“Buy Tractors and Keep the Children in School”: Agricultural Mechanization, Teenage Labor Supply, and High School Enrollment

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Abstract

This study examines how subsidies for agricultural machinery impact employment and high school enrollment among teenagers. Using rollout of a subsidy program across Chinese counties, we find that the subsidy led to more mechanization, decreased employment and increased high school enrollment for 15-19-year-olds. We propose a model in which a subsidy to agricultural machines could either increase or decrease teenage labor supply, depending on its effects on wages and farm profits. The model replicates our empirical results when agricultural machines are labor-saving and significantly boost household income. We estimate elasticity of substitution between agricultural machines and labor of 1.85, suggesting significant labor-saving. We also document significant effect of the subsidy on household wages and farm income.
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1 Introduction

Educational attainment in younger cohorts constitutes a pivotal driver of sustained long-term economic growth, particularly in economies undergoing the transition from low- to high-income status. A substantial empirical literature has documented how major macroeconomic shocks in developing countries such as India and Brazil—including trade liberalization, infrastructure development, and adverse weather events—can impair adolescent schooling by elevating the opportunity cost of education through heightened demand for teenage labor. By contrast, certain strands of research and scholarly commentary underscore the countervailing positive effects of technological progress, especially labor-saving innovations in agriculture, on educational outcomes. A prominent illustration appears in Steven Pinker's influential work *Enlightenment Now*, which argues that mechanization in early-20th-century rural United States substantially raised teenage school enrollment: the diffusion of tractors diminished the demand for boys' farm labor, thereby facilitating greater school attendance, while the adoption of washing machines reduced the burden of domestic chores, enabling improved educational attainment among girls (Pinker, 2018).

While a growing body of narrative evidence indicates that technological change—particularly in agriculture—may exert substantial influence on educational outcomes, rigorous causal evidence regarding the effect of agricultural mechanization on schooling attainment remains scarce. The present study seeks to address this gap by exploiting a large-scale agricultural machinery subsidy program implemented in China.

China exhibits one of the lowest secondary school attainment rates among middle-income countries, with approximately 70% of its labor force (roughly 500 million individuals) lacking high school education (Rozelle and Hell, 2022). Dropout rates among 15-year-old teenage laborers approach 40%, in stark contrast to the roughly 5% rate observed among non-working peers of the same age (Tang et al., 2018). Notwithstanding these challenges, high school enrollment has improved dramatically over the past two decades. Drawing on multiple rounds of census data, we document three key patterns among successive cohorts of Chinese teenagers aged 15–19. First, the share of 15–19-year-olds who had completed high school rose sharply from approximately 30% in 2000 to over 70% by 2015. Second, the proportion of employed teenagers in this age group fell precipitously from 33% in 2000 to only 10% in 2015. Third, among employed teenagers, the share working in agriculture declined from nearly 85% in 2000 to 45% in 2015. Collectively, these trends indicate that the substantial reduction in teenage employment over this period was predominantly driven by the contraction of agricultural sector opportunities.

Our empirical analysis exploits a large-scale subsidy program for agricultural machinery purchases as a quasi-experimental source of variation. Historically, agricultural mechanization in China had been constrained by widespread farmland fragmentation (Wang et al., 2020; Qiu et al., 2021) and by the *hukou* system, which restricted rural-to-urban migration and sustained surplus labor in agriculture (Imbert et al., 2022). Despite these barriers, the country experienced rapid mechanization over the past three decades. In the early phase, this process was primarily driven by the rapid emergence and expansion of agricultural mechanization services (AMS)–specialized firms that provide machine rental to smallholder farmers (Qiu et al., 2021). Since the early 2000s, however, direct government subsidies to households for machinery purchases have become the dominant policy instrument. The program was initially piloted in a small number of counties in 2004 and scaled nationwide, reaching nearly all counties by 2009. Subsidy coverage continued to broaden in subsequent years, both through the inclusion of additional machinery types and through increasing take-up among eligible farmers.

We leverage the staggered county-level rollout of the subsidy program to identify the causal effect of agricultural mechanization on teenage labor supply and high school enrollment. Our preferred estimates indicate that county-level subsidy exposure raised the stock of agricultural machines by up to 10% within five years. This mechanization-induced productivity gain was associated with a substantial reallocation of teenage time: the labor supply rate among 15–19-year-olds declined by approximately 6 percentage points, while their high school enrollment rate rose by 10.6 percentage points over the same horizon. These magnitudes are economically meaningful and imply that agricultural mechanization can account for roughly one-fifth of the national decline in teenage labor force participation and the concomitant increase in upper-secondary enrollment observed over our sample period.

Empirical estimation of causal effects in staggered policy rollouts, such as the subsidy program studied here, faces well-documented challenges in the recent DID literature (Goodman-Bacon, 2021; Callaway and SantAnna, 2021; Wooldridge, 2021; Borusyak et al., 2024). When treatment effects are heterogeneous across adoption cohorts or time since treatment, the conventional two-way fixed-effects (TWFE) estimator can produce biased averages of treatment effects on the treated (ATT), as it implicitly assigns heterogeneous—and sometimes negative—weights to different group-time observations. To obtain unbiased and efficient estimates of dynamic treatment effects while enabling formal tests of identifying assumptions, we adopt the imputation-based approach of Borusyak et al. (2024). A second identification concern arises from the likely non-random assignment of treatment across counties, as the program prioritizes areas critical to national food security and therefore tends to favor counties with high agronomic potential for major staple crops. Drawing on recent advances in non-parametric first-stage estimation for instrumental-variables settings (Belloni et al., 2012; Jat, 2024), we construct predicted rollout timing as follows. Using GAEZ data, we compute each county's national rank in potential yields under six crop-technique combinations (irrigated/rainfed wheat, rice, and maize). We then train a random forest classifier to predict each county's actual treatment year from these six rankings. The resulting predicted rollout closely tracks the observed program timing, delivering a strong first stage analogous to conventional 2SLS. Re-estimating our main specifications with this predicted timing as the treatment variable yields results that are highly comparable to the baseline estimates, reinforcing the credibility of our causal findings.

To rationalize our empirical findings, we develop a theoretical model on farm household's decision to send their teenager to labor market or high school, building on the seminal paper of Basu and Van (1998). In the model, households send their teenager to work only if the income generated from adult labor and farm profit is not sufficient to attain subsistence. Thus teenage leisure/school is a luxury good afforded by only households who could achieve subsistence consumption without sending their teenager to work. On the production side, households own land and run their farm business by employing labor and capital (machines). In such environment, a subsidy to agricultural machines may increase or decrease teenage labor. The model replicates our empirical findings when agricultural machines are substitute for labor (thus decreasing the demand for labor) and/or agricultural mechanization significantly increases household income. When both these conditions are met, the income and substitution effects operate in the same direction to significantly decrease teenage labor and increase high school enrollment. We provide further empirical evidences confirming these mechanisms in the model. Household overall income, including farm income and wage income, increases significantly following the subsidy, allowing them to send their teenagers to school. We also estimate the elasticity of substitution between agricultural machines and farm labor. Our estimated elasticity of substitution range between 1.85-3.75 (depending on estimation strategy), suggesting significant labor-saving nature of agricultural mechanization.

Overall, our findings indicate that agricultural mechanization substantially reduces labor force participation among individuals aged 15–19 while significantly increasing their high school enrollment rates. These results suggest that policies subsidizing agricultural mechanization may generate meaningful positive externalities on human capital accumulation, over and above their direct productivity gains in agriculture. Furthermore, directing such subsidies preferentially toward households with school-age adolescents could enhance the cost-effectiveness of these interventions in promoting long-term human capital development.

This paper directly contributes to limited studies on the effect of adoption of agricultural technology on child labor and school outcomes. Self and Grabowski

(2009) study the effect of adoption of biochemical and mechanical agricultural technologies on child labor. They find that biochemical technology has both positive and negative effects on child labor, while the mechanical technology is found to have a statistically significant and negative impact. Vos and Takeshima (2021) use data from seven low-income countries to study the effect of adoption of farm tractors on child labor use, and find modest decrease in child labor. While these studies suggest a decrease in child labor following agricultural modernization, they are not informative of whether the time saved from agricultural labor was used to gain more schooling or transferred to non-agricultural works (such as domestic chores or works in manufacturing or service sectors). The current paper fills this void by tracing the link between agricultural mechanization, teenage labor and school enrollment. To the best of our knowledge, the current paper is the first to attempt to establish this causal link.

A growing body of literature studies how expansion of job opportunities affect teenager's opportunity costs of school enrollment and their choices. An influential paper by Atkin (2016) finds that expansion of export-oriented manufacturing industries led to increased school drop-out in Mexico during the period 1986-2000. The effect is particularly larger for teenager aged 16 (typical age to start high school). Similarly, Lu et al. (2023) find that special economic zones (SEZs) in China have heterogeneous effect on enrollment. High tech SEZs encourage high-school enrollment while low-skill export oriented SEZs discourage high school enrollment by expanding employment opportunity for unskilled labor. A related paper by Oster and Steinberg (2013) finds that increases in return to schooling following India's IT sector boom increased school enrollment.

Other papers that study the effect of employment opportunity on human capital development using trade or infrastructure shock include Adukia et al. (2020); Edmonds et al. (2009, 2010). In agricultural setting, Bai and Wang (2020) find that decrease in returns to adult crops (crops intensive in adult labor) reduces educational achievement of teenager while decrease in the returns to child crops (crops intensive in child labor) has the opposite effect, and Shah and Steinberg (2017) use rainfall variation to show that positive income shocks increase human capital investment for younger children but decreases it for older children by increasing the opportunity cost of school attendance in India.[1] The underlying mechanism dominantly at work in most of the above papers is the substitution effect (i.e., changes in opportunity costs of schooling affecting teenager's enrollment). In the current paper, agricultural mechanization's direct effect on household farm income dominates any substitution effect, thus decreasing teenage labor supply and increasing school enrollment.

Another strand of this literature focuses on the effect of child labor on academic

[1] See also Kruger (2007), and Levy (1985).

achievements of enrolled students. Vasey (2020), using data from Mexico, shows that child labor decreases student efforts and test scores and, the more the number of days a child works, the larger the decrease in test scores. Child labor policies could decrease dropout by over 6%. Similarly, Keane et al. (2022) use data from four low- and middle-income countries and show that child work (both chore and market labor) crowds out child time allocated to study time and significantly reduces their cognitive development.

A closely related literature studies the long run effect of child labor on adulthood income. Emerson and Souza (2011) using data from Brazil find that child labor has a large negative effect on adulthood income, even conditional on education. Similar result is echoed in Posso (2017) who finds that child workers earn significantly less during their adulthood compared to their cohorts who did not work during their childhood. A related paper by Carrillo (2020) uses fluctuations in the international coffee prices as exogenous variation to the return to work for Brazilian teenager and find that cohorts that faced higher return to coffee related work during childhood completed fewer years of schooling and earned less income as adults. In contrast to these papers, Le Barbanchon et al. (2023) using randomized job offers to students, find that working while in school increased participants' earnings by 8% two years later, mainly via acquired work-related skills.[2]

The rest of the paper is organized in seven sections. Section 2 describes the data sets. In Section 3 we present our main empirical analysis. We discuss our robustness exercises in section 4. Section 5 presents our theoretical model that rationalizes our empirical results and presents evidence on the main mechanisms at work. Section 6 concludes the paper.

2 Data

We combine several datasets obtained from various sources. Our primary dataset is county-level rollout implementation of subsidy for purchase of agricultural machines, which is discussed in brief below. We collect educational attainment and employment information across cohort aged 15-19 from waves of Chinas population censuses, including the 0.095% sample of the 2000 census, the 20% sample of the 2005 one percent mini-census, the 3.3% sample of the 2010 census, and the 10% sample of the 2015 one percent mini-census.[3] The combined census and mini-census data give us

[2]See also Psacharopoulos (1997), Ray (2002), and Emerson et al. (2017)

[3]These data were obtained via systematic sampling of the census records using the following procedure: (1) Households are assigned sequential codes; (2) A random starting point (between 1 and 10) is determined for each census unit (villages in rural areas and communities in urban areas); (3) Samples are selected at fixed intervals (e.g., every 10th household). Specific mathematical logic is applied to handle remainders and census units with fewer than 10 households to ensure statistical rigor. A recent paper by Dong et al. (2025) evaluates the representativeness of such sub-

information on labor supply and school enrollment of millions of school-age teenager of several cohorts raised in different locations. In addition to this, we also use county- and prefecture-level panel data since 1996 on the stock of agricultural machinery, GDP, population, number of students enrolled in high school and number of schools. This panel data originates from the official government statistics annually published on China County Statistical Yearbooks as well as Provincial Yearbooks (PYBs). Agricultural mechanization is measured as the total stock of agricultural machines used for ploughing, harvesting, threshing, irrigation, etc. Various machines are aggregated and reported in 10,000KW. Further, we digitize various years of PYBs to construct a panel data of agricultural wage for the period 2000-2012 for 222 prefectures.

Measurement of key variables: Employment status is inferred from respondent's answer to the question: if s/he "worked for income" in the week before the census date. For those who worked, we also observe the industries in which they worked. In this definition unpaid jobs, such as domestic chores, are not considered as employment though part-time jobs are considered as employment. Moreover, our employment measure does not capture seasonal changes in employments as it is based on employment status at the time of census.

Another key variable is high school enrollment. We infer this from educational attainment of the respondents at the time of the census. High school enrollment has a value of 1 if the person has completed some high school or is still enrolled in high school at the time of the census. For our analysis, we focus on individuals with 15-19 years of age. We provide summary statistics of these variables in Table 1 and their trends over census years in Figure 1.

Unit of analysis: China's administrative regions include provinces, prefectures, counties, towns, and villages, ranging from high to low hierarchy.[4] For our main analysis, we use counties as unit of analysis. This is for two reasons. First, we use rollout of agricultural machinery subsidy across counties as a source of variation in our identification strategy. Second, counties are the most granular level administrative regions for which data is available.

While county-level variation is the ideal for our purpose, we face limitation of sample size when we construct measures high school enrollment rate and employment rate for 15-19 year-olds at the county levels. This is because our subjects of analysis

samples, specifically the 1% 2000 census micro-records which Chinas Statistics of Bureau provided on IPUMS. Using the sample data in Chongqing, they found that this sampling method yields highly representative sub-samples that closely mirror the structural characteristics of the entire population, with small discrepancies between estimated totals and actual census counts.

[4]Chinese counties could be considered as the equivalent of U.S counties (though Chinese counties are smaller on average). Prefectures are comparable to U.S's metropolitan statistical area (MSA).

in the censuses are teenager aged 15-19 and in small number of counties the number of teenagers in this age bracket are less than 10 while the vast majority of counties have 10 or more teenagers in the age bracket. We drop counties with only one child in this age bracket. Also, we weight all our regressions using the number of teenagers in the age bracket as importance weights so that counties with more precisely measured outcomes receive higher weights.[5]

As a robustness exercise, we also provide analysis at the prefecture level. Because there are, on average, about eight counties in a prefecture, prefecture-level analysis resolves the small sample issue to reliably estimate the high school enrollment rate and employment rate of each cohort. However, because the rollout of subsidy was implemented at the county level we cannot use the rollout program for our estimation. Instead we use variation in the stock of agricultural machines across prefectures and over years.

3 Empirical analysis

3.1 Stylized facts

Before we tackle the causal relationship between agricultural mechanization and teenagers' labor supply and high school enrollment, we first present trends in labor supply and high school enrollment of teenagers by combining various rounds of census data. Figure 1 presents a series of facts about trends in high school enrollment rate and employment rate across cohorts of teenagers, which are summarized as follows.

Fact-1: The fraction of 15-19 year-olds with some high school education (including those in enrollment) has shown a dramatic increase over the years starting at a low level in 2000. Figure 1 shows that only 32% of 16-year-olds had some high school education in 2000. This number increased to 39% by 2005 before climbing up to over 56% by 2010 and nearly 70% in 2015. Very similar trajectory can be observed for teenagers aged 15-19.

Fact-2: Employment rate of high school-aged teenagers decreased significantly over decades. Figure 1 shows that the fraction of 16-year-old teenagers employed was about 33% in 2000. This number decreased to 19% by 2005 before it plummets to just under 10% by 2015. Similar trend can be observed for 15, 17, 18, and 19 year old teenagers over decades.

[5]However, dropping this weights does not affect any of the results.

Fact-3: Figure 1 also shows that among 15-19 year-old teenagers who were employed, nearly 80% of them worked in the primary sector in 2000, but this number decreased significantly to just over 30% by 2015. On the contrary, the fraction of 16-year-olds who were working in the secondary sector increased from 13% in 2000 to just under 40% by 2015. Again, this trend is similar across 15-20 year-olds. This result is consistent with significant structural change in the Chinese economy over the past three decades where the share of employment in agriculture decreased and the share of employment in non-agricultural sectors increased. However, it shows that employment reallocation from agriculture to manufacturing and services observed in aggregate data is probably mostly driven by young cohorts joining the labor market for the first time.

Our empirical exercises in the following sections aim to explain the dramatic changes in high school enrollment and employment status of high school-aged teenagers discussed above. In particular, we seek to understand how much of the increase in high school enrollment and decrease in employment is explained by agricultural mechanization, given that the agricultural sector had been the sector absorbing the vast majority of the labor supply by 15-19 year-olds in 2000 census.

Figure 1 shows trends in the total agricultural machinery where the stock of agricultural machinery increased nearly three folds over the sample period, with substantial heterogeneity across counties. Because agricultural machines such as tractors, combine harvesters, threshers, etc. are likely labor-saving technologies, adoption of these machines would decrease agricultural labor demand and wages, potentially driving teenagers into the labor market to cope with reduced household wage income. However, these technologies are also productivity-enhancing and may increase farm profit, thus allowing parents to send their teenagers to school. Figure 2 shows that across countries, agricultural mechanization is negatively related to labor supply and positively associated with school enrollment of 5-17-year-olds, even after accounting for GDP per capita. However, such cross-country comparison masks significant heterogeneity across countries in institutional environments, education culture, economic structure, education policy, etc.. Below we explore the effect of subsidy to agricultural mechanization on teenage labor and school enrollment by using geographic and time variation within a country (China).

3.2 The agricultural machine subsidy program

China has long recognized mechanization as a key strategy for ensuring grain self-sufficiency and boosting agricultural productivity. In 2004, the government launched Agricultural Machinery Purchase Subsidy (AMPS), a program that provides subsidies to farmers for the purchase of selected agricultural machinery. Initially, the subsidy program focused on three core machine types: large and medium-sized tractors, rice and corn combine harvesters, and rice transplanters. Over time, the program's coverage grew to twelve different machine categories.

All registered farmers or agricultural production organizations within a designated county are eligible to receive the subsidy as long as they are interested in buying the subsidized machines. As the number of machines covered by the subsidy increased over time, more farmers benefited from the program. The subsidy is tied to specific machinery purchases, so that farmers are eligible to receive subsidy for more than one machine. In particular, the subsidy supports equipments for key grain production stages (plowing, planting, harvesting), particularly for wheat, rice, corn, and soybeans. During early years, the maximum subsidy was 50,000 RMB per machine. Later, large tractors (100 horsepower and above), rice and corn combine harvesters, and rice transplanters are eligible for a maximum subsidy of 150,000 RMB each.

Funding for this initiative comes primarily from the central government, with local governments encouraged to contribute as well. The size of subsidies for agricultural machinery provided by both central and local governments increased dramatically since 2004 as the subsidy program incorporated more and more counties and its coverage of different machine types expanded over time. The central government funding increased substantially over time, rising from 70 million yuan (approximately 10 million US dollars) in 2004 to 23.64 billion yuan (around 3.5 billion US dollars) in 2015. Similar growth was seen in local government funding, which increased from 560 million yuan (about 80 million US dollars) in 2004 to 2.8 billion yuan (approximately 0.4 billion US dollars) in 2013 after which the local government funding was discontinued. These subsidies have benefited approximately 1.69 million rural households which significantly increased farmers' ability to invest in machinery. For instance, an average rural household received 500 RMB in subsidies in 2004, which corresponded to 25% of its annual disposable income per capita.

Our main empirical analysis uses the rollout of AMPS across counties as a source of variation to agricultural mechanization. The subsidy rollout program started in 2004 with 66 pilot counties. Gradually, it expanded to 500 counties in 2005, 1,126 in 2006, 1,716 in 2007, and 2,653 in 2008, before reaching nationwide coverage by 2009. By 2009, nearly all counties in our data received the subsidy. See Figure 3 and Column 1 of Table 4. The rollout of the AMPS program adhered closely to official guidelines set by the Ministry of Agriculture and Rural Affairs (MARA) and the Ministry of Finance (MOF). These guidelines initially prioritized traditional grain-producing areas, selecting them as pilot regions for the subsidy before gradually expanding the program nationwide.[6] As an example, all 66 pilot counties in 2004

[6] https://www.ers.usda.gov/webdocs/outlooks/40443/30113_wrs0501_002.pdf?v=6973.

were located within key grain-producing regions, with subsidies allocated specifically to leading grain farmers.[7] This targeted approach reflected the program's core objectives: to bolster grain security and enhance agricultural productivity throughout China. By focusing on regions with established grain production, the AMPS aimed to maximize its impact from the outset, later extending these benefits to counties across the nation.

3.3 Methodology

Our baseline estimation equation is written as follows:

$$y_{ct} = \sum_{h=-a}^{h=a} \tau_h \mathbf{1}(D_{ct} = h) + \gamma_p * t + \gamma_c + \gamma_t + \varepsilon_{ct} \tag{1}$$

where c denotes county and t denotes cohorts. Thus for county c, y_{ct} measures outcome variable for cohorts that turned 16 in year $t = 2000, ..., 2015$, which mainly includes secondary school enrollment and employment rates. $D_{ct} = t - G_c$ is a treatment indicator, where $G_c \in \{2004, ..., 2009\}$ is year when county c received the subsidy. For few counties that never received the subsidy (never-treated counties), $G_c = \infty$. For illustration, consider county c_1 which enrolled to the subsidy in 2005. The parameter τ_0 captures the estimated effect for teenagers who were born in a county and turned 16 in 2005. The estimated effect on those born in the county and turned 16 in 2006 -2010 is denoted by τ_1-τ_5, respectively. The effect on those who turned 16 in 2004, 2003, 2002, 2001 and 2000 is denoted by τ_{-1}-τ_{-5}, respectively. Hence, our identification strategy compares: (i) teenagers who turned 16 before the county was enrolled into the subsidy program against those who turned 16 after the county was enrolled into the program and (ii) counties that enrolled into the program across different years between 2004-2009.

The parameters γ_c and γ_t are county and year/cohort fixed effects capturing, respectively, time-invariant county features such as geographic location and year (or cohort)-specific factors affecting all counties. $\gamma_p * t$ captures province specific time trends, accounting for time-varying changes across provinces such as unobserved policy changes. We choose the value of $a = 5$ to ensure that each cohort has at least five years of pre-treatment and five years of post-treatment cohorts for comparison. Including further distant outcomes may introduce confounding factors.

Under the assumptions of parallel trends and no anticipation effects, the above model can be estimated consistently following recent advances in the literature of staggered adoption of treatment effects (Goodman-Bacon, 2021; Sun and Abraham,

9

[7] http://www.moa.gov.cn/govpublic/CWS/201006/t20100606_1533228.htm

2021; Callaway and SantAnna, 2021; Wooldridge, 2021; Roth et al., 2023; Borusyak et al., 2024). This is regardless of whether treatment effect varies across units, cohorts or over time, which is the key advantage of the above model over the Two-Way Fixed-Effect (TWFE) model which is consistent only under homogeneous treatment effect. In our setting, the assumption of treatment effect homogeneity across units and time is not warranted[8] and the TWFE model would give biased estimates of average treatment effect (Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and SantAnna, 2021). The main reason is that when there is treatment effect heterogeneity, the average treatment effect on the treated (ATT) is the weighted average of heterogeneous treatment effects τ_{ct} across units and/or time and some of the units and times receive negative weights. In other words, OLS estimation of TWFE model combines two terms: DIDs between treated and not-yet-treated units (also called "clean comparison") and DIDs between already treated groups who received treatment at different times (also called "forbidden comparison"). The main source of bias in TWFE arises from the second term involving forbidden comparisons. If treatment effect increases over time (for instance), groups that received treatment at different times would have different outcomes, which enters the calculation of $\hat{\beta}$ negatively, thus biasing the OLS estimate downward (Roth et al., 2023; Borusyak et al., 2024). Our model above addresses this bias.

The above literature suggests a number of closely related approaches to consistently estimate the model in equation 1. Here we mainly adopt the method suggested by Borusyak et al. (2024) for three reasons. First, this approach has an intuitive appeal as it is based on a transparent imputation estimator where the unit and period fixed effects γ_c and γ_t are estimated from regressions using untreated observations only and these fixed effects are used to impute the untreated potential outcomes and therefore obtain an estimated treatment effect $\hat{\tau}_{ct} = Y_{it} - \hat{\gamma}_c - \hat{\gamma}_t$ for each treated observation. Finally, a weighted sum of these treatment effect estimates is taken, with weights corresponding to the estimation target. The second appeal of this procedure is that it comes with simple tests of identifying assumptions. Third, the procedure gives better efficiency by utilizing data on multiple pre-treatment periods, unlike other approaches in the literature such as Callaway and SantAnna (2021) who utilize only the period immediately before the treatment year.

[8]This is partly because the treatment intensity (the amount of subsidy disbursement) increased over time.

3.4 Main results

3.4.1 High school enrollment and teenagers' labor market participation

Before we delve into our results on the link between agricultural mechanization and high school enrollment, we first present how high school enrollment rate and labor market participation rate are correlated within counties. Table 2 presents the correlation between the fraction of teenagers (ages 15-19) employed and the fraction enrolled in high school. Panel A of the table includes all teenagers aged 15-19 while Panel B restricts estimation to teenagers in agricultural households. In both panels, we find a strong negative correlation of 0.44-0.54 between high school enrollment rate and employment rate of teenagers across counties. In counties where a larger fraction of teenagers are employed, high school enrollment rate is significantly lower.

This negative correlation is significantly lower (0.46) if we restrict our sample to teenagers in agricultural households relative to the correlation based on the entire sample of teenagers (0.54). This suggests that employment in agriculture does not hinder school enrollment as much as employment in the non-agricultural sectors. A potential explanation for this is that teenagers in agricultural households are more likely to work on family farms with a flexible schedule which would allow them to attend school. Outside agriculture (in sectors such as manufacturing or services), teenagers are more likely to be employed outside family business which would mean they have to choose either education or work if flexible working condition is not available. Overall, the correlations presented in Table 2 suggest that labor market participation significantly hinders high school enrollment of teenagers aged 15-19.

3.5 The effect of the subsidy

We now present our main results on the effect of the subsidy on agricultural mechanization, employment and high school enrollment in Table 3. The table shows the coefficients of dynamic effects estimated from equation 1.

Column 1 of the table presents the dynamic effects of subsidy on the stock of agricultural machines (measured in log units). It shows that the effect of the subsidy on the stock of agricultural machine is insignificant in the first year but becomes statistically significant starting from second year of admission to the subsidy program. The effect gradually increases over time, peaking at 11% increase in the stock of agricultural machines five years after a county's first admission to the program. This increasing effect could be attributed to the fact that the scope of the agricultural machines covered under the subsidy and eligibility of farmers to the subsidy program continuously evolved and expanded over years following the program's first commencement.

Column 2 of Table 3 reports the effect of the subsidy on teenagers' employment rate. The results show that the effect of subsidy is weak and even positive in the first few years. However, the effect becomes negative and statistically significant three years after a county's first admission to the subsidy program. The negative effect on employment reaches its peak in the fourth and fifth year after treatment where teenage employment decreases by 6 percentage points in counties admitted to the subsidy program relative to the control group. Again, the increasing effect of the subsidy over years could be attributed to the expansion of the program in its scope and coverage.

Together, the results in column 1 and column 2 imply that the subsidy program led to an increase in the adoption of agricultural machinery and reduced labor market participation of teenagers aged 15-19. These effects particularly become stronger over years after counties' first admission to the program as the program's scope and coverage of agricultural machines expanded.

Column 3 of Table 3 reports the effect of the subsidy on high school enrollment rate of teenagers. The effect on high school enrollment is positive and statistically significant starting from the year of treatment. However, the effect significantly increases over years since first treatment, reaching its peak fours years after a county's admission to the program where high school enrollment rate increases by over 10 percentage points. Notice that the effect of the subsidy program on employment kicks in later than the effect on high school enrollment. One explanation for this is that our employment rate measures only the extensive margin and not the intensive margin. In other words, we observe only if a child worked a positive hours and we do not observe how long the child worked. Hence, it is likely that during the initial years the subsidy program where the scope of the machines covered by the program is narrower, the program might have only reduced how long the teenagers worked without totally altering their employment status. As the scope and intensity of the subsidy grew overtime, it may affect employment status of teenagers as the machines fully replace teenage labor and teenagers abandon working altogether. In the meantime, the decrease in teenagers' hours of work at the early stage of the subsidy could be enough to induce moderate improvement in high school enrollment.

Parallel trend and no anticipation assumptions: The two key assumptions required for consistent estimation and inference of the model in equation 1 are the parallel trend assumption (PTA) and no anticipation effect assumption (NAEA). A typical approach to evaluate the validity of this assumptions is based on event-study plot. Figures 4-6 present the event-study plots for each of our outcome variables: the stock of agricultural machine, employment rate and high school enrollment rate, respectively.

To create the event study plot, we compare a cohort that turned 16 when its county enrolled into the subsidy program against up to five years older and up to five years younger cohorts born in the same county as well as cohorts born in other counties not yet treated. The regression includes county fixed effects, cohort/year fixed effects and prefecture-specific time trends. Standard errors are clustered at county level.

Figure 4 presents the event-study plot of the effect of the subsidy on the stock of agricultural machinery power. The figure clearly shows the subsidy program had null effect on the stock of agricultural power over the pre-treatment period. All the pre-treatment coefficients are very small in magnitude and statistically indistinguishable from zero which implies that both the PTA and NAEA hold strongly. Table A.1 presents the point estimates of all the pre-treatment coefficients and test statistics for their joint statistical significance. Column 1 of the table shows that all the pre-treatment period coefficients are statistically insignificant. The last two rows of the table also show that the F-statistics for the joint significance of pre-treatment coefficients is small and the null of joint significance is strongly rejected. Apart from this pre-treatment coefficients, the figure also shows significant positive effect of the program on the stock of agricultural machines highlighted in Table 3.

Figure 5 presents the event-study plot of the effect of the subsidy on employment status of teenagers. The figure shows that all the pre-treatment coefficients are individually statistically insignificant and are very close to zero, suggesting that both the PTA and NAEA hold. However, notice that joint test of the statistical significance of all the pre-treatment coefficients has an F-statistics of 4 which is large enough to reject the null. As we show below, this test statistics improves as we address potential endogeneity concern of the treatment rollout.

Figure 6 presents the event-study plot of the effect of the subsidy on high school enrollment rate of teenagers. In this figure, all the pre-treatment coefficient estimates are statistically insignificant and are very close to zero, suggesting that both the PTA and NAEA hold. The test-statistics for the joint significance of the pre-treatment coefficients is 2.16 which is relatively small and we fail to reject the null that PTA and NAEA hold at 5 percent significance level.

Overall, the results in Figures 4-6 and Table A.1 strongly suggest that both the PTA and NAEA hold. This is crucial in that the validity of the imputation approach suggested by Borusyak et al. (2024) critically relies on the validity of these two assumptions.

Discussion of the magnitude: To benchmark the magnitude of our estimation results, we compare our preferred estimates in table 3 against changes in the high school enrollment rate and employment rate of 15-19 year-olds presented in figure 1.

Using our estimates on the effect of the subsidy five years after first treatment, the estimates suggest that the subsidy program led to 9.6 ppts increase in high school enrollment rate. This suggests that the subsidy program alone accounts for roughly 25 percent of the increase in high school enrollment rate between 2000 and 2015. Similarly, our estimates in table 3 show that the subsidy program led to 6 ppts decrease in employment rate of teenagers, which accounts for about 20 percent of the decrease in employment rate between the 2000 and 2015 censuses. Given the fact that the vast majority of teenage employment was in the agricultural sector at the beginning of our sample period (see figure 1), we believe that our results give a reasonable estimate of the magnitude of effect of agricultural mechanization induced by the subsidy program.

4 Robustness exercises

4.1 Endogeneity concern

One concern in identification of the causal effect the subsidy program is that the rollout of the program may not be exogenous. Some of the concerns can be lessened by look at the pre-subsidy observable features of counties. Table A.3 presents pre-subsidy high school enrollment rate and employment rate of teenagers as well as share of employment in agricultural sector for counties that rolled into the subsidy program each year. We construct these statistics using averages across the four years 2000-2003 prior to the onset of the program. Across the three columns, there is no clear distinction across counties that received treatment in different years.[9] The counties seem to be comparable in their pre-treatment characteristics such as high school enrollment and employment rates of teenagers and agricultural employment share. In particular, counties that were selected into treatment early (the first two years) are not different from the rest of the counties.

However, authorities may favor counties that were already ahead in agricultural mechanization rate as this may signal improved success chance of the program. We find suggestive evidence that counties that received treatment earlier had higher agricultural mechanization rate prior to the commencement of the rollout program, compared to counties that received the subsidy during the latter years of the roll-out (see table 6). However, the mechanization rate of even these relatively more mechanized counties is very low prior to the subsidy program and these counties had similar agricultural employment share as the rest of the counties. The subsidy program was aimed at addressing the low mechanization rate.

[9] The only exception is that counties that received treatment in 2008 tend to have lower agricultural employment shares and higher high school employment rate.

Another plausible scenario is that counties that enjoy political favoritism may obtain the subsidies earlier than others. If the same counties also enjoy similar favoritism in other policies or resource allocation, our estimation results may capture the effect of such favoritism rather than the true effect of the machinery subsidy. To address the endogeneity concern, we use counties' exogenous productivity measure in major crops to construct predicted rollout of the subsidy program. Chinese government's primary goal in the subsidy program is to boost national food security by providing farmers with modern equipment and technology. Thus, it is likely that the program prioritized the most agriculturally productive counties at the beginning. We use GAEZ data (Fischer et al., 2021) to construct yield measure for each county for each of the main grains under the high input scenario and under two alternative farming techniques: rainfed and irrigation. We construct the counties' national ranking in their yield for maize, wheat, and rice. This gives us six different national rankings of a county, i.e., in rainfed-maize, irrigation-maize, rainfed-wheat, irrigation-wheat, rainfed-rice and irrigation-rice. Note that this rankings are time invariant because the underlying GAEZ data is time invariant. While the rankings across crops are positively correlated, they are not necessarily strongly correlated due to significant geographic variation in suitability to different crops and variation in farming techniques (rainfed vs irrigation). For instance, the southern counties are well suited to rice while the north eastern counties are more suited to wheat.

Next, we use a non-parametric method, random forest classification model, to predict the rollout of subsidy using the above rankings of counties. The model predicts the year when a county would receive the subsidy based on the county's national ranking in each of the above six rankings and choice of parameters (tree depth and leaf length). The procedure strongly predicts the rollout of the subsidy program.[10] This gives us predicted rollout, which is equivalent to the first-stage fitted value in 2SLS procedure. We then use this predicted rollout in our "second-stage" regression. A growing recent literature in econometrics explores the potential advantage of such non-parametric first-stage and application of machine learning techniques in prediction of the endogenous regressor based on exogenous IVs (see for instance Belloni et al. (2012) and Jat (2024)). The key advantage of the non-parametric first-stage is that they allow to predict the endogenous variable well without overfitting (Belloni et al., 2012).

Results: First, we present how our predicted rollout compares with the actual rollout in Table 4. Column 1 of the table shows the actual rollout. Column 2 shows the predicted rollout. Column 3 shows the success rate of our prediction, i.e., fraction

[10]This suggests that any concern of selection based on political favoritism or some other potentially non-exogenous criteria is minimal.

of counties that received the subsidy in a particular year that are also predicted to receive the subsidy in the same year based on their national yield rankings. Two points are worth highlighting. First, our procedure underpredicts the number of counties treated for all years except for 2008 when nearly 40% of the counties were treated. Second, prediction success rate in column 3 varies systematically based on the number of counties treated in a particular year. The inflated success rate for the year 2008 is because our model predicts over 200 more counties to have received the treatment than the number of counties actually treated. In other words, 99% of counties that received treatment in 2008 are predicted to receive treatment in the same year, but the rate of false positive is also significant in that about 20% of the counties that are predicted to receive treatment in 2008 actually received the treatment in a different year. Such false positive is minimal for other years. The above comparison of the predicted rollout to the actual rollout is equivalent to assessment of the relevance of IV using the strength of first-stage regression in 2SLS. Because our predicted rollout closely mimics the actual rollout, this suggests a strong first-stage.

We now present our "second-stage" estimation results based on the predicted rollout in Table 5. Column 1 of the table shows a persistent and positive effect of the subsidy on agricultural mechanization rate. The effect peaks three years after a county's admission to the program where agricultural mechanization increases by 15.2 ppts, and decreases afterwards. Column 2 of the table shows the subsidy program has muted effect on employment over the first two years but the effect turns negative and become stronger starting from two years after treatment culminating at 6 ppts reduction in employment rate four years after treatment. Column 3 presents the effect on high school enrollment rate. The effect on high school enrollment is positive and statistically significant starting from the year of first treatment and becomes stronger over time.

Overall, the results in Table 5 are largely in line with our baseline results in Table 3. However, there are some notable differences regarding the effect on agricultural mechanization in column 1 and the effect on high school enrollment in column 3. Our IV estimation result shows stronger effect of the subsidy program on agricultural mechanization compared to our baseline result though it shows a smaller effect on high school enrollment compared to our baseline result. A potential explanation for the stronger effect on agricultural mechanization in the IV estimation is that the subsidy rollout might have favored counties which had headstart in agricultural mechanization. Table 6 shows that the subsidy rollout varies systematically with counties' agricultural mechanization rate in 2000. Counties that received the subsidy in 2004-2006 generally had significantly higher mechanization rate in 2000 than counties that received the subsidy later. As a result, the marginal gain from agricultural mechanization due to the subsidy is likely smaller in these counties. Hence, our estimation result based on actual rollout of the subsidy may underestimate the causal effect of the subsidy program. In this sense, our estimation results based on the predicted rollout might be viewed as correcting for this downward bias.[11]

4.2 Prefecture-level analysis

One issue in our county-level analysis is that our measurement of high school enrollment rate and employment rate of teenagers aged 15-19 is based on small sample sizes. As a robustness exercise to our baseline analysis, we estimate the effect of agricultural mechanization using prefecture level variation.

The key difference in our prefecture level analysis is that we can no longer use the rollout of the subsidy program as a source of variation because this policy was conducted at county level, and counties that received subsidy during a given year are often not in the same prefecture. Instead, our prefecture analysis uses variation in the stock of agricultural machineries across prefectures and over time. This robustness exercise also offers two additional benefits. First, it allows us to investigate if our results based on the subsidy program can be replicated using an alternative source of variation in agricultural mechanization. Second, it accounts for variation in treatment intensity over time since a continuous measure of mechanization is used.

To address potential endogeneity problem, we construct a plausibly exogenous shift-share type instrumental variable for agricultural mechanization rates across prefectures and years. The instrument is constructed from agricultural machines subsidy disbursements over years and pre-subsidy variation in the stock of agricultural machines across prefectures.

The results from our prefecture-level analysis, reported in appendix B in more details, strongly complement our main results. We find strong evidence showing positive effect on high school enrollment and negative effect on employment rate of teenagers. Moreover, the magnitudes of the estimated effects are broadly consistent with our county-level estimates.

[11]Intuitively, counties that received the treatment in a given year but are predicted to receive the treatment in later year based on their rankings in the crop yields have probably been favored in some other criteria which may not be exogenous. By using predicted rollout based on exogenous factors (GAEZ crop yields), instead of the actual rollout, our procedure attempts to correct for the selection based on these other criteria that may not be exogenous.

5 Theoretical model

In this section we outline a simple theoretical mechanism that could generate our empirical findings on the causal relationship between agricultural mechanization and teenagers' labor supply and high school enrollment and provide supporting empirical evidence that validate these mechanisms.

5.1 Main model

Our theoretical model builds on the seminal paper by Basu and Van (1998). We adopt the conventional view in the literature that teenage labor exists because parents are compelled to send their teenagers to work to cope with poverty. If parents' income is large enough to provide some threshold level of living standard to the family, parents would not send their teenagers to work. Instead they send them to school. That is, teenagers' leisure or school is a luxury good in household's utility. This is consistent with the fact that teenagers from non-poor households in poor countries rarely work.[12]

The household utility function takes the following Stone-Geary form:[13]

$$U = (C - c)E \tag{2}$$

where C is household consumption, c is exogenous minimum subsistence consumption ($C \geq c$); and E is the number of teenagers in education ($0 \leq E \leq n_c$) where n_c is exogenous number of teenagers per household.

For later use, we also define the following notations. $L_c^h = n_c - E$ is teenage labor per household, N is exogenous number of households, $L_c = NL_c^h$ is total teenage labor in the economy, and $L_a = N$ is total adult labor (i.e., following Basu and Van (1998), we assume that adults always work). However, teenagers work only if income generated by adults falls short of the minimum required consumption c.

Basu and Van (1998) treat households as *pure* laborers. We depart from this characterization of households because in our context farm households not only earn labor income but may also receive profit from their farms. In our baseline model, we assume that all households are land-owners and thus potentially receive farm profit. Almost all rural households in China are landholders due to the legacy of communist land rationing, with average landholding of 0.6 hectares.[14] Household consumption

[12] See Basu and Van (1998) and Basu (2001) for detailed justification of this view about child labor.

[13] The advantage of this preference function is that with CRS technology, the income and substitution effects of capital subsidy do not fully cancel out as in, for instance, log linear utility with $c = 0$.

[14] As an extension of the model, later we consider heterogeneity across households where a fraction of households are land-less laborers with no other income while the remaining fraction own land

is given by:

$$C = w_a + w_c(n_c - E) + R \tag{3}$$

where w_a is adult wage, w_c is child wage and $R = \pi/N$ is redistributed profit per household. Note that because households are ex-ante identical, each household's profit income is equivalent to aggregate profit divided by number of households.

We assume that households own and operate their land as businesses. They produce a homogeneous good and we normalize its price. We assume that their decision as households and as businesses are separable. That is, households act as utility maximizer as family and as profit maximizer as business, and these dual roles of the households are independent. Separability is a reasonable tractability assumption widely adopted in agricultural and development economics. To obtain tractability, we assume the farm production function (per unit of land) takes the following CRS CES form

$$Y = A\left[\delta K^{\rho} + (1-\delta)(N + \gamma L_c)^{\rho}\right]^{1/\rho} \tag{4}$$

where K is capital (endogenously chosen by firms), $A > 0$ is total factor productivity, $\delta \in (0,1)$ is capital share parameter, $\gamma \in (0,1)$ is teenage labor efficiency relative to adult labor, and $\sigma = \frac{1}{1-\rho}$ is elasticity of substitution. For latter use we define $L_e = N + \gamma L_c$ as effective unit of labor. Firms only care about the effective unit of labor and not about its composition.[15]

Note that $\sigma > 1$ or $\rho > 0$ implies that agricultural machines are substitute labor. Empirical observation of decrease in teenage labor suggests that either the agricultural machines are labor saving and/or the machines have significant income effect that parents no longer make their teenagers work on farms. In the context of smallholder farmers such as China, agricultural machines covered under the subsidy program (such as tractors, combine-harvesters, etc) are likely labor-saving. In other contexts where farmland is abundant, this may not be the case as machines can be used to expand farm areas towards fallowed lands, which may also increase the demand for labor.

The government provides an exogenous subsidy rate of s for annual costs of machineries. Profit, accounting for the subsidized capital cost, is:

$$\pi = Y - w_a N - w_c L_c - (1-s)rK \tag{5}$$

and receive farm profit in addition to labor income.

[15] While capital is typically treated as dynamic input in macroeconomic models, here we treat capital as variable input with annualized costs r.

Equilibrium

Households: Utility maximization yields the following teenage labor supply condition:

$$L_c = NL_c^h = N\left(\frac{w_c n_c - w_a - R + c}{2w_c}\right) \tag{6}$$

Thus teenage labor supply increases with child wage and decreases with adult wage and farm profit.

Firm optimization: As businesses, households choose the quantities of labor and capital to employ to maximize their farm profit, given wages, rental price of capital, subsidy, and technology.

The equilibrium values of key variables are given as follows:

1. **teenage labor (L_c)** (assuming interior solution):

$$L_c = \frac{N}{\gamma}\left[\frac{c}{A(1-\delta)}\left(\frac{1-\delta\left[\frac{A\delta}{(1-s)r}\right]^{\frac{\rho}{1-\rho}}}{(1-\delta)^{\frac{1}{\rho}}}\right)\left(\frac{A\delta}{(1-s)r}\right)^{\frac{\rho}{\rho-1}} - \frac{\gamma n_c\left(1-\delta\left[\frac{A\delta}{(1-s)r}\right]^{\frac{\rho}{1-\rho}}\right)}{\delta\left[\frac{A\delta}{(1-s)r}\right]^{\frac{\rho}{1-\rho}}} - 1\right] \tag{7}$$

2. **Capital (K)**:

$$K = Z\left[\frac{(1-\delta)\left[\frac{A\delta}{(1-s)r}\right]^{\frac{\rho}{1-\rho}}}{1-\delta\left[\frac{A\delta}{(1-s)r}\right]^{\frac{\rho}{1-\rho}}}\right]^{1/\rho} \tag{8}$$

where $Z = N + \gamma L_c$ (effective labor).

3. **Wages**:

$$w_a = A(1-\delta)Z^{\rho-1}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}}, \quad w_c = \gamma w_a \tag{9}$$

4. **Profit**:

$$\pi = Y - w_a N - w_c L_c - (1-s)rK \tag{10}$$

5. **Consumption**:

$$C = \frac{Y}{N} = \frac{A\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{1/\rho}}{N} \tag{11}$$

Proposition 1. *If agricultural machines are labor-saving ($\sigma > 1$), an increase in subsidy:*

1. *Increases adoption of agricultural machines:* $\frac{dK}{ds} > 0$
2. *Decreases teenage labor:* $\frac{dL_c}{ds} < 0$
3. *Increases teenage education enrollment:* $\frac{dE}{ds} > 0$

Proof. Proof is given in the Appendix C. □

5.2 Calibration and Numerical Exercise

To illustrate the theoretical mechanisms of the model, we perform a numerical calibration that anchors the economy to a specific baseline at $s = 0$. This ensures that differences in the transition paths are driven solely by the elasticity of substitution σ, rather than differing initial conditions. Details of the parameter choices for the calibration exercise are provided in appendix D. A key target in the choice of the parameter values is to obtain an economy in an initial state characterized by low capital intensity and binding consumption constraint (i.e., adult wage falls short of minimum consumption requirement so that teenage labor supply is high).

The effect of agricultural machine subsidy on teenage labor supply and school enrollment critically hinges on whether the machines substitute or complement labor, and the effect of the machines on household income. To illustrate this, we consider three alternative values of $\sigma \in \{0.7, 2, 4\}$. $\sigma = 0.7$ represents the case where the machines complement labor, $\sigma = 2$ represents the case of significant labor-saving and $\sigma = 4$ represents the case where machines are highly labor-saving. As we show below, the latter two cases closely mimic our estimation results for σ using IV and OLS estimations, respectively. We vary the subsidy level from 0 to 50%.[16] The results are presented in figure 7.

The top-left panel of this figure shows the effect of agricultural machine subsidies on employment rate of teenagers while top-right panel shows the corresponding effect on their high school enrollment. The figure shows that when machines complement labor ($\sigma = 0.7$), the effects on teenage labor supply and school enrollment are weaker. Any decrease in teenage labor and increase in school enrollment here is driven by strong enough income effect from rising marginal product of labor and farm income. This effect should outweigh the *substitution effect* triggered by the increase in wage, potentially increasing teenage labor supply.[17]

[16]This mimics the actual subsidy rates offered, which increased gradually and reached approximately 50% of the prices of the machines for tools such as large tractors.

[17]In other contexts, recent empirical studies on effect of expansion of non-labor-saving economic opportunities find decrease, not increase, in school enrollments. For instance, job opportunities from booming exports decreased child schooling in Mexico (Atkin, 2016) and while Shah and

When machines are labor-saving ($\sigma = 2 \quad \text{or} \quad 4$), the effect on teenage labor and school enrollment is stronger as the substitution and income effects reinforce each other. Wages and farm profits increase faster when machines are strongly labor-saving as shown in the bottom panels. The faster wage increase in this case is driven by shrinks in labor supply from teenagers. Because adult labor supply is inelastic in our model, adult wage income increases following wages. However, family labor income may not increase due to lost income from decrease in teenage labor. Nevertheless, strong increase in farm profit means household total income increases significantly.

A key takeaway from the numerical exercise is that, empirical observation of strong decrease in teenage employment and increase in their school enrollment implies that the machines are labor-saving and/or the machines raise household income significantly. On the contrary, muted response in teenage labor and high school enrollment is consistent with the case where the agricultural machines are complementary to labor and/or have no significant effect on income. Below, we examine these conditions empirically.

5.3 Elasticity of substitution between machines and labor

Our empirical investigation reveals that agricultural machine subsidies significantly decreased teenage labor supply. Our numerical exercise above suggests that our model reproduces this significant decrease in teenage labor supply when agricultural machines are strongly labor-saving ($\sigma >> 1$). A natural question here is whether the agricultural machines are indeed significantly labor-saving. We attempt to answer this question by estimating the magnitude of σ.

From equation 4, using $Z = N + \gamma L_c$ denote effective units of labor and w denote effective wage, we obtain the following equation by combining the FOCs for the choice of capital and effective units of labor: $\ln(K/Z) = 1/\sigma \ln w - 1/\sigma \ln(1-s)r$, which states that increases in wage rate raise capital-labor ratio. We estimate the following empirical counterpart of this equation using variation in agricultural wages:

$$\ln\left(\frac{K_{pt}}{Z_{pt}}\right) = \frac{1}{\sigma}\ln w_{pt} - \frac{1}{\sigma}\ln(1 - s_{pt})r + \varsigma_{pt}$$

where K is the stock of agricultural machines, Z is the agricultural employment and w measures average agricultural wage at prefecture level.[18] We instrument for wage

Steinberg (2017) find that positive rainfall shock reduce teenagers' school enrollment and increase their labor supply. In these cases, clearly the substitution effects dominate the (likely modest) income effects.

[18]We use prefecture-level variation, instead of county level, because we do not have county-level panel data on agricultural wage and exports. To utilize significant variation in wages and exports across prefectures, we estimate the above equation including province and year fixed effects.

using prefecture manufacturing exports. The exclusion restriction assumption is that prefecture-level manufacturing export booms affect capital-labor ratio in agriculture only via affecting local wages and drawing labor from agriculture to manufacturing. We replace the second term by the cumulative proportion of counties enrolled into the subsidy program within a prefecture across years.

Figure 8 presents the scatter plots of the the variations in our data. The top panel presents the correlation between log capital-labor ratio and log rural wage while the bottom panel presents the correlation between log rural wage and log exports (i.e. the first-stage regression). Both panels show fairly strong positive correlations. The estimation results are reported in Table 7. Column 1 reports OLS result and Column 2 reports the IV estimation result. The point estimate in column 1 implies $\hat{\sigma} = 3.7$. The concern with OLS estimation is reverse causality, i.e., migration of agricultural labor may cause increase in local agricultural wages. We mitigate this by using IV estimation in Column 2. The IV point estimate is double the OLS estimate and it implies $\hat{\sigma} = 1.85$. The scatter plot in figure 8 and the F-stat in Table 7 both suggest a strong instrument.

Overall, our estimation results suggest that agricultural machines are significantly labor-saving. Our theoretical model above suggests that this a necessary condition for the mechanization to decrease teenage labor and increase their high school enrollment.

5.4 Evidence on income effect

Our theoretical results suggest that adoption of agricultural technology would reduce teenage labor and increase school enrollment if it significantly raises household income so that households can afford subsistence consumption without the need to send their teenagers to work. We test if this key theoretical mechanism is at work by investigating the effect of the subsidy rollout on per-capita income of rural households. This income measure includes both wage income and income from farm business. Our theory suggests that agricultural mechanization raises both farm profit and wages (by increasing marginal product of labor).

Figure 9 presents event-study plot of the effect of subsidy rollout on per-capita income of rural residents (measured in Yuan). Per-capita income of rural residents increases by about 200 Yuan in the year of treatment. This effect increased over time, reaching over 600 Yuan (which is about 8 percent growth) four years after first treatment. The pre-treatment period effects are all close to zero and statistically insignificant. The formal test of the validity of parallel trend assumption gives F-stat of 1.21 for joint test of significance of pre-trend coefficients, with a p-value of 0.30. This suggests that the parallel trend assumption strongly holds.

In sum, the increase in per capita household income documented in Figure 9 suggests that the positive effect of subsidy rollout on farm profit (the *direct* income effect) dominates any potential decrease in labor demand and adult wage induced by labor-saving nature of the technology. This strong direct income effect thus explains why we find a decrease in teenage labor and an increase in high school enrollment following the subsidy program.

A downside of our rural income measure is that it does not separate wages and farm profit. To see the effect on wage income, we use prefecture-level data on share of wage income in the total income of rural households to construct the county-level wage income as $s^w_{pt} * \text{Totalincome}_{ct}$, where s^w_{pt} is share of wage income in prefecture p's rural household income and is rural household total per capita income, and Totalincome_{ct} is total per capital income for rural households in county c. To construct our measure of s^w_{pt} we digitize Provincial Yearbooks for the year 2000-2012 from which we construct average income of farm households disaggregated into wage income and farm profit. The assumption we are making here is that the share of wage income in the total household income is the same for counties within a prefecture.

Figure 10 presents the event plot result on log wage. The results show that the subsidy has a muted effect on wage income in the first two years. However, the effect on wage becomes stronger over time, reaching about 10% increase five years after enrollment of a county to the subsidy program. However, this result should be cautiously interpreted in view the way the wage data is constructed.

Overall, this relatively modest effect on agricultural wage suggests weaker substitution effect. Hence, the strong positive effect on household income suggests that the decrease in teenage labor and increase in high school enrollment is driven by stronger income effect.

6 Conclusions

In developing countries where teenage labor is widely used in agricultural sector, agricultural mechanization may reduce the demand for teenage labor. This decrease in demand for teenage labor would allow teenagers to acquire more years of schooling if the teenage labor is not channeled to other sectors such manufacturing or services or domestic chores.

In this paper we use staggered rollout of subsidy to agricultural machine purchase across Chinese counties and successive census data to provide strong and robust evidence that agricultural mechanization reduces employment rate of 15-19 year-olds and increases their high school enrollment rate. We outline a theoretical model that generates these outcomes if agricultural machines are significantly labor-saving and have strong positive effect on household income. We provide empirical evidence in support of both these conditions.

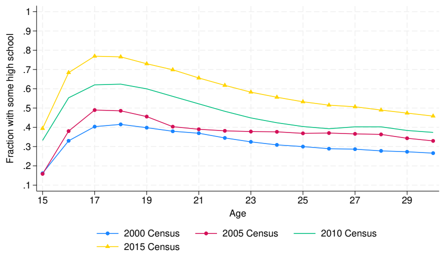
Overall, our results in this paper inform policy makers on teenage labor and human capital development. For instance, subsidies to agricultural machine purchase may have spillover effect on human capital development if they are targeted towards households with school-age teenagers. Such policies could be more effective than teenage labor laws in reducing teenage labor use, particularly in agricultural sector where the practice is most common.

Future studies investigating the effect of agricultural mechanization on teenagers' performance such as absenteeism, grade achievements and long-term outcomes would further our understanding of the effectiveness of labor-saving technologies on teenagers' short- and long-term outcomes.

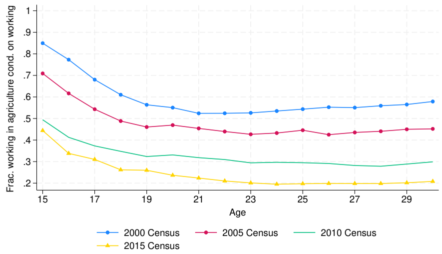
Figures

Figure 1: High school enrollment, employment and the stock of agricultural machine

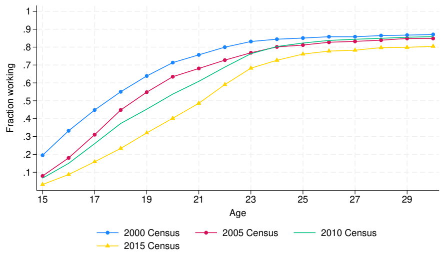
(a) Fraction with some high school education



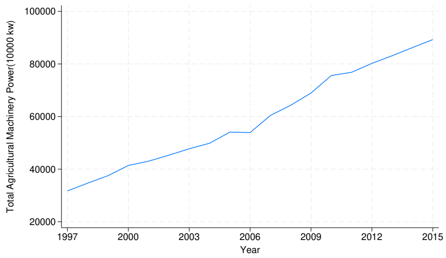
(c) Employment in agriculture conditional on employment



(b) Employment rate

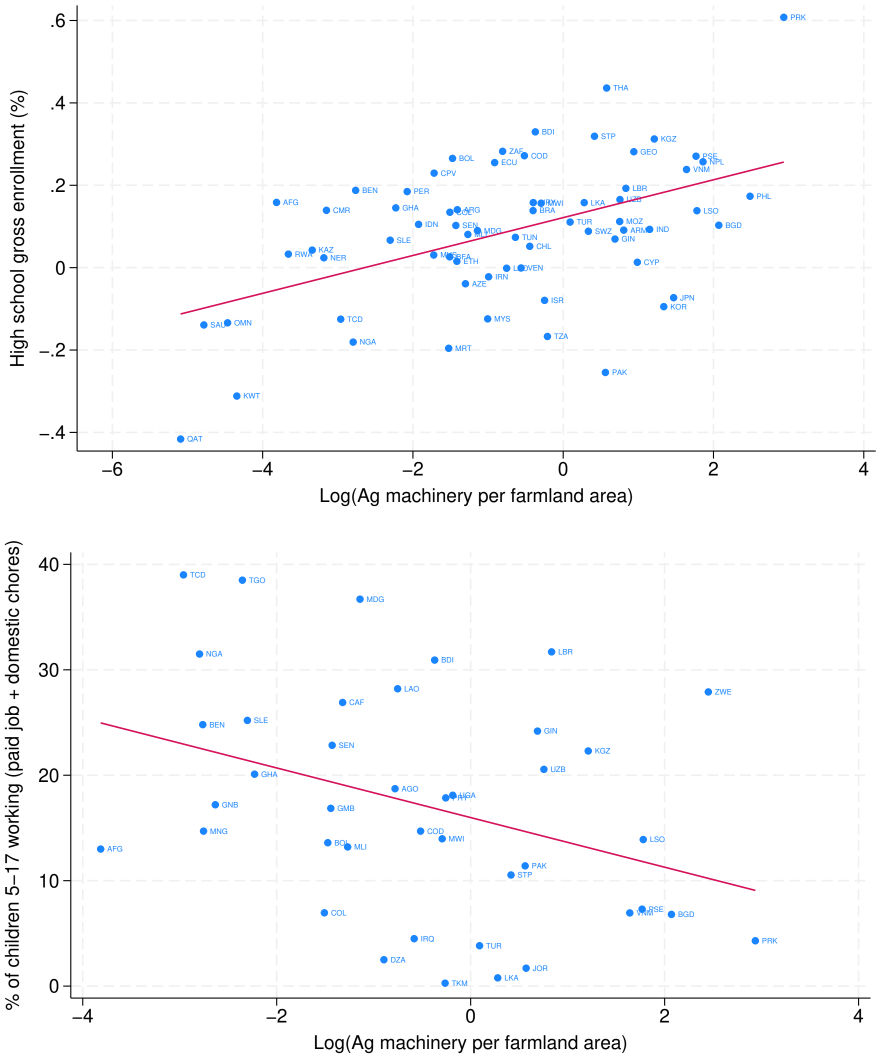


(d) Total agricultural machine stocks over time



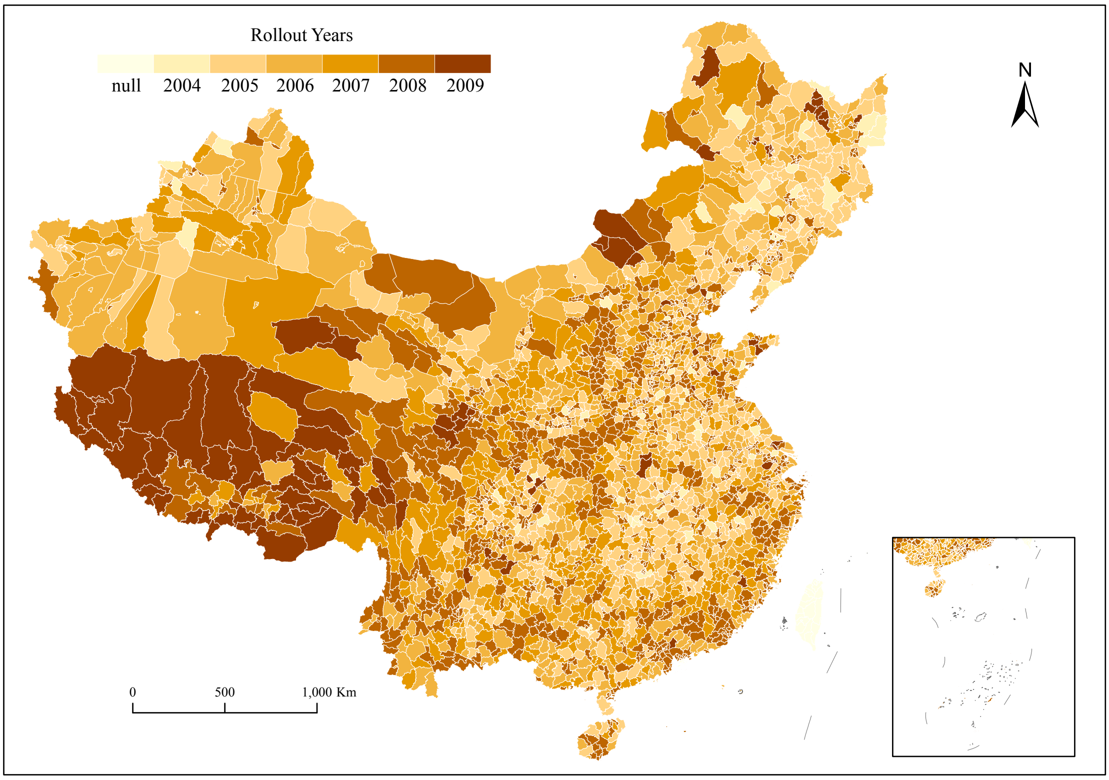
Notes: Panel (a) presents fraction of people aged 15-30 with some high school education, including those enrolled in school across censuses. Panel (b) presents fraction of people 15-30 employed by age across censuses. Panel (c) presents the fraction of those who work who are employed in the primary sector across censuses. Panel (d) This figure presents total agricultural machine power (in 10,000KW) over time.

Figure 2: Agricultural machinery, teenage labor, and high school enrollment across countries



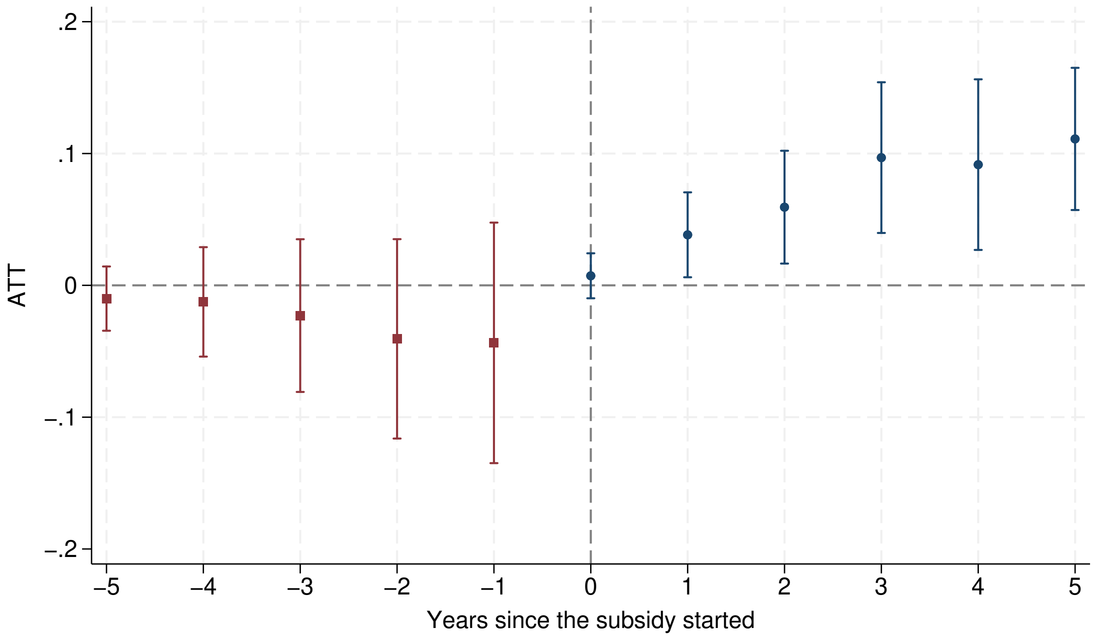
Notes: This figure presents the correlation between log of agricultural machine power (measured in horse powers per hectare of farmland) on one hand and gross high school enrollment and percentage of teenagers aged 5-17 working (paid job and domestic chores). In the first panel, we use residuals from regression of log of agricultural machine power and gross high school enrollment on log GDP per capita and log population size, and plot the correlation based data in 2015. In the second panel, we plot most recently available data on percentage of teenagers aged 5-17 working (paid job and domestic chores) against the above mentioned residual for log of agricultural machine power for the year 2015. In all graphs, we include countries in Africa, Asia and Latin America only. Note that some countries do not have teenage labor data.

Figure 3: Rollout of subsidy program



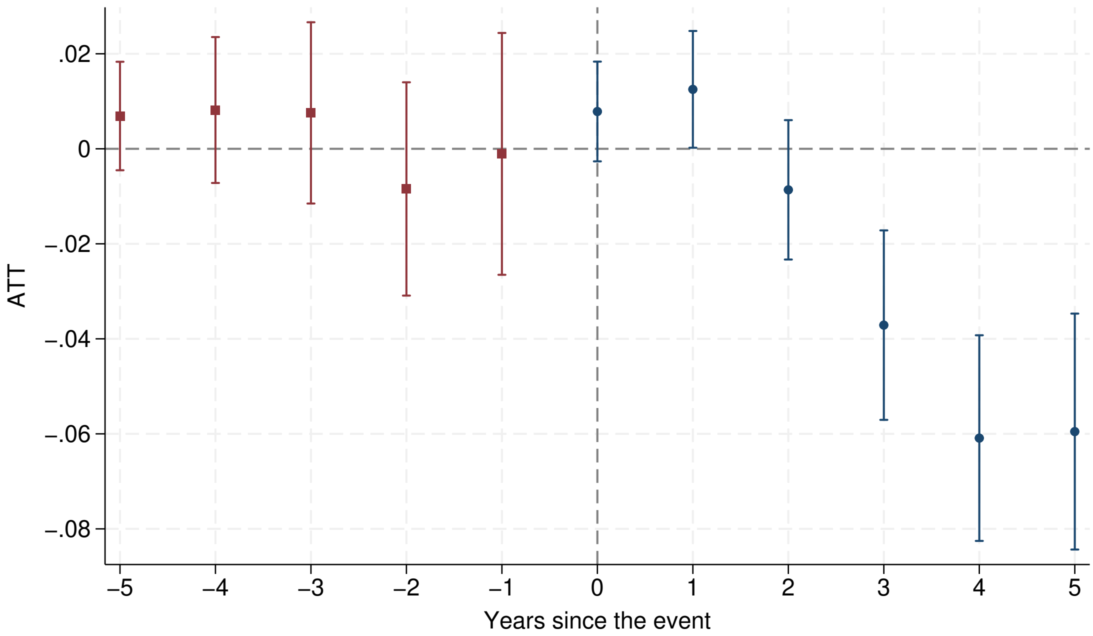
Notes: This figure presents the rollout of the agricultural machineries subsidy program over the 2004-2009 period.

Figure 4: The effect of subsidy on agricultural machine stock (in log units)



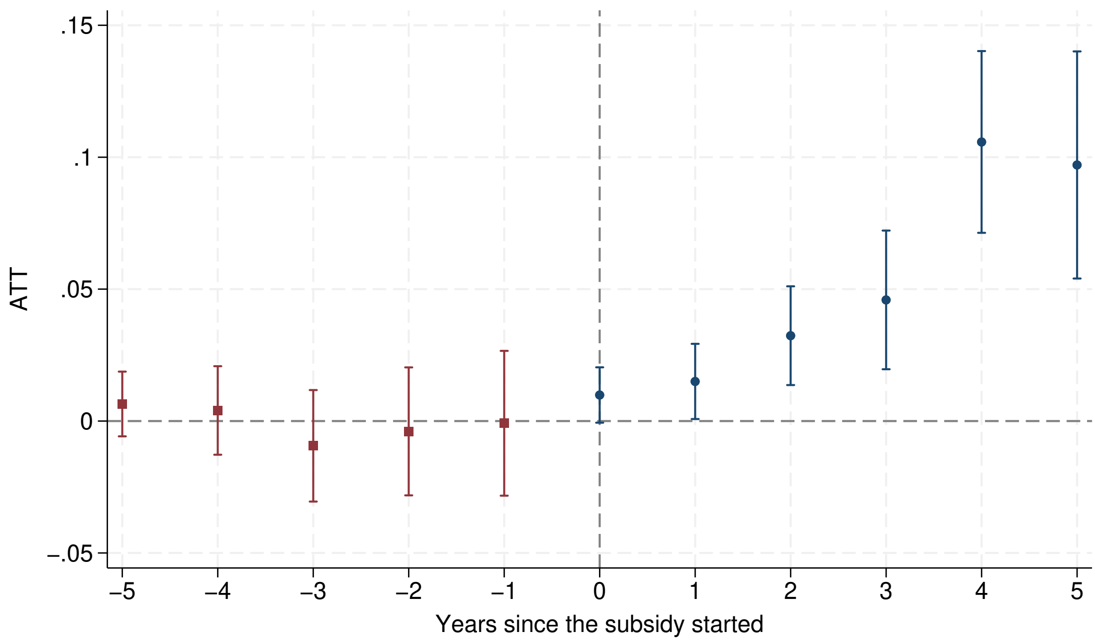
Notes: This figure presents event plot of the effect of the subsidy rollout on the stock of agricultural machine (measured in log units). To create the event study plot, we allow each county has five years of pre-treatment period and six years of post-treatment period. The regression includes county fixed effects, year fixed effects and prefecture-specific time trends. Standard errors are clustered at county level.

Figure 5: The effect of subsidy on teenage employment rate: event plot



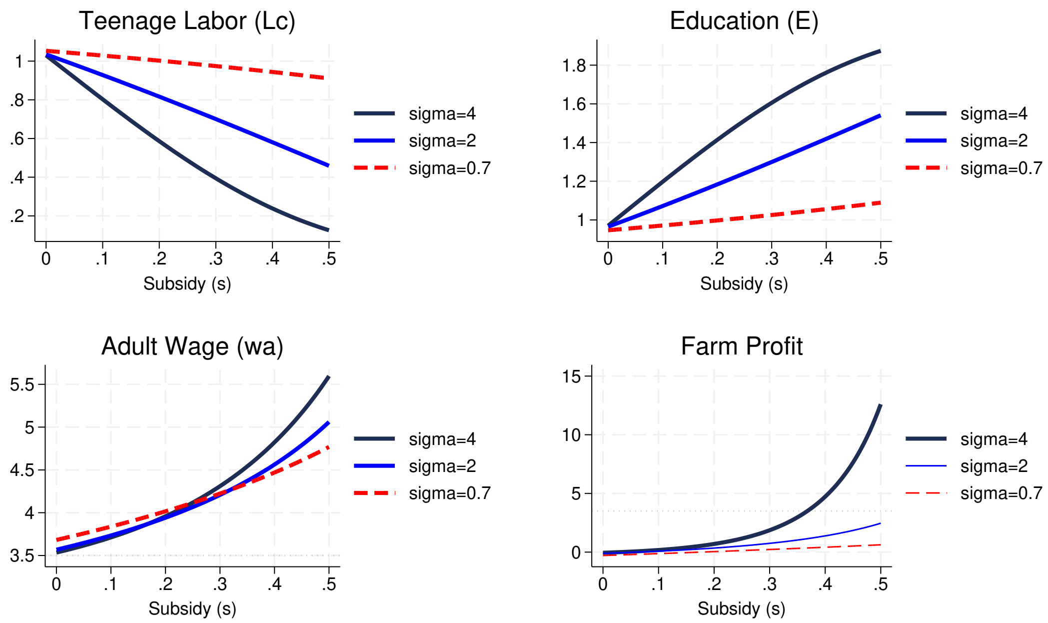
Notes: This figure presents event plot of the effect of the subsidy rollout on teenage employment rate. To create the event study plot, we compare a cohort that turned 16 when its county enrolled into the subsidy program against up to five years older and up to five years younger cohorts born in the same county as well as cohorts born in other counties not yet treated. The regression includes county fixed effects, cohort/year fixed effects and prefecture-specific time trends. Standard errors are clustered at county level.

Figure 6: The effect of subsidy on high school enrollment rate



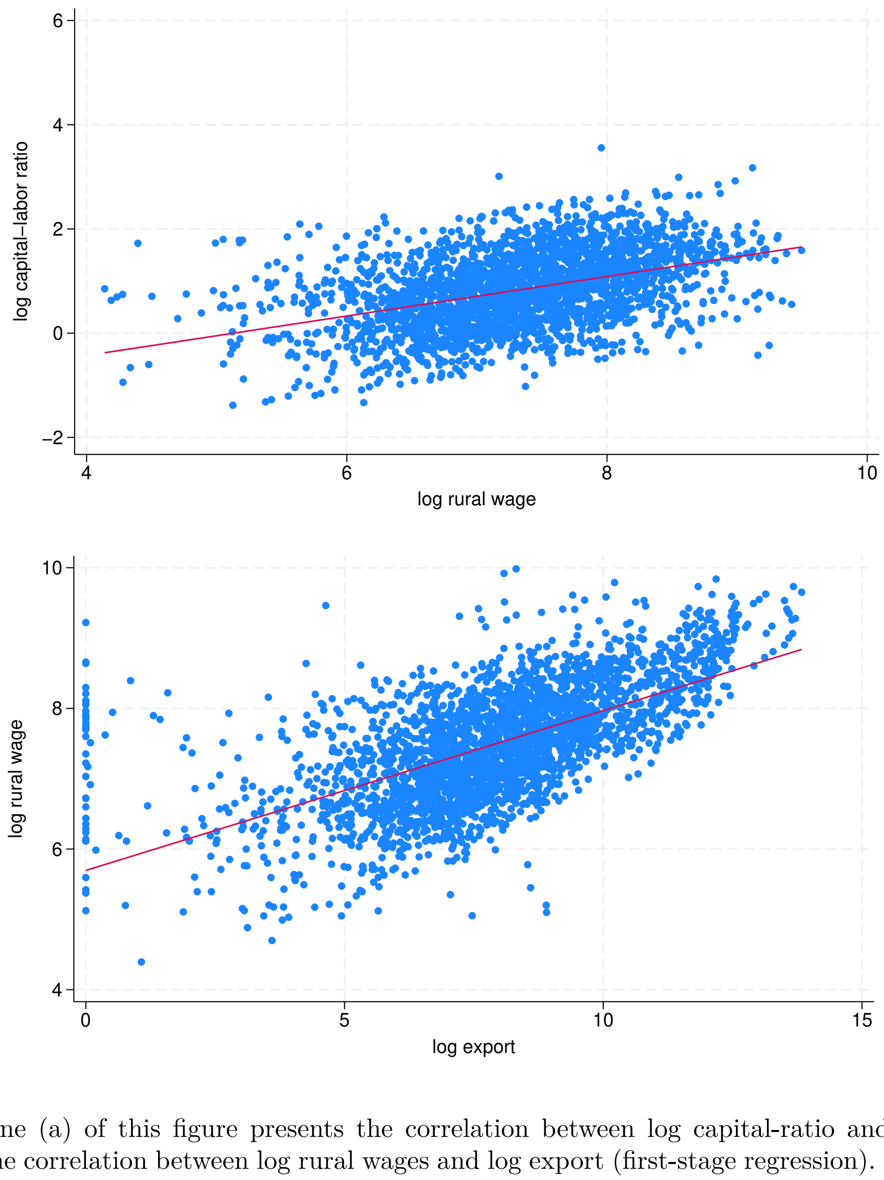
Notes: This figure presents event plot of the effect of the subsidy rollout on high school enrollment. To create the event study plot, we compare a cohort that turned 16 when its county enrolled into the subsidy program against up to five years older and up to five years younger cohorts born in the same county as well as cohorts born in other counties not yet treated. The regression includes county fixed effects, cohort/year fixed effects and prefecture-specific time trends. Standard errors are clustered at county level.

Figure 7: Numerical exercise: the effect of agricultural machine subsidy



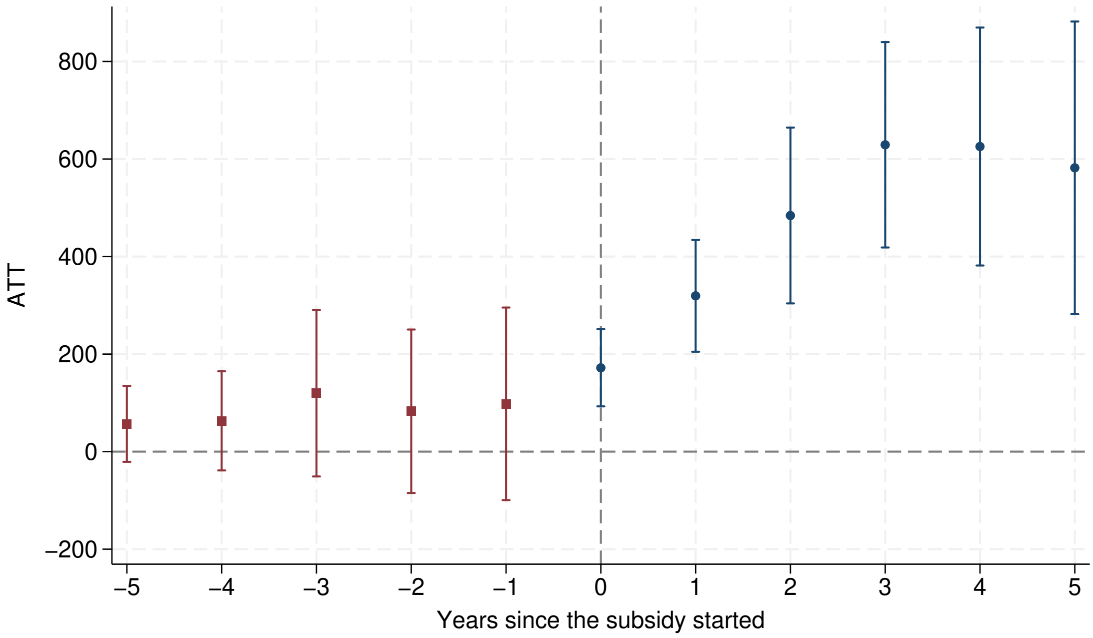
Notes: This figure presents the effect of agricultural machine subsidy on equilibrium values of teenage labor supply, school enrollment, adult wage and farm profit for different values of elasticity of substitution between agricultural machines and labor.

Figure 8: Estimation of elasticity of substitution between agricultural machines and farm labor



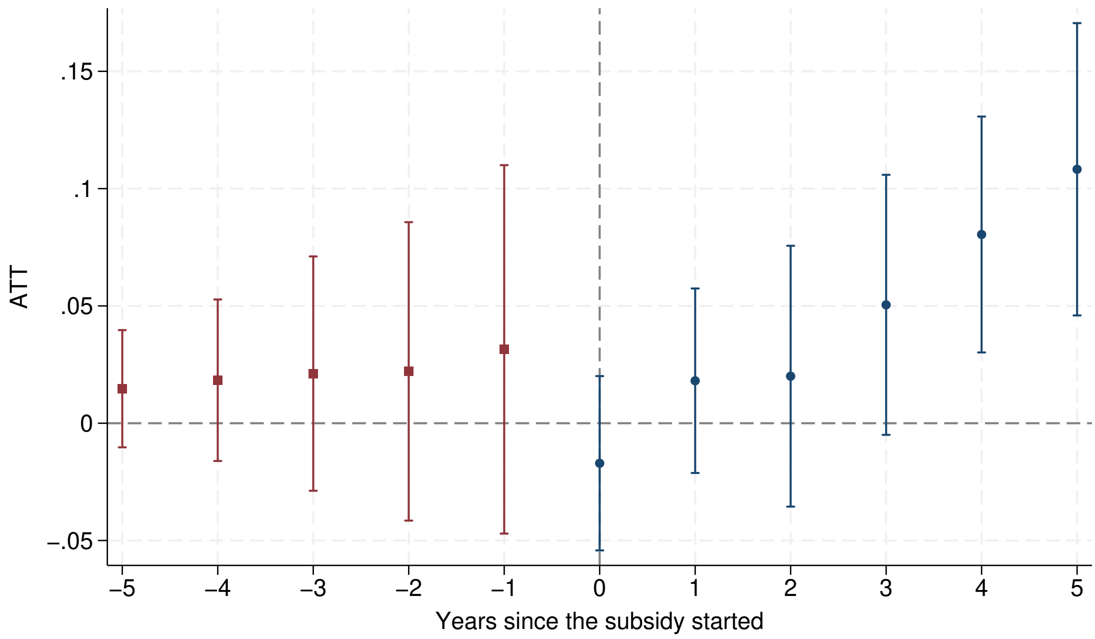
Notes: Pane (a) of this figure presents the correlation between log capital-ratio and Panel (b) presents the correlation between log rural wages and log export (first-stage regression). Prefecture-level panel data for the period 2000-2012 is used to plot the graphs.

Figure 9: The effect of subsidy on per-capita income of rural residents (measured in Yuan): event plot



Notes: This figure presents event plot of the effect of the subsidy rollout on per-capita income of rural residents (measured in Yuan). To create the event study plot, we allow each county has five years of pre-treatment period and six years of post-treatment period. The regression includes county fixed effects, year fixed effects and prefecture-specific time trends. Standard errors are clustered at county level.

Figure 10: The effect of subsidy on log wage income of rural residents: event plot



Notes: This figure presents event plot of the effect of the subsidy rollout on wage income of rural residents. To create the event study plot, we allow each county has five years of pre-treatment period and six years of post-treatment period. The regression includes county fixed effects, year fixed effects and prefecture-specific time trends. Standard errors are clustered at county level.

Tables

Table 1: Summary statistics

	(1) Mean	(2) S.d
Log agricultural machine	2.94	1.09
High school enrollment (both gender)	0.48	0.29
High school enrollment (boys)	0.47	0.32
High school enrollment (girls)	0.49	0.33
Employment rate (both gender)	0.30	0.27
Employment rate (boys)	0.31	0.29
Employment rate (girls)	0.30	0.30
Cohort size (both gender)	29.60	47.21
Cohort size (boys)	15.27	21.80
Cohort size (girls)	14.33	26.87

Notes: This table presents summary statistics of log agricultural machine stocks, high school enrollment rate, employment rate, and cohort sizes across counties. The enrollment rate, employment rates and cohort sizes are based on teenagers aged 15-19 in the 2000 and 2010 censuses and 2005 and 2015 mini-censuses.

Table 2: Correlation between high school enrollment and teenage employment

	(1) Both gender	(2) Boys	(3) Girls
	Panel A: All sample		
Fraction working	-0.528***	-0.538***	-0.510***
	(0.009)	(0.009)	(0.009)
N	35694	34306	33766
R^2	0.719	0.633	0.623
	Panel B: Agrarian households		
Fraction working	-0.464***	-0.465***	-0.443***
	(0.010)	(0.009)	(0.008)
N	32426	32426	32426
R^2	0.598	0.521	0.515

Notes: The dependent variable is fraction with high school education. All regressions include county and cohort fixed effects and province-specific time trends. Standard errors are clustered at county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: The dynamic effects of agricultural machine subsidy on agricultural mechanization, teenage employment and high school enrollment

	Agricultural Mechanization	Employment	High school enrollment
τ_0	0.007	0.008	0.010*
	(0.009)	(0.005)	(0.005)
τ_1	0.038**	0.013**	0.015**
	(0.016)	(0.006)	(0.007)
τ_2	0.059***	-0.009	0.032***
	(0.022)	(0.007)	(0.010)
τ_3	0.097***	-0.037***	0.046***
	(0.029)	(0.010)	(0.013)
τ_4	0.092***	-0.061***	0.106***
	(0.033)	(0.011)	(0.018)
τ_5	0.111***	-0.060***	0.097***
	(0.028)	(0.013)	(0.022)
N	18933	23590	23285

Notes: All regressions include county and cohort fixed effects and province-specific time trends. Standard errors are clustered at county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Actual rollout, predicted rollout and successful prediction rate

Year	Actual rollout	Predicted rollout	Success rate
2004	60	35	0.55
2005	441	374	0.83
2006	631	575	0.89
2007	433	386	0.88
2008	1,092	1,298	0.99
2009	68	57	0.84
Total	2,725	2,725	0.91

Notes: The first column shows the actual rollout of the subsidy program. Column 2 shows the predicted rollout program based on counties' national rankings in maize, wheat and rice yield (both in rainfed and irrigation farming systems) using the random forest classification model. Column 3 gives proportion of counties that received the subsidy in the same year as predicted by the model.

Table 5: The dynamic effects of agricultural machine subsidy on agricultural mechanization, teenage employment and high school enrollment, second- stage regression using *predicted* rollout

	Agricultural Mechanization	Employment	High school enrollment
τ_0	0.021*	-0.002	0.016***
	(0.013)	(0.005)	(0.005)
τ_1	0.097***	-0.006	0.019***
	(0.023)	(0.006)	(0.007)
τ_2	0.138***	-0.039***	0.035***
	(0.027)	(0.006)	(0.007)
τ_3	0.152***	-0.034***	0.031***
	(0.030)	(0.006)	(0.008)
τ_4	0.114***	-0.062***	0.049***
	(0.033)	(0.006)	(0.009)
τ_5	0.075***	-0.051***	0.041***
	(0.029)	(0.007)	(0.010)
N	19273	31056	30727

Notes: All regressions include county and cohort fixed effects and province-specific time trends. Standard errors are clustered at county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Subsidy rollout and pre-subsidy agricultural mechanization rate

	(1)	(2)
Rollout year	Mean	Median
2004	39.23	30.00
2005	27.10	20.00
2006	28.78	18.00
2007	16.23	9.00
2008	15.68	8.00
2009	9.80	1.00

Notes: This table presents the relationship between the subsidy rollout program and counties' pre-subsidy agricultural mechanization rate. Columns 1 and 2 report the mean and median agricultural mechanization rate (total power of agricultural machinery in 10,000 watts) in the year 2000.

Table 7: Estimation of $1/\sigma$

	(1)	(2)
	OLS	2SLS
Log rural wage	0.269***	0.541***
	(0.027)	(0.044)
Province FE	Yes	Yes
Year FE	Yes	Yes
N	2431	2431
First-stage F-stat		299

Notes: This table presents results for estimation $1/\sigma$. The dependent variable is log capital-labor ratio, where capital is measured as the stock of agricultural machines and labor is total agricultural employment. Prefecture-level panel data for the period 2000-2012 is used for estimation.The second column reports an IV estimation result where average rural wage in a prefecture is instrumented for by the prefecture's exports.

Appendix A Appendix tables

Table A.1: The dynamic effects of agricultural machine subsidy on agricultural mechanization, teenage employment and high school enrollment: pre-treatment effects

	Agricultural Mechanization	Employment	High school enrollment
τ_{-1}	-0.044	-0.001	-0.001
	(0.047)	(0.013)	(0.014)
τ_{-2}	-0.041	-0.008	-0.004
	(0.039)	(0.011)	(0.012)
τ_{-3}	-0.023	0.008	-0.009
	(0.030)	(0.010)	(0.011)
τ_{-4}	-0.013	0.008	0.004
	(0.021)	(0.008)	(0.009)
τ_{-5}	-0.010	0.007	0.006
	(0.012)	(0.006)	(0.006)
N	18933	23590	23285
$F-stat$	0.96	4	2.16
$P-value$	0.44	0.001	0.056

Notes: All regressions include county and cohort fixed effects and province-specific time trends. Standard errors are clustered at county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: The dynamic effects of agricultural machine subsidy on agricultural mechanization, teenage employment and high school enrollment: pre-treatment effects for second- stage regression using predicted rollout

	Agricultural Mechanization	Employment	High school enrollment
τ_{-1}	-0.044	-0.001	-0.001
	(0.047)	(0.013)	(0.014)
τ_{-2}	-0.041	-0.008	-0.004
	(0.039)	(0.011)	(0.012)
τ_{-3}	-0.023	0.008	-0.009
	(0.030)	(0.010)	(0.011)
τ_{-4}	-0.013	0.008	0.004
	(0.021)	(0.008)	(0.009)
τ_{-5}	-0.010	0.007	0.006
	(0.012)	(0.006)	(0.006)
N	18933	23590	23285
$F - stat$	0.07	2.9	2.56
$P - value$	0.99	0.012	0.025

Notes: All regressions include county and cohort fixed effects and province-specific time trends. Standard errors are clustered at county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Pre-subsidy high school enrollment, employment and agricultural employment rate by rollout year

(1)	(2)	(3)	(4)
Rollout year	High school enrollment	Employment	Agri emp share
2004	0.24	0.27	0.67
2005	0.24	0.27	0.67
2006	0.24	0.29	0.67
2007	0.23	0.30	0.72
2008	0.36	0.28	0.52
2009	0.25	0.38	0.76

Notes: This table presents the relationship between the subsidy rollout program and counties' pre-subsidy characteristics of high school enrollment rate, employment rate, and agricultural employment share. We use average characteristics of counties for the pre-subsidy years 2000-2003.

Appendix B Prefecture-level analysis

One issue in our county-level analysis is that our measurement of high school enrollment rate and employment rate of teenagers aged 15-19 is based on small sample sizes. In particular, for a small fraction of county-cohort cells we had to rely on fewer than ten sample size to construct our measures. We try to mitigate potential issues with sample size by weighting our regressions by sample sizes used to construct our measures in each county-cohort cell.

As a robustness exercise to our baseline analysis, we estimate the effect of agricultural mechanization using prefecture level variation. Because a prefecture includes about eight counties on average, this resolves the small sample issue. The key difference in our prefecture level analysis is that we can no longer use the rollout of the subsidy program as a source of variation because this policy was conducted at county level, and counties that received subsidy during a given year are often not in the same prefecture. Instead, our prefecture analysis uses variation in the stock of agricultural machineries across prefectures and over time. This robustness exercise also offers two additional benefits. First, it allows us to investigate if our results based on the subsidy program can be replicated using an alternative source of variation in agricultural mechanization. Second, it accounts for variation in treatment intensity over time since a continuous measure of mechanization is used. Our estimation equation is written as follows:

$$y_{rt} = \beta_0 + \beta_1 m_{rt} + \mathbf{x}'_{rt}\delta + \gamma_v * t + \gamma_r + \gamma_t + \varepsilon_{rt} \tag{12}$$

where y_{rt} is outcome variable for prefecture r in year t which includes mainly secondary school enrollment and fraction of cohorts of teenagers working. m_{rt} measures log of agricultural mechanization rate in prefecture r in year t. We measure exposure to agricultural mechanization when a child is at age 16. Agricultural mechanization is measured by total agricultural machinery measured in 10,000 kilowatts. This includes all agricultural machines such as those used for ploughing, harvesting, threshing, pumping, etc aggregated together. γ_r and γ_t are prefecture and year fixed effects capturing, respectively, time-invariant prefecture features such as geographic location and year-specific factors affecting all prefectures. $\gamma_v * t$ represents province specific time trends, capturing differential trends across provinces. To increase statistical power, particularly for our age- and gender-specific regressions below, we use data from 1996-2015 for our analysis. We weight our regression by the number of observations used in the calculation of our outcome variables at the prefecture-cohort levels.

A challenge in estimating the causal effect of agricultural mechanization on teenage labor and school enrollment in equation 12 is that unobserved factors (such as expected future skill premium) could increase the demand for school enrollment, reducing the amount of teenage labor available for agriculture and forcing households to adopt machines. Similarly, unobserved policies that are directed towards increasing high school enrollment may also increase agricultural mechanization by creating labor shortage in agriculture. Overall, these factors would cause spurious positive correlation between high school enrollment and agricultural mechanization.

To address this identification challenge, we construct a plausibly exogenous variation to agricultural mechanization rates across prefectures and years driven by the agricultural machinery subsidy program. However, the subsidy allocation data is available at province level. We thus construct a "shift-share" type instrumental variable, where the "shifts" are province-level subsidies to agricultural mechanization (financed both by provincial and central governments) and the "shares" are each prefecture's share of agricultural machine stock in the nation at the start of our sample (1996) which also precedes the commencement of the subsidy program.

$$\text{IV}_{rt} = \text{MachineryShare}_{r,1996} \times \text{Log } (1{+}\text{Subsidy})_{vt} \tag{13}$$

where $\text{MachineryShare}_{r,1996}$ is the share of agricultural machine stock in China that existed in prefecture r in 1996. Subsidy_{vt} the total amount of subsidy disbursement in province v and year t by both provincial and central governments. The monetary value of the subsidy disbursements by both provincial and central governments increased dramatically over years since 2004. Prefectures that were ahead in the agricultural mechanization process generally received more subsidies than prefectures that had less mechanization to begin with. We find that our IV predicts growth in agricultural machine stock across prefectures. In the shift-share research design, Goldsmith-Pinkham et al. (2020) argue that exogeneity of "shares" ensures identification regardless of exogeneity of the shifts while Borusyak et al. (2021) show that exogeneity of the "shifts" alone yield identification, regardless of whether or not the "shares" are exogenous. In our setting, it is more plausible to assume that the shifts are exogenous because it is unlikely that variation in the machinery subsidy disbursements across provinces and years would affect high school enrollment across prefectures via other mechanism than decreasing the demand for agricultural labor or increasing farm profit in the prefectures.

Results: Table A.5 presents our main estimation result for the prefecture-level analysis. OLS results are reported in Panel A and IV results in Panel B. One log point increase in agricultural machine power (which is roughly equivalent to the increase in agricultural machine power in a median prefecture over our sample period) led to 2.5 percentage point increase in high school enrollment rate and 4 percentage point decrease in employment rate. The IV results in panel B show a stronger effect of agricultural mechanization on both high school enrollment and employment rate - one log point increase in agricultural mechanization causes increases in high school enrollment rate by 7.3 percentage points and decreases employment rate by 16.3 percentage points. The prefecture level results show no significant heterogeneity across gender though we detect heterogeneity across ages (see below).

Heterogeneity across gender and ages: One advantage of our prefecture level analysis is that it allows us to explore treatment heterogeneity across gender and age groups without worrying about smaller sample sizes when calculating high school enrollment and employment rates for each age group.

The results in Table A.5 show that there is no significant difference in the effect of agricultural mechanization across boys and girls. This is true for both the effect of mechanization on employment rate and on high school enrollment. We do not also find any systematic difference across boys and girls when we breakdown our samples by age (see Table A.6). While this is in contrast to Pinker (2018)'s recount of the U.S's experience during its early days of mechanization, it is not surprising in the context of modern China where gender gap in educational attainment is far less than historical gender gap in the early 20th century U.S.

Though we find that non-negligible fraction of 15 year-olds enroll in high school in our data, the vast majority of teenagers make decision to enroll in high school at the age of 16. Thus, it is expected that agricultural mechanization would have stronger effect on teenagers at this critical age than their younger or older cohorts. In Table A.6 we provide estimation results for each age group separately. Panel A reports the OLS results. It shows that the effect of agricultural mechanization is strongest for teenagers aged 16 and slightly smaller for those aged 17 and 18, while it is statistically insignificant for the 15- and 19-year-olds. The negative effect on employment rate follows similar trend, except that it is statistically significant for the 15-year-olds.

The IV results in Panel B of Table A.6 also show more or less similar trends. The negative employment effect is strongest for the 15-year-olds and significantly decreases with age. However, the positive effect on high school enrollment is strongest for 16-18 year-olds. Overall, both the OLS and IV estimation results in Table A.6 show that the effect of agricultural mechanization on employment and high school enrollment rates varies across age groups. The effect on employment rate tends to decrease with age while the effect on high school enrollment rate is particularly stronger for 16 or 17 year olds.

Table A.4: Correlation between high school education and teenage employment

	(1) Both gender	(2) Boys	(3) Girls
	Panel A: 16 year-olds		
Fraction working	-0.319***	-0.334***	-0.349***
	(0.059)	(0.055)	(0.054)
N	1321	1320	1320
R^2	0.927	0.903	0.902
	Panel B: 15-19 year-olds		
Fraction working	-0.469***	-0.488***	-0.434***
	(0.030)	(0.025)	(0.027)
N	6628	6619	6615
R^2	0.911	0.891	0.882

Notes: The dependent variable is fraction with high school education. All regressions include prefecture and cohort fixed effects. Standard errors are clustered at prefecture level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: The effect on high school education and labor market participation, prefecture level analysis (15-19 year-olds)

	Both Genders		Boys		Girls	
	(1) Frac. with High sch edu	(2) Frac. Working	(3) Frac. with High sch edu	(4) Frac. Working	(5) Frac. with High sch edu	(6) Frac. Working
	Panel A: OLS					
Log Ag.machinery	0.025***	-0.040***	0.029***	-0.044***	0.020***	-0.036***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)
N	6178	6178	6171	6177	6166	6177
	Panel B: IV $MachineryShare_{1996} \times Log(1 + Subsidy)$					
	High school	Working	High school	Working	High school	Working
Log Ag.machinery	0.073**	-0.163***	0.053**	-0.144***	0.088**	-0.182***
	(0.029)	(0.025)	(0.026)	(0.022)	(0.035)	(0.030)
N	5778	5778	5771	5777	5766	5777
First-stage F-stat	51	51	52	52	51	51

Notes: The estimation is based on prefecture-level unbalanced data of between 1996 and 2015. All regressions include pre and cohort fixed effects. Standard errors clustered at prefecture level are in parenthesis. $\text{MachineryShare}_{p,1996}$ the st agricultural machineries in prefecture p as a share of the national stock for the year 1996. Subsidy is subsidy (in 10,000 for purchase of agricultural machines by the province and central governments, and it varies at province-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: The effect on high school education and labor market participation, heterogeneity across ages

	Both Genders		Boys		Girls	
	(1) Frac. with High sch edu	(2) Frac. Working	(3) Frac. with High sch edu	(4) Frac. Working	(5) Frac. with High sch edu	(6) Frac. Working
			Panel A: OLS			
			Age 15			
Log Ag.machinery	-0.006	-0.084***	-0.005	-0.078***	-0.009	-0.092***
	(0.012)	(0.010)	(0.012)	(0.009)	(0.014)	(0.012)
N	1277	1277	1277	1277	1275	1276
			Age 16			
Log Ag.machinery	0.056***	-0.091***	0.058***	-0.097***	0.058***	-0.084***
	(0.015)	(0.012)	(0.016)	(0.011)	(0.017)	(0.017)
N	1276	1276	1275	1276	1275	1276
			Age 17			
Log Ag.machinery	0.048***	-0.064***	0.053***	-0.063***	0.037*	-0.061**
	(0.018)	(0.021)	(0.017)	(0.020)	(0.020)	(0.026)
N	1267	1267	1267	1267	1263	1267
			Age 18			
Log Ag.machinery	0.042***	-0.048***	0.040***	-0.055***	0.036**	-0.048**
	(0.014)	(0.015)	(0.014)	(0.016)	(0.015)	(0.020)
N	1251	1251	1246	1250	1249	1251
			Age 19			
Log Ag.machinery	-0.005	0.002	0.004	-0.005	-0.009	0.011
	(0.008)	(0.008)	(0.010)	(0.009)	(0.008)	(0.012)
N	1095	1095	1093	1095	1092	1095
			Panel B: IV $MachineryShare_{1996} \times Log(1 + Subsidy)$			
			Age 15			
Log Ag.machinery	-0.078	-0.225***	-0.115**	-0.193***	-0.058	-0.264***
	(0.063)	(0.039)	(0.055)	(0.036)	(0.066)	(0.048)
N	1193	1193	1193	1193	1191	1192
First-stage F-stat	20	20	21	21	18	18
			Age 16			
Log Ag.machinery	0.064*	-0.197***	0.064**	-0.184***	0.065	-0.203***
	(0.037)	(0.030)	(0.030)	(0.028)	(0.052)	(0.035)
N	1192	1192	1191	1192	1191	1192
First-stage F-stat	39	39	43	43	36	36
			Age 17			
Log Ag.machinery	0.105**	-0.152***	0.072	-0.122***	0.136**	-0.183***
	(0.052)	(0.027)	(0.048)	(0.024)	(0.057)	(0.034)
N	1183	1183	1183	1183	1179	1183
First-stage F-stat	43	43	42	42	43	43
			Age 18			
Log Ag.machinery	0.094***	-0.084***	0.073**	-0.084***	0.104**	-0.081**
	(0.032)	(0.021)	(0.032)	(0.024)	(0.052)	(0.038)
N	1167	1167	1162	1166	1165	1167
First-stage F-stat	65	65	64	64	67	67
			Age 19			
Log Ag.machinery	0.144	-0.019	0.168	-0.020	0.139	-0.041
	(0.132)	(0.068)	(0.114)	(0.056)	(0.167)	(0.094)
N	1021	1021	1019	1021	1018	1021
First-stage F-stat	2	2	3	3	2	2

Notes: The estimation is based on prefecture-level unbalanced data of between 1996 and 2015. All regressions include prefecture and cohort (census) fixed effects. Standard errors are clustered at Prefecture level. $MachineryShare_{p,1996}$ the stock of agricultural machineries in prefecture p as a share of the national stock for the year 1996. $Subsidy$ is subsidy (in 10,000RMB) for purchase of agricultural machines by the province and central governments, and it varies at province-year level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix C Theoretical results

A Derivation of equilibrium

Firm optimization: Wages are determined by marginal products from FOCs with respect to L_a and L_c:

$$w_a = \frac{\partial Y}{\partial L_a} = A(1-\delta)(N+\gamma L_c)^{\rho-1}\left[\delta K^\rho + (1-\delta)(N+\gamma L_c)^\rho\right]^{\frac{1-\rho}{\rho}} \tag{14}$$

$$w_c = \frac{\partial Y}{\partial L_c} = A(1-\delta)\gamma(N+\gamma L_c)^{\rho-1}\left[\delta K^\rho + (1-\delta)(N+\gamma L_c)^\rho\right]^{\frac{1-\rho}{\rho}} = \gamma w_a \tag{15}$$

The FOC with respect to K:

$$\frac{\partial \pi}{\partial K} = A\delta K^{\rho-1}\left[\delta K^\rho + (1-\delta)(N+\gamma L_c)^\rho\right]^{\frac{1-\rho}{\rho}} - (1-s)r = 0 \tag{16}$$

Substituting profit income into the teenage labor supply condition (Eq. 6):

$$L_c = N\left(\frac{\gamma w_a n_c - w_a - \frac{Y - w_a N - \gamma w_a L_c}{N} + c}{2\gamma w_a}\right) \tag{17}$$

which simplifies to

$$Y = Nc + w_a(Z - N\gamma n_c) \tag{18}$$

where $Z = N + \gamma L_c$ (effective labor).

Using Y and w_a from equations 14 in equation 18 we obtain:

$$A\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{1/\rho} = Nc + A(1-\delta)Z^{\rho-1}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}}(Z - N\gamma n_c) \tag{19}$$

Using the above expression for Z, the FOC for K (eq. 16) can be written as follows:

$$A\delta K^{\rho-1}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}} = (1-s)r \tag{20}$$

Equations 19 and 20 give system of equations to solve for equilibrium values of L_c and K. The attractive feature of our setup is that we obtain closed form solutions for the endogenous variables, which are given in the main paper.

B Proof of Proposition 1

Write the equilibrium conditions 19 and 20 in implicit form:

$$F_1(Z,K,s) = A\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{1/\rho} - Nc$$
$$- A(1-\delta)Z^{\rho-1}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}}(Z - N\gamma n_c) = 0 \quad (21)$$
$$F_2(Z,K,s) = A\delta K^{\rho-1}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}} - (1-s)r = 0 \quad (22)$$

Total differential:

$$\begin{bmatrix} \frac{\partial F_1}{\partial Z} & \frac{\partial F_1}{\partial K} \\ \frac{\partial F_2}{\partial Z} & \frac{\partial F_2}{\partial K} \end{bmatrix} \begin{bmatrix} dZ \\ dK \end{bmatrix} = - \begin{bmatrix} \frac{\partial F_1}{\partial s} \\ \frac{\partial F_2}{\partial s} \end{bmatrix} ds \quad (23)$$

Compute partial derivatives:

$$\frac{\partial F_1}{\partial Z} = A(1-\delta)Z^{\rho-1}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}}$$
$$- A(1-\delta)\Big[(\rho-1)Z^{\rho-2}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}}(Z - N\gamma n_c)$$
$$+ Z^{\rho-1}\left(\frac{1-\rho}{\rho}\right)\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-2\rho}{\rho}}(1-\delta)\rho Z^{\rho-1}(Z - N\gamma n_c)$$
$$+Z^{\rho-1}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}}\Big] > 0$$
$$\frac{\partial F_1}{\partial K} = A\delta K^{\rho-1}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}}$$
$$- A(1-\delta)Z^{\rho-1}\left(\frac{1-\rho}{\rho}\right)\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-2\rho}{\rho}}\delta\rho K^{\rho-1}(Z - N\gamma n_c) > 0$$
$$\frac{\partial F_2}{\partial Z} = A\delta K^{\rho-1}\left(\frac{1-\rho}{\rho}\right)\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-2\rho}{\rho}}(1-\delta)\rho Z^{\rho-1} > 0 (\text{if } \rho{>}0)$$
$$\frac{\partial F_2}{\partial K} = A\delta(\rho-1)K^{\rho-2}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}}$$
$$+ A\delta K^{\rho-1}\left(\frac{1-\rho}{\rho}\right)\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-2\rho}{\rho}}\delta\rho K^{\rho-1} < 0$$
$$\frac{\partial F_1}{\partial s} = 0$$
$$\frac{\partial F_2}{\partial s} = r > 0$$

Solving the system:

$$\begin{bmatrix} \frac{dZ}{ds} \\ \frac{dK}{ds} \end{bmatrix} = \begin{bmatrix} \frac{\partial F_1}{\partial Z} & \frac{\partial F_1}{\partial K} \\ \frac{\partial F_2}{\partial Z} & \frac{\partial F_2}{\partial K} \end{bmatrix}^{-1} \begin{bmatrix} -\frac{\partial F_1}{\partial s} \\ -\frac{\partial F_2}{\partial s} \end{bmatrix} \quad (24)$$

$$\begin{bmatrix} \frac{dZ}{ds} \\ \frac{dK}{ds} \end{bmatrix} = \frac{1}{\frac{\partial F_1}{\partial Z} * \frac{\partial F_2}{\partial K} - \frac{\partial F_1}{\partial K} * \frac{\partial F_2}{\partial Z}} \begin{bmatrix} \frac{\partial F_2}{\partial K} & -\frac{\partial F_1}{\partial K} \\ -\frac{\partial F_2}{\partial Z} & \frac{\partial F_1}{\partial Z} \end{bmatrix} \begin{bmatrix} -\frac{\partial F_1}{\partial s} \\ -\frac{\partial F_2}{\partial s} \end{bmatrix} \tag{25}$$

$$= \frac{1}{\frac{\partial F_1}{\partial Z} * \frac{\partial F_2}{\partial K} - \frac{\partial F_1}{\partial K} * \frac{\partial F_2}{\partial Z}} \begin{bmatrix} \frac{\partial F_2}{\partial K} & -\frac{\partial F_1}{\partial K} \\ -\frac{\partial F_2}{\partial Z} & \frac{\partial F_1}{\partial Z} \end{bmatrix} \begin{bmatrix} 0 \\ -r \end{bmatrix} \tag{26}$$

Given the signs of the partial derivatives, the determinant $\frac{\partial F_2}{\partial K} - \frac{\partial F_1}{\partial K}$ $- \frac{\partial F_2}{\partial Z}\frac{\partial F_1}{\partial Z}$ is negative when $\sigma > 1$. As a result $\frac{dZ}{ds} < 0$ and $\frac{dK}{ds} > 0$. Because $Z = N + \gamma L_c$ and $E = n_c - L_c$, we infer that $\frac{dL_c}{ds} < 0$ and $\frac{dE}{ds} > 0$.

C The case of heterogeneous households

We now consider an extension of our basic model to the case where there are two groups of households: land owners and land-less households. In the context of China almost all households owned land as is common in communist land allocation system. Suppose α fraction of the households are land owners, so that the agricultural land and farm profit is shared across these households equally. These households' income includes their labor income as well as the farm profit. The remaining $1 - \alpha$ fraction of the households are land-less laborers whose only income is labor income. This model nests the our main model discussed above when $\alpha = 1$.

In the current model, agricultural mechanization has different effects on the land owners and land-less households and their teenagers. Consider the case when $\sigma > 1$ (i.e., machines are labor saving) first. Under this case, agricultural mechanization has stronger income effect for the land owners because farmland and profit is shared among smaller number of households. The decrease in teenage labor is likely larger for these households. For the landless households, there is no *direct* income effect now. Furthermore, because the mechanization decreases wages by decreasing the demand for labor, labor supply by the adults alone may not be sufficient to achieve subsistence consumption. That is, the decrease in wage causes a strong *indirect income effect*. While the low wage discourages teenage labor, the negative indirect income effect may dominate, causing increase in teenage labor and decrease in school enrollment. When $\sigma < 1$, the effect of the subsidy on teenage labor supply for the landowners is again likely to be positive driven by the direct income effect. The effect on the landless households depends on how much wages increase in response to the mechanization. If wages rise sufficiently so that adult income is enough to meet the subsistence consumption, teenage labor may decrease. If the complementarity between machine and labor is weak (hence the wage increase is smaller), the subsidy could worsen teenage labor by encouraging them to join the labor market.

Detailed derivations of the extended model

Utility: For both household types utility is given by the same function:

$$U = (C - c)E \tag{27}$$

where $C \geq c$, $E \in [0, n_c]$, $L_c^h = n_c - E$, $L_c = NL_c^h$, $L_a = N$.

A fraction α of households are land owners (αN households). The remaining $(1-\alpha)N$ households are landless. The budget constraints for each type of household is given as:

$$C_1 = w_a + w_c(n_c - E_1) + \frac{\pi}{\alpha N} \quad \text{(landed)} \tag{28}$$

$$C_2 = w_a + w_c(n_c - E_2) \quad \text{(landless)} \tag{29}$$

where $\frac{\pi}{\alpha N} \equiv R$ is the profit share of a landowner household.

Household Optimization

- Landed:

$$E_1 = \frac{w_a + w_c n_c + R - c}{2w_c}, \quad L_{c1}^h = \frac{w_c n_c - w_a - R + c}{2w_c} \tag{30}$$

- Landless:

$$E_2 = \frac{w_a + w_c n_c - c}{2w_c}, \quad L_{c2}^h = \frac{w_c n_c - w_a + c}{2w_c} \tag{31}$$

Aggregate teenage labor:

$$L_c = \alpha N L_{c1}^h + (1-\alpha)N L_{c2}^h = \frac{N}{2w_c}\left[(w_c n_c - w_a + c) - \alpha R\right] \tag{32}$$

Aggregate education:

$$E = \alpha N E_1 + (1-\alpha)N E_2 = N n_c - L_c \tag{33}$$

Firm's problem The firm's problem is similar to the homogeneous household case, except that now there are only αN firms. The FOCs for profit maximization are thus the same as homogeneous firm case.

Equilibrium Conditions Substitute (32) into household budget:

$$2w_cL_c = N(w_cn_c - w_a + c) - (Y - w_aN - w_cL_c - (1-s)rK) \tag{34}$$
$$Y = Nc + w_aN + w_cL_c + (1-s)rK \tag{35}$$

Firm condition:

$$A\delta K^{\rho-1}\left[\delta K^{\rho} + (1-\delta)Z^{\rho}\right]^{\frac{1-\rho}{\rho}} = (1-s)r \tag{36}$$

where $Z = N + \gamma L_c$.

Comparative Statics: Rewriting the equilibrium conditions in 35 and 36 in implicit form we obtain:

$$F_1(Z,K,s) = A\left[\delta K^{\rho} + (1-\delta)Z^{\rho}\right]^{1/\rho} - Nc - A(1-\delta)Z^{\rho-1}\left[\delta K^{\rho} + (1-\delta)Z^{\rho}\right]^{\frac{1-\rho}{\rho}} Z - (1-s)rK = 0 \tag{37}$$

$$F_2(Z,K,s) = A\delta K^{\rho-1}\left[\delta K^{\rho} + (1-\delta)Z^{\rho}\right]^{\frac{1-\rho}{\rho}} - (1-s)r = 0 \tag{38}$$

Taking total differential:

$$\begin{bmatrix} \frac{\partial F_1}{\partial Z} & \frac{\partial F_1}{\partial K} \\ \frac{\partial F_2}{\partial Z} & \frac{\partial F_2}{\partial K} \end{bmatrix} \begin{bmatrix} dZ \\ dK \end{bmatrix} = -\begin{bmatrix} \frac{\partial F_1}{\partial s} \\ \frac{\partial F_2}{\partial s} \end{bmatrix} ds \tag{39}$$

Partial derivatives signs

- $\frac{\partial F_1}{\partial Z} = A(1-\delta)Z^{\rho-1}\left[\delta K^{\rho} + (1-\delta)Z^{\rho}\right]^{\frac{1-\rho}{\rho}} - A(1-\delta)\Big[(\rho-1)Z^{\rho-2}\left[\delta K^{\rho} + (1-\delta)Z^{\rho}\right]^{\frac{1-\rho}{\rho}} Z + Z^{\rho-1}($ 0
- $\frac{\partial F_1}{\partial K} = A\delta K^{\rho-1}\left[\delta K^{\rho} + (1-\delta)Z^{\rho}\right]^{\frac{1-\rho}{\rho}} - A(1-\delta)Z^{\rho-1}\left(\frac{1-\rho}{\rho}\right)\left[\delta K^{\rho} + (1-\delta)Z^{\rho}\right]^{\frac{1-2\rho}{\rho}} \delta\rho K^{\rho-1}Z - (1-s)r < 0$
- $\frac{\partial F_1}{\partial s} = rK > 0$
- $\frac{\partial F_2}{\partial Z} = A\delta K^{\rho-1}\left(\frac{1-\rho}{\rho}\right)\left[\delta K^{\rho} + (1-\delta)Z^{\rho}\right]^{\frac{1-2\rho}{\rho}}(1-\delta)\rho Z^{\rho-1}$ (negative for $\rho > 0$, positive for $\rho < 0$)
- $\frac{\partial F_2}{\partial K} = A\delta(\rho-1)K^{\rho-2}\left[\delta K^{\rho} + (1-\delta)Z^{\rho}\right]^{\frac{1-\rho}{\rho}} + A\delta K^{\rho-1}\left(\frac{1-\rho}{\rho}\right)\left[\delta K^{\rho} + (1-\delta)Z^{\rho}\right]^{\frac{1-2\rho}{\rho}} \delta\rho K^{\rho-1} < 0$
- $\frac{\partial F_2}{\partial s} = r > 0$

Determinant:

$$\text{Det} = \frac{\partial F_1}{\partial Z}\frac{\partial F_2}{\partial K} - \frac{\partial F_2}{\partial Z}\frac{\partial F_1}{\partial K} > 0 \tag{40}$$

Solutions

$$\frac{dZ}{ds} = \frac{-\left(\frac{\partial F_1}{\partial K}\frac{\partial F_2}{\partial s} - \frac{\partial F_2}{\partial K}\frac{\partial F_1}{\partial s}\right)}{\text{Det}} = \frac{r\left(K\left|\frac{\partial F_2}{\partial K}\right| - \left|\frac{\partial F_1}{\partial K}\right|\right)}{\text{Det}} < 0 \tag{41}$$

$$\frac{dK}{ds} = \frac{-\left(\frac{\partial F_1}{\partial s}\frac{\partial F_2}{\partial Z} - \frac{\partial F_2}{\partial s}\frac{\partial F_1}{\partial Z}\right)}{\text{Det}} = \frac{r\left(K\left|\frac{\partial F_2}{\partial Z}\right| + \frac{\partial F_1}{\partial Z}\right)}{\text{Det}} > 0 \tag{42}$$

$$\frac{dL_c}{ds} = \frac{1}{\gamma}\frac{dZ}{ds} \tag{43}$$

$$\frac{dE}{ds} = -\frac{dL_c}{ds} = -\frac{1}{\gamma}\frac{dZ}{ds} \tag{44}$$

In the above comparative statics, $\frac{dK}{ds} > 0$ is always positive, as higher s reduces capital cost, increasing K. For $\sigma > 1$: (i) $\frac{dZ}{ds} < 0$, $\frac{dL_c}{ds} < 0$: K substitutes for L_e, reducing L_c; and (ii) $\frac{dE}{ds} > 0$: education increases as L_c falls. For $\sigma < 1$: (i) $\frac{dZ}{ds} \gtrless 0$, $\frac{dL_c}{ds} \gtrless 0$: K complements L_e, potentially increasing L_c if substitution effect dominates income effect; and (ii) $\frac{dE}{ds} \gtrless 0$: opposite sign to L_c.

The key insight from the heterogeneous households case is that higher α weakens the per-household profit share R, reducing the income effects impact on L_c and E, making $\frac{dL_c}{ds}$ less negative and $\frac{dE}{ds}$ less positive for $\sigma > 1$, while amplifying ambiguity for $\sigma < 1$.

D Notes on Calibration and Numerical Exercise

To illustrate the theoretical mechanisms of the model, we perform a numerical calibration that anchors the economy to a specific baseline at $s = 0$. This ensures that differences in the transition paths are driven solely by the elasticity of substitution σ, rather than differing initial conditions.

E Choice of parameter values

The choice of parameters reflects a developing agricultural economy characterized by subsistence constraints and labor-intensive production:

- **Subsistence level ($\bar{c} = 4.5$):** We assume $\bar{c} > w_a$, implying that an adult's wage is insufficient to meet the household's minimum consumption needs. This reflects the "poverty trap" logic where child labor is a necessity for survival at the baseline.

- **Rental Rate of Capital ($r = 3.0$):** This is a relative price normalization set against the target wage ($w_0 = 3.5$). It ensures that while capital is accessible, the subsidy s provides a meaningful shift in the firm's cost structure.

- **Relative teenage productivity ($\gamma = 0.5$):** This assumes a teenager provides half the effective labor units of an adult, determining the opportunity cost of education in the household's budget constraint.

- **Initial capital-labor Ratio ($k_0 = 0.8$):** This parameter reflects the baseline level of mechanization. We choose a value below unity to characterize a labor-intensive agricultural sector where human and animal power still play a dominant role. From a numerical standpoint, setting k_0 at this moderate level is crucial; it ensures the model is sensitive enough to capture the *substitution effect*. If k_0 were set too high (a highly mechanized baseline), further subsidies would yield diminishing returns in labor displacement, whereas setting it too low would cause the farm productivity growth to mathematically drown out the wage-suppressing effects of capital adoption.

- **Number of adults ($N = 1$):** We normalize the household to a single adult decision-maker (or a single adult labor unit). This simplification allows us to focus on the marginal trade-offs of child labor supply relative to a fixed unit of adult labor, without loss of generality regarding household scale.

- **Number of teenagers ($n_c = 2$):** The choice of $n_c = 2$ represents a typical rural household size in the developmental context of the study. This value provides a sufficient "endowment" of potential child labor units to observe meaningful variation in the education-labor trade-off. When combined with the adult unit N, it establishes the maximum potential effective labor supply Z and anchors the subsistence requirement $\bar{c}$ relative to the household's total earning capacity.

- **Structural normalization:** A key challenge in the calibration is ensuring that for all values of σ, the equilibrium starts at the same origin when the subsidy $s = 0$. To achieve this, we treat the total factor productivity A and the capital weight δ as endogenous to the calibration target.

  For each σ, we solve for the unique pair of (A, δ) that satisfies the firm's first-order conditions for a pre-specified target wage w_0 and capital-labor ratio k_0. Specifically, we derive:

$$\delta(\sigma) = \frac{1}{1 + \frac{w_0}{r} k_0^{\rho-1}} \tag{45}$$

$$A(\sigma) = \frac{w_0}{(1-\delta)[\delta k_0^{\rho} + (1-\delta)]^{\frac{1-\rho}{\rho}}} \tag{46}$$

  where $\rho = \frac{\sigma-1}{\sigma}$. By anchoring the firm's marginal productivities at $s = 0$, we ensure that the household's initial labor supply L_c and farm profits π are numerically identical across all scenarios. This normalization allows for a clean visualization of how the elasticity of substitution dictates whether the responses of the endogenous variables to change in the subsidy.

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