality improvements are unobserved. If they influence outcomes and are correlated with price reductions but not fully

⁵³See <https://www.worldbank.org/en/topic/energy/publication/making-power-work-for-africa>. Source: World Bank.

⁵⁴In China, each village is typically divided into several groups.

⁵⁵This 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.

captured by controls, they could bias the estimated effects of affordability. However, [Berkouwer et al. \(2024\)](#) finds that voltage quality has limited economic impact. To further address this concern, Section 7 tests whether such time-varying unobservables significantly bias the results.

5.2 Empirical Strategy

To assess the impact of electricity affordability on human capital, this paper uses a cohort difference-in-differences (DiD) approach with continuous treatment.⁵⁶ 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.⁵⁷ The treatment group includes individuals born between 1988 and 1994, all of whom had at least one year of overlap with TROP (1999) during their primary school years. The control group consists of cohorts born between 1979 and 1984, the youngest of whom had already surpassed middle school age. Figure 2 illustrates the cohort definitions.

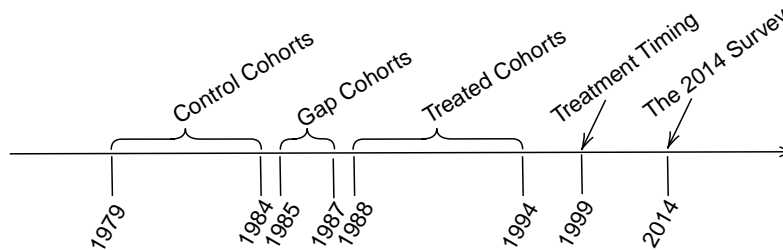


Figure 2: Definition of Cohorts. *Note:* Cohorts born between 1985 and 1987 are classified as “gap cohorts.” They are included in the event study but excluded from the baseline regression. To ensure at least one year of overlap with TROP, the oldest cohort in the treatment group is those born in 1988,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

Because TROP was implemented nationwide,⁵⁸ there is no clean untreated group. Instead, I

⁵⁶This 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 \(2024\)](#).

⁵⁷For example, if the policy takes a few years to have full effect, the control cohorts were already beyond high school age and therefore unlikely to be affected, assuming the treatment effect operates mainly during primary school age or at most through middle school age. Section 10 provides evidence for this assumption.

⁵⁸Although implementation timing may have varied slightly across regions, the program was broadly simultaneous.

exploit variation in pre- and post-TROP electricity prices across counties, which led to heterogeneous price reductions after implementation.⁵⁹ 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 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.

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

⁵⁹Post-TROP prices show significantly less variation than pre-TROP prices. See Appendix Table A5.

$Y_{i,t,c}$ 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 \times birth year fixed effects ($\mu_{prov} \times \tau_t$) in the model.⁶⁰ 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 6–11) when TROP was implemented to those who were of senior high school age or older (15+) in the same county. I exploit variation from county-level differences in electricity price reductions to identify the effects. The baseline estimation equation is given by:

$$Y_{i,t,c} = \alpha + \beta \times Reduction_c \times \mathbf{1}\{1988 \leq t \leq 1994\} + \varphi X_{i,t,c} + \gamma_c + \mu_{prov} \times \tau_t + \varepsilon_{i,t,c} \quad (10)$$

⁶⁰Another 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.

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.

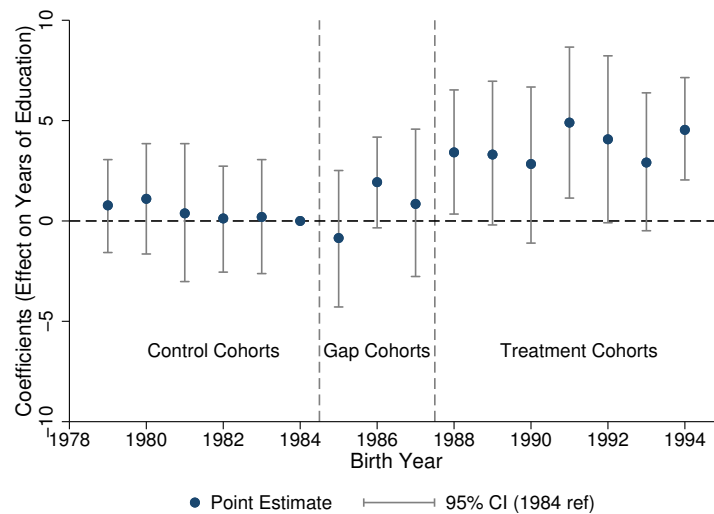


Figure 3: Event Study Results. *Note:* The y-axis represents the coefficients estimated from Eq. 9. The “gap cohorts,” shown between the two dashed lines, are included in the event study but excluded from the baseline regression.

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 1.⁶¹ These results indicate that the observed insignificant pre-trend in Figure 3 provides strong support for the parallel trends 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 2 reports the baseline results: a one standard deviation reduction in rural electricity prices (0.21 CNY, about 25% of the average pre-TROP price) increases educational attainment by 0.605 years (0.21×2.879).⁶² This effect is large—more than six times the impact of China’s Send-Down Movement in the 1960s–70s (Chen et al., 2020a),⁶³ and more than twice the effect of China’s 1986 Compulsory Education Law (Chen and Park, 2021).⁶⁴ At the aggregate level, about 74 million rural children were of primary school age when TROP began in 1999. A one standard deviation price reduction implies roughly 45 (74×0.605) million additional years of schooling. Because TROP was permanent, this corresponds to a sustained annual gain of about 7 (12×0.605) million person-years of schooling in rural areas after 1999.

Note again that the coefficient of interest 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. Lowering electricity prices in isolation would not have been sustainable.

⁶¹The 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.

⁶²This 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).

⁶³Effect 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.

⁶⁴Treatment in Chen and Park (2021) is binary.

Columns (2) and (3) of Table 2 examine the effects on cognitive ability, measured by standardized math and Chinese word recognition test scores from the 2014 CFPS.⁶⁵ To ensure comparability, I standardize the original scores into z-scores.⁶⁶ 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 2 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 2 present falsification tests, based on the premise that TROP primarily targeted rural areas and had limited direct impact on urban households.⁶⁷ If this holds, TROP should not significantly affect urban counterparts of the treated rural cohorts. Column (7) of Table 2 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.

Figure 4 plots the estimated effects of TROP exposure on alternative outcome variables: 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 suggests that children exposed to lower electricity prices during middle childhood were more likely to remain in school through later stages, consistent with the model’s prediction. The effects on earlier grades are smaller, likely

⁶⁵The 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.issp.pku.edu.cn/cfps/cjwt/cfpsxkt/1295348.htm>.

⁶⁶ $z\text{-score} = (x - \mu) / \delta$, where x represents the value being evaluated, μ is the mean, and δ is the standard deviation.

⁶⁷Anecdotal 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 2: 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 \geq 6) ^a	(5) Complete junior (edu \geq 9) ^a	(6) Complete senior (edu \geq 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.

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 the effects of middle childhood exposure on completion through primary, junior high, senior high, and the first year of college. Estimates are from regressions analogous to the baseline specification but using binary indicators for each grade level as outcomes. China’s 6-3-3 system includes 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 2 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.⁶⁸ The impacts of consolidation on education are mixed (Hannum, Liu, and Wang, 2021; Hannum and Wang, 2022), and treated cohorts in my sample might be affected.

⁶⁸In 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.

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 3 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 3 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 3 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.⁶⁹ 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 3 reports the results. The coefficient of interest remains nearly identical to

⁶⁹The 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 2.⁷⁰ 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 3: 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 × affected cohorts (1988–1994)	2.869*** (0.711)	2.925*** (0.737)	2.8820*** (0.719)	2.862*** (0.698)
Consolidation intensity × affected cohorts (1988–1994)	0.004 (0.010)			
FDI intensity × affected cohorts (1988–1994)			-0.0007 (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

⁷⁰ Appendix Figure B6 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 rural 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 4 implement incremental restrictions. In addition to the baseline requirement of rural Hukou at ages 3 and 12,⁷¹ 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 rural 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. Rural 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 4 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

⁷¹In the baseline regression, my sample includes only individuals with rural Hukou at both ages 3 and 12.

Table 4: 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) + rural Hukou at survey	Drop county-level districts
Reduction \times affected cohorts (1988–1994)	2.932*** (0.722)	2.925*** (0.654)	3.154*** (0.745)	2.701*** (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 \times 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 rural 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.⁷²

Column (1) of Table 5 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 may

⁷²Some studies suggest girls benefit more (Khandker, Barnes, and Samad, 2013; Dasso Arana, Fernandez, and Ñopo, 2015; Van de Walle et al., 2017), while others find no significant effects on girls (Lee, Miguel, and Wolfram, 2020b; Burlig and Preonas, 2024). Lipscomb, Mobarak, and Barham (2013) and Khandker et al. (2014) find positive impacts on both boys' and girls' education. See Lee, Miguel, and Wolfram (2020a) for a comprehensive review.

reflect the reality that in rural China, boys and girls alike often helped with agricultural 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 1999.⁷³ 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,⁷⁴ rural electrification may have a greater impact in areas more dependent on precipitation, particularly drier regions. In such areas, access to cheaper electricity can support water pumping for irrigation, potentially boosting agricultural income. I collect annual county-level precipitation data from 1999 to 2007 using the ERA5-Land reanalysis dataset via Google Earth Engine.⁷⁵ 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.⁷⁶ Column (4) of Table 5 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 drought months from 1999 to 2007, based on the Standardized Precipitation Evapotranspiration

⁷³1736.63 CNY, approximately 208 USD in 2000. Source: National Bureau of Statistics of China. <https://www.stats.gov.cn/sj/ndsj/zgnj/2000/J16c.htm>.

⁷⁴Section 3 provides an example of rural electricity consumption patterns in China.

⁷⁵Source: https://developers.google.com/earth-engine/datasets/catalog/ECMWF_ERA5_LAND_MONTHLY_AGGREGATED. Monthly data are aggregated to annual values. The period 1999–2007 aligns with the primary school years of the treatment cohorts.

⁷⁶See https://www.gov.cn/test/2005-06/24/content_9220.htm.

Index (SPEI).⁷⁷ 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 likely, in part, linked to agricultural production. 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.

⁷⁷Source: 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 5: Heterogeneity

Dependent var:	Years of education					
	(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
Heterogeneity:						
Reduction \times affected cohorts (1988–1994)	2.133*** (0.749)	2.500*** (0.625)	3.578*** (1.050)	2.521*** (0.625)	-0.129 (1.929)	2.122** (1.045)
Reduction \times affected cohorts (1988–1994) \times gender	1.491 (0.947)					1.560* (0.940)
Reduction \times affected cohorts (1988–1994) \times low income		4.274 (2.887)				0.749 (3.041)
Reduction \times affected cohorts (1988–1994) \times siblings			-1.272 (1.099)			-0.586 (1.145)
Reduction \times affected cohorts (1988–1994) \times non-humid area				5.494** (2.606)		4.881* (2.717)
Reduction \times affected cohorts \times (1988–1994) \times drought months					0.681* (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 \times 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

This section investigates potential mechanisms through which TROP affected human capital. If electrification operates as an adult-labor-biased technical change in agriculture, it should raise agricultural productivity. This paper first presents evidence consistent with this mechanism: direct improvements in agricultural productivity at the prefectural level, along with suggestive evidence

of gains in child nutrition and health. Since electricity is also a critical input for education infrastructure, I then examine whether reductions in electricity prices increased public investment in education as another mechanism.

9.1 Rural Electrification Enhances Agricultural Productivity

Direct Evidence

As mentioned earlier, evidence suggests that rural electrification increases crop yields, improves productivity, and supports agricultural expansion (Kitchens and Fishback, 2015; Assunção et al., 2017; Lewis and Severnini, 2020; Fried and Lagakos, 2021). If these effects hold, they 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,⁷⁸ industrial GDP, and arable land area at the prefectural level for the period 1994–2007.⁷⁹ Columns (1) and (2) of Table 6 show the impact of rural electricity price reductions on agricultural productivity, measured by agricultural GDP per unit of arable land.⁸⁰ 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 1999.⁸¹ For

⁷⁸In China’s statistical classification, the broader definition of agriculture refers to the primary industry, encompassing farming, forestry, fishing, and animal husbandry. Electricity is vital to these sectors, enabling production, processing, and modernization.

⁷⁹For prefectures where electricity price data are unavailable, I use provincial-level data instead.

⁸⁰GDP is reported in 10 million CNY, and one unit of arable land equals 1,000 hectares.

⁸¹In 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>.

context, annual tuition in 2000 was about 200 CNY for primary school and 400 CNY for middle school. (Liu, 2000).

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 6 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.

These results provide strong support for the mechanism that TROP enhances children's human capital by improving agricultural productivity. The findings also align with the model and existing literature.

Table 6: TROP's Impact on Agricultural Productivity at the Prefectural Level

Mechanism	Boost agricultural productivity and agricultural output					
Dependent var:	(1) Agricultural GDP per unit arable land	(2) Agricultural GDP per unit arable land	(3) Agricultural GDP	(4) Areas of arable land	(5) Agricultural GDP share	(6) Industrial GDP share
Reduction × after TROP	1.103** (0.431)	0.970** (0.435)	470.380*** (169.562)	89.872 (106.535)	0.093* (0.054)	-0.040 (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 16.⁸² I use this child sample to examine whether TROP improved birth weight and reduced hospital visits, providing suggestive evidence of an income effect.⁸³

Specifically, I compare children born between 1999 and 2005 to those born between 1995 and 1998. Columns (1) and (2) of Table 7 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. Taken together with the direct evidence above, they support the mechanism that TROP enhances children's human capital by boosting agricultural productivity and, in turn, raising rural household income. As mentioned earlier, household income is a key determinant of educational attainment.

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.

⁸²Note that the baseline analysis in this paper focuses on adults, defined by CFPS as individuals aged 16 or older.

⁸³Higher 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 7: 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To investigate whether more affordable electricity encourages public educational investment, 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 7 present the results. Column (3) includes all counties in the sample, while column (4) excludes county-level districts, which typically have a higher concentration of urban schools.⁸⁴ If lower electricity prices truly affected public investment in rural education, the

⁸⁴Since 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.

estimate excluding county-level districts should be more precise.

The results confirm this. Column (3) shows that TROP significantly increased the share of public expenditure allocated to education, and column (4) provides a more precise estimate. 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. The effect is modest in absolute size, but meaningful given the large base of public educational spending and the relatively small share typically devoted to electricity-related infrastructure. Since the data include urban schools, the true effect on rural schools may be even larger.

10 Why Focus on Middle Childhood

This paper focuses on middle childhood (primary school age) because children at this stage are more likely to benefit from improved electricity affordability. The theoretical model in Section 2 assumes imperfect substitution between adult and child labor, so the income effect dominates. Middle childhood children fit this scenario. By contrast, if children provide labor nearly equivalent to adults, both income and substitution effects arise, with the latter potentially offsetting the former.

If electrification is an adult-labor-biased technical change in agriculture and productivity gains are an important mechanism, near-equivalence arises when exposure occurs during secondary school age or later, as children then function as close substitutes for adult laborers. In this case, more affordable electricity raises productivity for both groups, and the substitution effect may offset 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.⁸⁵

To test this argument, 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

⁸⁵Statistics 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.

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.

Appendix Figure B7 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 in column (1) is small (-0.391) and statistically insignificant, indicating that exposure during secondary school age has little impact on educational attainment. This finding is in line with Shah and Steinberg (2017), which shows that a higher opportunity cost of schooling reduces human capital. I also examine heterogeneous effects across gender, as boys in secondary school are typically closer substitutes for adult laborers than girls. If the substitution effect is indeed at work, we should expect more negative effects for boys. Column (2) of Appendix Table A7 supports this expectation: the effect for boys is negative and larger in magnitude, although still imprecisely estimated.

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 re-

ductions, 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 lower electricity prices during middle childhood significantly increase 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 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 socioeconomic indicators comparable to many developing countries today.

References

- Aaronson, Daniel, Daniel Hartley, Bhashkar Mazumder, and Martha Stinson. 2023. “The long-run effects of the 1930s redlining maps on children.” *Journal of Economic Literature* 61 (3):846–862.
- Abeberese, Ama Baafra. 2017. “Electricity cost and firm performance: Evidence from India.” *Review of Economics and Statistics* 99 (5):839–852.
- Abeberese, Ama Baafra, Charles Godfred Ackah, and Patrick Opoku Asuming. 2021. “Productivity losses and firm responses to electricity shortages: Evidence from Ghana.” *The World Bank Economic Review* 35 (1):1–18.
- Acemoglu, Daron. 1998. “Why do new technologies complement skills? Directed technical change and wage inequality.” *The Quarterly Journal of Economics* 113 (4):1055–1089.
- . 2002. “Technical change, inequality, and the labor market.” *Journal of Economic Literature* 40 (1):7–72.
- Acemoglu, Daron and J-S Pischke. 2001. “Changes in the wage structure, family income, and children’s education.” *European Economic Review* 45 (4-6):890–904.
- Adhvaryu, Achyuta, Teresa Molina, Anant Nyshadham, and Jorge Tamayo. 2024. “Helping children catch up: Early life shocks and the progresca experiment.” *The Economic Journal* 134 (657):1–22.
- Aizer, Anna and Flavio Cunha. 2012. “The production of human capital: Endowments, investments and fertility.” Working Paper 18429, National Bureau of Economic Research.
- Akpandjar, George and Carl Kitchens. 2017. “From darkness to light: The effect of electrification in Ghana, 2000–2010.” *Economic Development and Cultural Change* 66 (1):31–54.
- Allcott, Hunt, Allan Collard-Wexler, and Stephen D O’Connell. 2016. “How do electricity shortages affect industry? Evidence from India.” *American Economic Review* 106 (3):587–624.

- Almond, Douglas and Janet Currie. 2011. “Killing me softly: The fetal origins hypothesis.” *Journal of Economic Perspectives* 25 (3):153–172.
- Almond, Douglas, Janet Currie, and Valentina Duque. 2018. “Childhood circumstances and adult outcomes: Act II.” *Journal of Economic Literature* 56 (4):1360–1446.
- Anderson, Michael L, Justin Gallagher, and Elizabeth Ramirez Ritchie. 2018. “School meal quality and academic performance.” *Journal of Public Economics* 168:81–93.
- Assunção, Juliano, Molly Lipscomb, Ahmed Mushfiq Mobarak, and Dimitri Szerman. 2017. “Agricultural productivity and deforestation in Brazil.” *Mimeo* .
- Barker, David J. 1990. “The fetal and infant origins of adult disease.” *BMJ: British Medical Journal* 301 (6761):1111.
- Barnes, D, A Domdom, V Peskin, and H Peskin. 2002. “Rural Electrification and Development in the Philippines: Measuring the Social and Economic Benefits.” *UNDP/ESMAP Report* .
- Becker, Gary S. 1960. “An economic analysis of fertility.” In *Demographic and Economic Change in Developed Countries*. Columbia University Press, 209–240.
- Becker, Gary S and H Gregg Lewis. 1973. “On the interaction between the quantity and quality of children.” *Journal of Political Economy* 81 (2, Part 2):S279–S288.
- Becker, Gary S and Nigel Tomes. 1976. “Child endowments and the quantity and quality of children.” *Journal of Political Economy* 84 (4, Part 2):S143–S162.
- Beguiría, Santiago, Sergio M Vicente-Serrano, and Marta Angulo-Martínez. 2010. “A multiscalar global drought dataset: the SPEIbase: a new gridded product for the analysis of drought variability and impacts.” *Bulletin of the American Meteorological Society* 91 (10):1351–1354.
- Berkouwer, Susanna B, Pierre E Biscaye, Maya Mikdash, Steven L Puller, and Catherine Wolfram. 2024. “Voltage quality and economic activity.” *Working Paper, Wharton School, University of Pennsylvania, Philadelphia* .
- Bernard, Tanguy. 2012. “Impact analysis of rural electrification projects in sub-Saharan Africa.”

The World Bank Research Observer 27 (1):33–51.

- Bernard, Tanguy and Maximo Torero. 2015. “Social interaction effects and connection to electricity: experimental evidence from rural Ethiopia.” *Economic Development and Cultural Change* 63 (3):459–484.
- Bharadwaj, Prashant, Juan Pedro Eberhard, and Christopher A Neilson. 2018. “Health at birth, parental investments, and academic outcomes.” *Journal of Labor Economics* 36 (2):349–394.
- Bhatia, Mikul and Niki Angelou. 2015. “Beyond Connections: Energy Access Redefined.” World Bank, Washington, DC. ESMAP Technical Report 008/15. License: CC BY 3.0 IGO.
- Bianchi, Nicola, Yi Lu, and Hong Song. 2022. “The effect of computer-assisted learning on students’ long-term development.” *Journal of Development Economics* 158:102919.
- Borenstein, Severin. 2012. “The redistributive impact of nonlinear electricity pricing.” *American Economic Journal: Economic Policy* 4 (3):56–90.
- Borenstein, Severin, James Bushnell, and Erin Mansur. 2023. “The economics of electricity reliability.” *Journal of Economic Perspectives* 37 (4):181–206.
- Bryan, Janet, Saskia Osendarp, Donna Hughes, Eva Calvaresi, Katrine Baghurst, and Jan-Willem Van Klinken. 2004. “Nutrients for cognitive development in school-aged children.” *Nutrition Reviews* 62 (8):295–306.
- Burgess, Robin, Michael Greenstone, Nicholas Ryan, and Anant Sudarshan. 2020. “The consequences of treating electricity as a right.” *Journal of Economic Perspectives* 34 (1):145–169.
- . 2023. “Electricity Demand and Supply on the Global Electrification Frontier.” Mimeo, Yale University.
- Burlando, Alfredo. 2014. “Transitory shocks and birth weights: Evidence from a blackout in Zanzibar.” *Journal of Development Economics* 108:154–168.
- Burlig, Fiona and Louis Preonas. 2024. “Out of the darkness and into the light? development effects of rural electrification.” *Journal of Political Economy* 132 (9):2937–2971.

- Callaway, Brantly, Andrew Goodman-Bacon, and Pedro HC Sant'Anna. 2024. "Difference-in-differences with a continuous treatment." Working Paper 32117, National Bureau of Economic Research.
- Carranza, Eliana and Robyn Meeks. 2021. "Energy efficiency and electricity reliability." *Review of Economics and Statistics* 103 (3):461–475.
- Case, Anne, Darren Lubotsky, and Christina Paxson. 2002. "Economic status and health in childhood: The origins of the gradient." *American Economic Review* 92 (5):1308–1334.
- Cattan, Sarah, Daniel A Kamhöfer, Martin Karlsson, and Therese Nilsson. 2023. "The long-term effects of student absence: Evidence from Sweden." *The Economic Journal* 133 (650):888–903.
- Chakraborty, Tanika and Rajshri Jayaraman. 2019. "School feeding and learning achievement: Evidence from India's midday meal program." *Journal of Development Economics* 139:249–265.
- Chan, Kam Wing and Li Zhang. 1999. "The hukou system and rural-urban migration in China: Processes and changes." *The China Quarterly* 160:818–855.
- Chen, Haoyong. 2018. "The Reform of the Power System Must Break Out of "Path Dependence" (Dianli Tizhi Gaige Yao Tiaochu "Lujing Yilai", in Chinese)." *China Energy News* 04.
- Chen, Jiaying and Albert Park. 2021. "School entry age and educational attainment in developing countries: Evidence from China's compulsory education law." *Journal of Comparative Economics* 49 (3):715–732.
- Chen, Pan. 2025. "Industrialization and pollution: The long-term Impact of early-life exposure on human capital formation." *Journal of Public Economics* 241:105270.
- Chen, Yi, Ziyang Fan, Xiaomin Gu, and Li-An Zhou. 2020a. "Arrival of young talent: The send-down movement and rural education in China." *American Economic Review* 110 (11):3393–3430.
- . 2020b. "Data and Code for: Arrival of Young Talent: The Send-down Movement and

- Rural Education in China.” Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2020-10-21. <https://doi.org/10.3886/E119690V1>.
- Chen, Yi, Sheng Jiang, and Li-An Zhou. 2020. “Estimating returns to education in urban China: Evidence from a natural experiment in schooling reform.” *Journal of Comparative Economics* 48 (1):218–233.
- Cole, Matthew A, Robert JR Elliott, Giovanni Occhiali, and Eric Strobl. 2018. “Power outages and firm performance in Sub-Saharan Africa.” *Journal of Development Economics* 134:150–159.
- Condliffe, Simon and Charles R Link. 2008. “The relationship between economic status and child health: evidence from the United States.” *American Economic Review* 98 (4):1605–1618.
- Cong, Shuchen, Destenie Nock, Yueming Lucy Qiu, and Bo Xing. 2022. “Unveiling hidden energy poverty using the energy equity gap.” *Nature communications* 13 (1):2456.
- Cunha, Flavio and James Heckman. 2007. “The technology of skill formation.” *American Economic Review* 97 (2):31–47.
- Cunha, Flavio, James J Heckman, and Susanne M Schennach. 2010. “Estimating the technology of cognitive and noncognitive skill formation.” *Econometrica* 78 (3):883–931.
- Currie, Janet and Nancy Cole. 1993. “Welfare and child health: The link between AFDC participation and birth weight.” *American Economic Review* 83 (4):971–985.
- Currie, Janet and Mark Stabile. 2003. “Socioeconomic status and child health: why is the relationship stronger for older children?” *American Economic Review* 93 (5):1813–1823.
- Dahl, Gordon B and Lance Lochner. 2012. “The impact of family income on child achievement: Evidence from the earned income tax credit.” *American Economic Review* 102 (5):1927–1956.
- Dasso Arana, Rosamaria, Fernando Fernandez, and Hugo Ñopo. 2015. “Electrification and Educational Outcomes in Rural Peru.” Working paper, Institute of Labor Economics (IZA).
- Deschênes, Olivier, Michael Greenstone, and Jonathan Guryan. 2009. “Climate change and birth weight.” *American Economic Review: Papers & Proceedings* 99 (2):211–217.

- Ding, Haoyuan, Cong Qin, and Kang Shi. 2018. “Development through electrification: Evidence from rural China.” *China Economic Review* 50:313–328.
- Dinkelman, Taryn. 2011. “The effects of rural electrification on employment: New evidence from South Africa.” *American Economic Review* 101 (7):3078–3108.
- Duflo, Esther. 2001. “Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment.” *American Economic Review* 91 (4):795–813.
- Dustmann, Christian, Rasmus Landersø, and Lars Højsgaard Andersen. 2024. “Unintended consequences of welfare cuts on children and adolescents.” *American Economic Journal: Applied Economics* 16 (4):161–185.
- Erten, Bilge and Jessica Leight. 2021. “Exporting out of agriculture: The impact of WTO accession on structural transformation in China.” *Review of Economics and Statistics* 103 (2):364–380.
- Fetter, T Robert and Faraz Usmani. 2024. “Fracking, farmers, and rural electrification in India.” *Journal of Development Economics* 170:103308.
- Fisher-Vanden, Karen, Erin T Mansur, and Qiong Juliana Wang. 2015. “Electricity shortages and firm productivity: evidence from China’s industrial firms.” *Journal of Development Economics* 114:172–188.
- Fiszbein, Martin, Jeanne Lafortune, Ethan G Lewis, and José Tessada. 2020. “Powering Up Productivity: The Effects of Electrification on US Manufacturing.” Working Paper 28076, National Bureau of Economic Research.
- Fried, Stephie and David Lagakos. 2021. “Rural electrification, migration and structural transformation: Evidence from Ethiopia.” *Regional Science and Urban Economics* 91:103625.
- . 2023. “Electricity and firm productivity: A general-equilibrium approach.” *American Economic Journal: Macroeconomics* 15 (4):67–103.
- Giles, John, Albert Park, and Meiyan Wang. 2019. “The great proletarian cultural revolution, disruptions to education, and the returns to schooling in urban China.” *Economic Development*

- and Cultural Change* 68 (1):131–164.
- Goldin, Claudia and Lawrence F Katz. 1998. “The origins of technology-skill complementarity.” *The Quarterly journal of economics* 113 (3):693–732.
- Gómez-Pinilla, Fernando. 2008. “Brain foods: the effects of nutrients on brain function.” *Nature Reviews Neuroscience* 9 (7):568–578.
- Greenwood, Jeremy, Ananth Seshadri, and Mehmet Yorukoglu. 2005. “Engines of liberation.” *Review of Economic Studies* 72 (1):109–133.
- Guangdong Electric Power Industry Bureau (Group Corporation). 2004. *History of the Electric Power Industry of the People’s Republic of China: Guangdong Volume*. Beijing: China Electric Power Press.
- Guangxi Zhuang Autonomous Region Electric Power Industry Gazetteer Compilation Commission. 2010. *Guangxi Zhuang Autonomous Region Electric Power Industry Gazetteer (1991–2002)*. Beijing: China Electric Power Press.
- Guttman, Louis. 1944. “A basis for scaling qualitative data.” *American Sociological Review* 9 (2):139–150.
- Hannum, Emily, Xiaoying Liu, and Fan Wang. 2021. “Estimating the effects of educational system consolidation: The case of China’s rural school closure initiative.” *Economic Development and Cultural Change* 70 (1):485–528.
- Hannum, Emily and Fan Wang. 2022. “Fewer, better pathways for all? Intersectional impacts of rural school consolidation in China’s minority regions.” *World Development* 151:105734.
- Hardy, Morgan and Jamie McCasland. 2021. “Lights off, lights on: The effects of electricity shortages on small firms.” *The World Bank Economic Review* 35 (1):19–33.
- Henan Electric Power Industry Gazetteer Compilation Commission. 2010. *Henan Electric Power Industry Gazetteer (1988–2002)*. Beijing: China Electric Power Press.
- Hoynes, Hilary, Diane Whitmore Schanzenbach, and Douglas Almond. 2016. “Long-run impacts

- of childhood access to the safety net.” *American Economic Review* 106 (4):903–934.
- Hubei Electric Power Industry Gazetteer Compilation Commission. 2012. *Hubei Electric Power Industry Gazetteer (1991–2002)*. Beijing: China Electric Power Press.
- International Energy Agency. 2002. *World Energy Outlook 2002*. Paris: IEA. URL <https://www.iea.org/reports/world-energy-outlook-2002>. Licence: CC BY 4.0.
- Isen, Adam, Maya Rossin-Slater, and W Reed Walker. 2017. “Every breath you take?every dollar you’ll make: The long-term consequences of the clean air act of 1970.” *Journal of Political Economy* 125 (3):848–902.
- Jha, Akshaya, Louis Preonas, and Fiona Burlig. 2022. “Blackouts: The Role of India’s Wholesale Electricity Market.” Working Paper 29610, National Bureau of Economic Research.
- Jiao, Yinyi. 2024. “Human Capital Enhancement Effect of Energy Transition: Analysis Based on the Chinese Rural Electrification.” *The Journal of Quantitative & Technical Economics (In Chinese)* 41 (08):197–217.
- Johnson, Rucker C and C Kirabo Jackson. 2019. “Reducing inequality through dynamic complementarity: Evidence from Head Start and public school spending.” *American Economic Journal: Economic Policy* 11 (4):310–349.
- Kassem, Dana. 2024. “Does electrification cause industrial development? Grid expansion and firm turnover in Indonesia.” *Journal of Development Economics* 167:103234.
- Khandker, Shahidur R, Douglas F Barnes, and Hussain A Samad. 2013. “Welfare impacts of rural electrification: A panel data analysis from Vietnam.” *Economic Development and Cultural Change* 61 (3):659–692.
- Khandker, Shahidur R, Hussain A Samad, Rubaba Ali, and Douglas F Barnes. 2014. “Who benefits most from rural electrification? Evidence in India.” *Energy Journal* 35 (2):75–96.
- Kitchens, Carl and Price Fishback. 2015. “Flip the switch: the impact of the rural electrification administration 1935–1940.” *The Journal of Economic History* 75 (4):1161–1195.

- Koima, Josephat. 2024. “School electrification and academic outcomes in rural Kenya.” *Journal of Development Economics* 166:103178.
- Kojima, Masami and Chris Trimble. 2016. *Making Power Affordable for Africa and Viable for Its Utilities*. Washington, DC: World Bank. URL <https://hdl.handle.net/10986/25091>.
- Lee, Kenneth, Edward Miguel, and Catherine Wolfram. 2020a. “Does household electrification supercharge economic development?” *Journal of Economic Perspectives* 34 (1):122–144.
- . 2020b. “Experimental evidence on the economics of rural electrification.” *Journal of Political Economy* 128 (4):1523–1565.
- Lenz, Luciane, Anicet Munyehirwe, Jörg Peters, and Maximiliane Sievert. 2017. “Does large-scale infrastructure investment alleviate poverty? Impacts of Rwandas electricity access roll-out program.” *World Development* 89:88–110.
- Levinson, Arik and Emilson Silva. 2022. “The electric gini: Income redistribution through energy prices.” *American Economic Journal: Economic Policy* 14 (2):341–365.
- Lewis, Joshua. 2018. “Infant health, women’s fertility, and rural electrification in the United States, 1930–1960.” *The Journal of Economic History* 78 (1):118–154.
- Lewis, Joshua and Edson Severnini. 2020. “Short-and long-run impacts of rural electrification: Evidence from the historical rollout of the US power grid.” *Journal of Development Economics* 143:102412.
- Li, Hongming. 2009. “Electricity Price Reduction: Boosting Jiangxi’s Rural Economy (Dianjia Dafu Xiajiang Jihuo Jiangxi Nongcun Jingji, in Chinese).” *State Grid News (Guojia Dianwang Bao)* 008:1–3.
- Lin, Youhong and Chunhua Xu. 2024. “Electrification and economic growth: Evidence from china’s rural primary electrification program.” *China Economic Review* 83:102084.
- Lipscomb, Molly, A Mushfiq Mobarak, and Tania Barham. 2013. “Development effects of electrification: Evidence from the topographic placement of hydropower plants in Brazil.” *American*

- Economic Journal: Applied Economics* 5 (2):200–231.
- Liu, Kun. 2000. “The Theory of ‘Reading is Useless’ Raises Its Head in Poor Mountainous Areas (‘Dushu Wuyong Lun’ Zai Pinkun Shanqu Taitou, in Chinese).” *Guangming Daily* .
- Luoding City Gazetteer Compilation Commission. 2003. *Luoding City Gazetteer of Electricity Power*.
- McRae, Shaun. 2015. “Infrastructure quality and the subsidy trap.” *American Economic Review* 105 (1):35–66.
- Meeks, Robyn and Meera Mahadevan. 2025. “Electricity Infrastructure.” *VoxDevLit* 15 (1).
- Mensah, Justice Tei. 2024. “Jobs! Electricity shortages and unemployment in Africa.” *Journal of Development Economics* 167:103231.
- Ministry of Finance of the People’s Republic of China, Budget Department. 1993–2007. *National Finance Statistics of Cities, Counties, and Districts (Quanguo Di Shi Xian Caizheng Tongji Ziliao, in Chinese)*. Beijing: China Financial and Economic Publishing House.
- Minnesota Population Center. 2020. *Integrated Public Use Microdata Series, International: Version 7.3 [dataset]*. Minneapolis, MN: IPUMS.
- Nag, Suryadepto. 2024. “Does reliable electricity mean lesser agricultural labor wages? Evidence from Indian villages.” *Energy Policy* 190:114151.
- Nandi, Arindam, Sonia Bhalotra, Anil B Deolalikar, and Ramanan Laxminarayan. 2017. *The Human Capital and Productivity Benefits of Early Childhood Nutritional Interventions*. The International Bank for Reconstruction and Development / The World Bank, Washington (DC), 3rd ed. URL <http://europepmc.org/books/NBK525244>.
- National Bureau of Statistics of China. 1999. *China Statistical Yearbook 1999*. Beijing: China Statistics Press.
- National Bureau of Statistics of China, Urban Social and Economic Survey and Statistical Division. 1995–2008. *China Statistical Yearbook*. Beijing: China Statistics Press.

- Onishi, Norimitsu. 2015. “Weak Power Grids in Africa Stunt Economies and Fire Up Tempers.” New York Times, July 2. <https://www.nytimes.com/2015/07/03/world/africa/weak-power-grids-in-africa-stunt-economies-and-fire-up-tempers.html>.
- Page, Marianne E. 2024. “New Advances on an Old Question: Does Money Matter for Childrens Outcomes?” *Journal of Economic Literature* 62 (3):891–947.
- Peters, Jörg and Maximiliane Sievert. 2016. “Impacts of rural electrification revisited—the African context.” *Journal of Development Effectiveness* 8 (3):327–345.
- Ponnusamy, Sundar. 2025. “The impact of rainfall shocks in childhood and adolescence on human capital development.” *American Journal of Agricultural Economics* .
- Roth, Jonathan. 2022. “Pretest with caution: Event-study estimates after testing for parallel trends.” *American Economic Review: Insights* 4 (3):305–322.
- Rud, Juan Pablo. 2012. “Electricity provision and industrial development: Evidence from India.” *Journal of Development Economics* 97 (2):352–367.
- Schultz, T Paul and John Strauss. 2008. *Handbook of development economics*, vol. 4. UK: Elsevier.
- Shah, Manisha and Bryce Millett Steinberg. 2017. “Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital.” *Journal of Political Economy* 125 (2):527–561.
- Sovacool, Benjamin and Ivan Vera. 2014. “Electricity and education: The benefits, barriers, and recommendations for achieving the electrification of primary and secondary schools.” *United Nations Department of Economic and Social Affairs* .
- Steinbuks, Jevgenijs and Vivien Foster. 2010. “When do firms generate? Evidence on in-house electricity supply in Africa.” *Energy Economics* 32 (3):505–514.
- Taubman, Paul. 1989. “Role of parental income in educational attainment.” *The American Economic Review* 79 (2):57–61.
- Thomas, Daniel Robert, SP Harish, Ryan Kennedy, and Johannes Urpelainen. 2020. “The effects of

- rural electrification in India: An instrumental variable approach at the household level.” *Journal of Development Economics* 146:102520.
- Trimble, Christopher Philip, Masami Kojima, Ines Perez Arroyo, and Farah Mohammadzadeh. 2016. “Financial viability of electricity sectors in Sub-Saharan Africa: quasi-fiscal deficits and hidden costs.” *World Bank Policy Research Working Paper* (7788).
- Van de Walle, Dominique, Martin Ravallion, Vibhuti Mendiratta, and Gayatri Koolwal. 2017. “Long-term gains from electrification in rural India.” *World Bank Economic Review* 31 (2):385–411.
- Vicente-Serrano, Sergio M, Santiago Beguería, Juan I López-Moreno, Marta Angulo, and Ahmed El Kenawy. 2010. “A new global 0.5 gridded dataset (1901–2006) of a multiscalar drought index: comparison with current drought index datasets based on the Palmer Drought Severity Index.” *Journal of Hydrometeorology* 11 (4):1033–1043.
- Vidart, Daniela. 2024. “Human capital, female employment, and electricity: Evidence from the early 20th-century United States.” *Review of Economic Studies* 91 (1):560–594.
- Warner, Geoffrey L. 1995. “Prenatal care demand and birthweight production of black mothers.” *The American Economic Review* 85 (2):132–137.
- Wong, Jason Chun Yu, Brian Blankenship, Johannes Urpelainen, Karthik Ganesan, Kapardhi Bharadwaj, and Kanika Balani. 2021. “Perceptions and acceptability of electricity theft: Towards better public service provision.” *World Development* 140:105301.
- World Bank. 2024. *The Critical Link: Empowering Utilities for the Energy Transition*. Washington, DC: World Bank. URL <http://hdl.handle.net/10986/41618>.
- Yangzhou Power Supply Company. 2012. *Gazetteer of Yangzhou Electric Power Industry (1991–2002)*. Beijing: China Electric Power Press.
- Zhao, Yaohui. 1997. “Labor migration and returns to rural education in China.” *American Journal of Agricultural Economics* 79 (4):1278–1287.

Appendix

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

Pan Chen

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 drawn from local gazetteers. Most counties don't have these records. In these cases, I use provincial level records instead. Other county-level indicators are drawn 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 drawn from local gazetteers. Most counties don't have these records. In these cases, I use provincial level records instead. Other county-level indicators are drawn 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	
	(1)	(2)
	Overall	Gender difference (male=1)
Reduction \times affected cohorts		-0.563
(1982–1987) \times gender		(1.064)
Reduction \times affected cohorts	-0.391	-0.012
(1982–1987)	(0.811)	(0.768)
Observations	3,582	3,582
R-squared	0.446	0.450
County FE	Yes	Yes
Province \times birth year FE	Yes	Yes
Mean of dep var	8.396	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. Column (1) shows the overall effect, while column (2) presents heterogeneous effects by gender. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix B: Figures

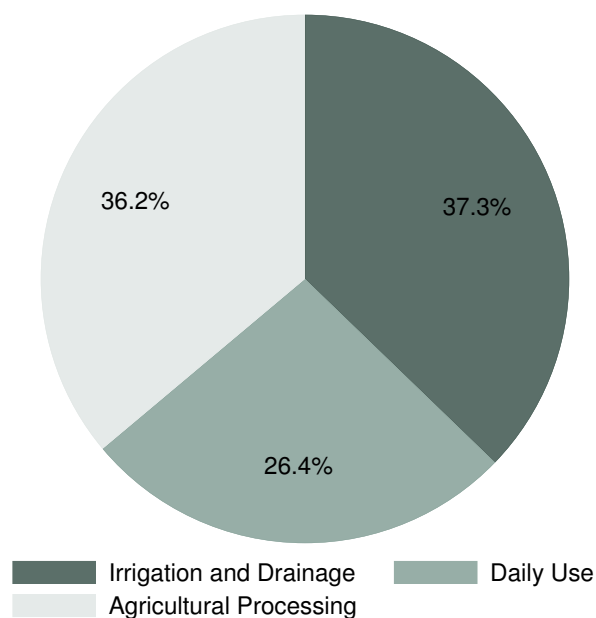


Figure B1: Rural Electricity Use Breakdown in Henan Province, 1997. *Note:* This figure shows rural electricity consumption in Henan Province in 1997. Although the category includes both drainage and irrigation, it primarily reflects irrigation, as most areas in Henan—located in northern China with limited water resources—rely heavily on irrigation. 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 \(2010\)](#).

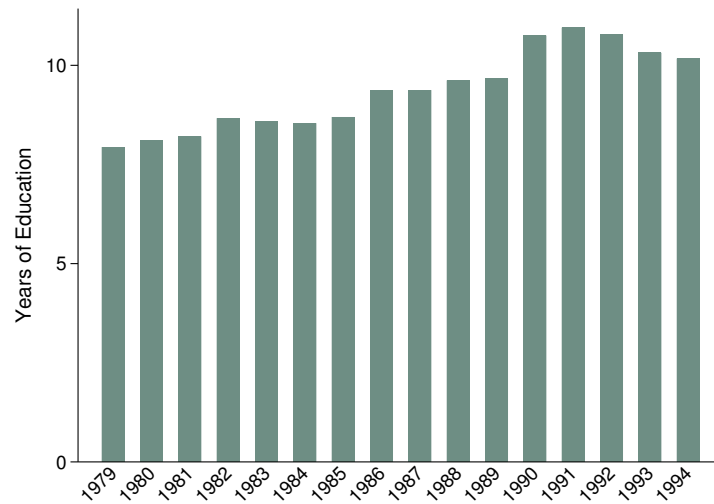
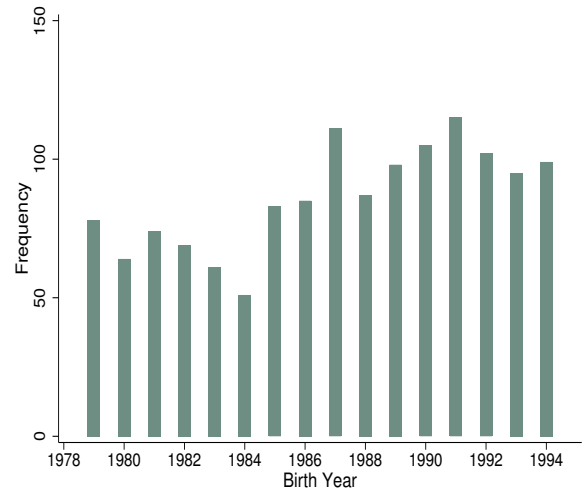
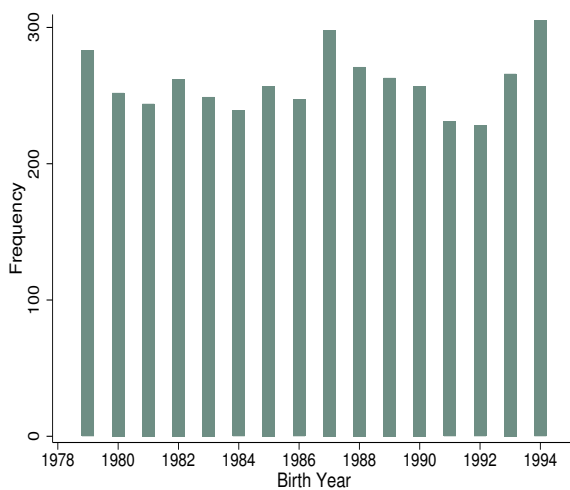


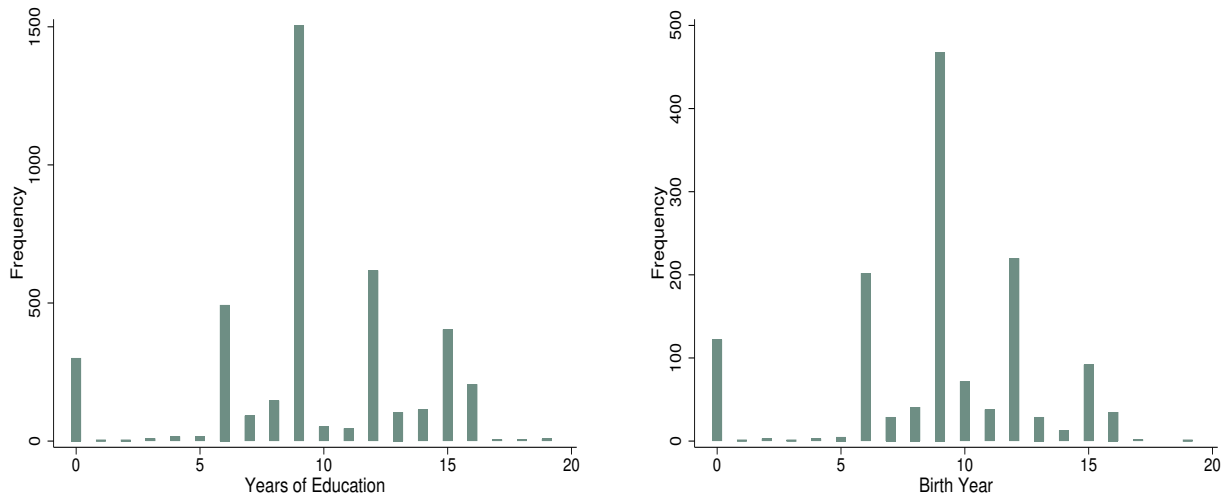
Figure B2: Years of Education by Birth Year. *Note:* This figure illustrates the average years of education by birth year in my sample.



(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 B3: 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 a rural 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 B4: 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 a rural Hukou at ages 3 and 12.

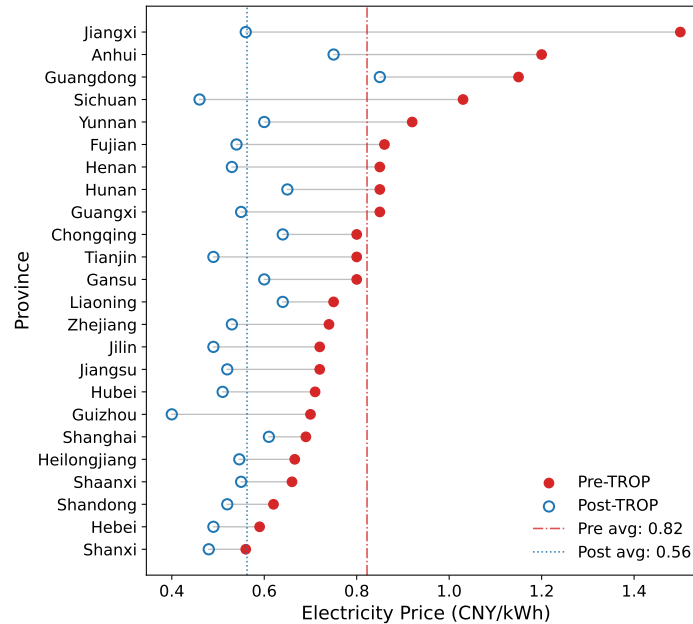


Figure B5: Provincial Electricity Prices: Pre- vs. Post-TROP.

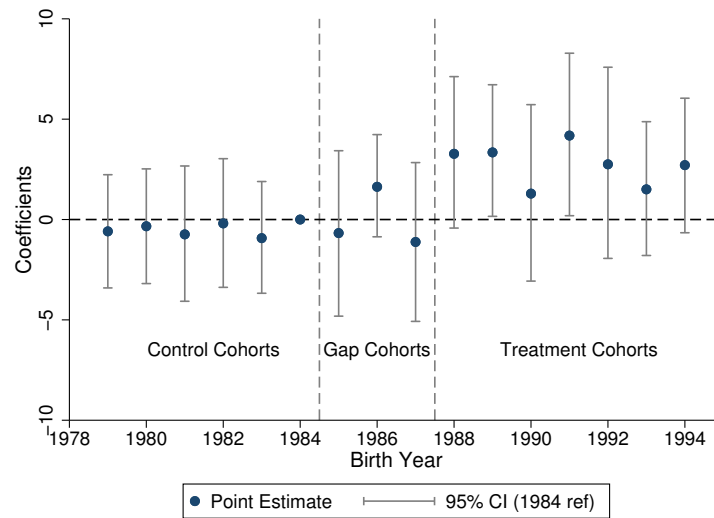


Figure B6: Event Study Results—Controlling for Heterogeneous Trends across Counties. *Note:* The y-axis represents the coefficients estimated from Eq. 9. “Gap cohorts,” which lie between the two dashed lines, are included in event study but excluded from the baseline regression.

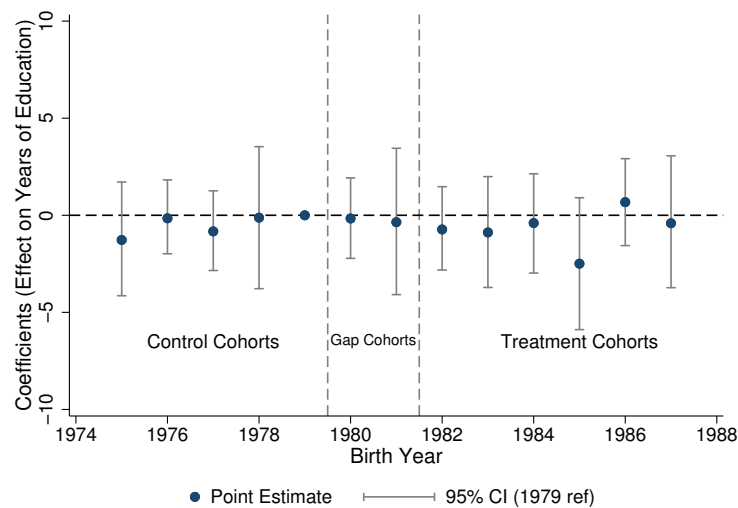


Figure B7: Event Study Results of Secondary School Age Exposure to TROP. *Note:* This figure presents event study estimates of secondary school age exposure to TROP. The treatment year is 1999. Estimates follow the baseline specification. The “gap cohorts,” shown between the dashed lines, are included in the event study but excluded from the DiD regression reported in Appendix Table A7.

Appendix C: Additional Robustness Checks

Price Data Availability. 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 under full exposure.

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:

$$Y_{i,t,c} = \alpha + \beta_1 \times Reduction_c \times \mathbf{1}\{Age \leq 12\} + \beta_2 \times \mathbf{1}\{Age \leq 12\} + \varphi X_{i,t,c} + \gamma_c + \mu_{prov} \times \tau_t + \varepsilon_{i,t,c} \quad (11)$$

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).

$$Y_{i,t,c} = \alpha + \beta'_1 \times Reduction'_c \times \mathbf{1}\{Age \leq 12\} + \beta'_2 \times \mathbf{1}\{Age \leq 12\} + \varphi X_{i,t,c} + \gamma_c + \mu_{prov} \times \tau_t + \varepsilon_{i,t,c} \quad (12)$$

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

¹If $\beta_1 \times Reduction_c \times \mathbf{1}\{Age \leq 12\}$ 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.

²In practice, the indicator $\mathbf{1}Age \leq 12$ 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 regression, I follow Bianchi, Lu, and Song (2022) and use observations from the 2010 wave to fill in missing outcome variables for these individuals. 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*** (0.703)	3.293*** (0.687)	2.740*** (0.752)			2.534*** (0.571)		3.018*** (0.692)	3.037*** (0.626)	2.794*** (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 ≤ 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 ≤ 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

References

Bianchi, Nicola, Yi Lu, and Hong Song. 2022. “The effect of computer-assisted learning on students’ long-term development.” *Journal of Development Economics* 158:102919.

Appendix D: Child Wages Respond 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:

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

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.

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

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

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

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:

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

Solving Eq. D3 gives the boundary condition:

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

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:

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

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