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

Hundanol Kebede [*] Jianfeng Wu [†]

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Abstract

This study examines how subsidies for agricultural machinery impact high school enrollment among teenagers. We propose a model in which a subsidy to labor-saving agricultural machines could either increase teenage labor supply due to reduced adult wages or decrease teenage labor if farm profits increase significantly. Using rollout of a subsidy program across Chinese counties, we find that the subsidy led to more mechanization, higher farm profits, decreased teenage employment, and increased high school enrollment for 15-19-year-olds. Similar results were observed using global data from over 170 countries since 1980, indicating that the findings are broadly applicable.
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[†]China Center for Economic Studies & School of Economics, Fudan University. Jianfeng Wu thanks the National Natural Science Foundation of China for the financial support (No.72173030 & No.72121002).

1 Introduction

Across the globe, more than 215 million children are trapped in child labor, with the overwhelming majority toiling in agriculture (ILO, 2010).[1] However, this figure likely underestimates the true scale of the issue, as a significant number of children aged 14-19 are also actively participating in the labor market, particularly in developing countries. The widespread prevalence of child and teenage labor undermines the positive impact of early childhood investments - such as those made during ages 0-5 - on a child's future human capital development. While these investments are proven to enhance academic success, they also unintentionally raise the economic value of child labor, creating a vicious cycle that deprives children of the opportunity to thrive both academically and economically in the long term (Bau et al., 2020).

In his recent influential book, *Enlightenment Now*, Steven Pinker highlights the transformative impact of technology on education, recounting how innovations like tractors enabled boys to spend more years in school, while devices such as washing machines had a similar, lasting effect on girls educational attainment during the first half of the 20th century in the U.S (Pinker, 2018). Pinker quotes a 1921 tractor advertisement that illustrates the point: "*By investing in a Case Tractor ..., your boy can get his schooling without interruption ... Keep the boy in school and let a Case Kerosene Tractor take his place in the field. You will never regret either investment.*" This raises a critical question: Does the adoption of labor-saving agricultural technologies generally lead to an increase in children's school attainment? In this study, we aim to answer this question.

We first explore how agricultural mechanization affects child labor and school enrollment theoretically, building on the seminal paper of Basu and Van (1998). In the model, households send their children to work only if the income generated from adult labor and farm profit is not sufficient to attain subsistence. Thus child leisure/school is a luxury good afforded by only households who could achieve subsistence consumption without sending their children to work. In such environment, increased adoption of agricultural technology may increase or decrease child labor. In the more relevant case where the agricultural technology is labor-saving (e.g., tractors), such technology increases farm productivity and profit income which would decrease child labor supply (direct income effect). However, the labor-saving technology also causes the demand for labor and wages to decrease. The decrease in wage induces two opposing effects. First, the low wage reduces child labor supply due to low return. Second, the low wage reduces income of adults and may increase child labor supply (an indirect income effect which is negative). Under CES agri-

[1] ILO (2010) defines child labor as work that is inappropriate for the child's age, interferes with education attainments and affects their physical and mental health. In this paper we refer to child labor more broadly as labor supply by school-age children.

cultural technology with constant returns to scale, the net effect is a decrease in child labor. But in general, the link between agricultural mechanization, child labor and children's human capital development is theoretically ambiguous and empirical research on this link is very informative to both policy makers on child labor as well as those on human capital development.

Our empirical analysis utilizes a subsidy program to agricultural machine purchase in China. Secondary school enrollment is the lowest among the middle income countries in China, with 70% of its labor force (500 million people) lacking a high school education (Rozelle and Hell, 2022). The school dropout rate for child-workers aged 15 is nearly 40%, compared to 5% dropout rate for same age non-working children (Tang et al., 2018). Several spectators link the recent relative stagnation of the Chinese economy to China's notable weakness in the supply of skilled labor force (Li et al., 2017). Perhaps in recognition of this, the Chinese government has been taking policy steps to increase the supply of skilled labor, including expansion of higher education (Huang et al., 2022).

While agricultural mechanization had been hampered in the past by farmland fragmentation (Wang et al., 2020; Qiu et al., 2021) and the *hukou* system limiting migration of rural workers to cities and keeping surplus labor in rural areas (Imbert et al., 2022), there has a been a rapid mechanization of the agricultural sector in China over the last nearly three decades. Early on, the mechanization was driven by the proliferation of the agricultural mechanization services (AMS) (firms that rent machines to farmers) (Qiu et al., 2021). Over the last two decades, government direct subsidies to households for purchases of agricultural machines increased dramatically. The subsidy started in a few pilot counties in 2004 and gradually expanded to nearly all counties by 2009. The subsidy disbursement continued across counties as the scope of the agricultural machines covered by the subsidies expanded and more farmers obtained access to the subsidy over the subsequent several years.

Using multiple censuses and mini-censuses since 2000, we first document a number of stylized facts about different cohorts of children aged 15-19 in China. First, the proportion of 15-19 year-olds with high school education dramatically increased from 30% in 2000 to over 70% in 2015. Second, the fraction of employed children in the same age bracket plummeted from 33% in 2000 to just 10% in 2015. Third, nearly 85% of children who worked were employed in the agricultural sector in 2000 but this figure decreased to 45% in 2015. That is, the decrease in the employment rate of 15-19 year-olds is driven by the decrease in the agricultural sector.

We use the rollout implementation of the subsidy program across counties to study the causal link between agricultural mechanization on one hand, and children's time use and school attainment on the other. We find that the subsidy increased the stock of agricultural machines in counties by up to 10% five years after the treatment of the counties. As a result, labor supply rate by children aged 15-19 decreased by 6ppt and their high school enrollment rate increased by 10.6ppt over the same time horizon. These effects are economically sizable and suggest that agricultural mechanization alone accounts for about 20% of the overall decrease in child labor and increase in high school enrollment between 2000 and 2015. We find a strong empirical evidence in support of the key mechanism in our theoretical model – the subsidy to agricultural mechanization significantly increased farm income thus allowing households to free the children from labor activity.

Empirical challenges in estimating the causal effect of staggered implementation of policies, such as the subsidy program we study here, have been the subject of recent literature on difference-in-differences (DID) estimation (Goodman-Bacon, 2021; Callaway and SantAnna, 2021; Wooldridge, 2021; Borusyak et al., 2024). These studies argue that when there is heterogeneity in treatment effect across groups receiving treatment at different time or over periods since treatment, the traditional Two-Way-Fixed-Effects (TWFE) model may lead to biased estimate of the average treatment effect because it assigns different weights to different observations and some observations (particularly those further from the treatment time) are assigned negative weights. The above studies suggest alternative but closely related approaches to correct for this bias. We adopt the method proposed by Borusyak et al. (2024) to obtain unbiased treatment effects. This method not only enables us to consistently and efficiently estimate the treatment effects but also allows us to test the key assumptions underlying the estimation.

Another challenge in identification of the causal effect of the subsidy program is that the rollout of the program across counties may not be exogenous. The program's main goal is to ensure national food security by providing farmers with modern agricultural equipments. It is thus likely that the program favored major grain producing areas such as counties that have high potential yields in wheat, rice and maize. Inspired by recent literature in econometrics on non-parametric first-stage estimation in IV regression (Belloni et al., 2012; Jat, 2024), we tackle this problem as follows. First, we use GAEZ data to construct each county's national rankings in its potential yields across three crops and two farm techniques: irrigated-wheat, rainfed-wheat, irrigated-rice, rainfed-rice, irrigated-maize and rainfed-maize. We then use these rankings and the random forest classification model to predict the treatment year of each county based on its rankings across the six yield measures, targeting the actual rollout of the program. This is a non-parametric equivalent of the first-stage regression in classic 2SLS and gives us *predicted* rollout. We find that the predicted rollout closely mimics the actual rollout which is equivalent to a strong first-stage regression in classic 2SLS. Using the predicted rollout in our "second-stage" regression we find comparable results to our baseline ones.

Our main analysis uses county-level variation to take advantage of the rollout of the subsidy program which was implemented at county level and the fact that there is massive heterogeneity across counties in both the outcome variables as well as agricultural mechanization rates. One downside of the county-level analysis is that we have to rely on a small number of observations in county-cohort cells when calculating our outcome variables (employment and high school enrollment rates of children aged 15-19) for a significant fraction of the counties.[2] To resolve this issue, we redo our analysis at prefecture level as a robustness exercise. A prefecture consists of eight counties on average, thus resolving any concern of small sample size to precisely estimate our outcome variables. However, because the rollout of the subsidy program was implemented at county level, we cannot use this program in our prefecture-level analysis. Instead, we use prefecture-level panel data on the stock of agricultural machinery (total stock of agricultural machines used for ploughing, harvesting, threshing, irrigation, etc. measured in 10,000KW). To obtain exogenous variation to the stock of agricultural machinery, we construct shift-share instrumental variable by combining each prefecture's share of the stock of agricultural machinery available in China in 1996 (the "shares") and data on annual disbursement of subsidy which is available at province level (the "shifts"). Our prefecture-level analysis yields results that are quantitatively and qualitatively very similar result to our county-level analysis. Besides addressing concerns about sample size, our prefecture-level analysis also confirms that our estimates on the causal effect of agricultural mechanization on labor supply and high school enrollment of children aged 15-19 remain stable regardless of the source of variation we utilize. Moreover, the prefecture-level analysis allows us to account for variation in treatment intensity over time as a continuous measure of mechanization is used instead of binary treatment dummy.

To explore whether our results from China generalize to broader group of developing countries, we compile comparable cross-country data to our Chinese data on agricultural mechanization and estimate its effect on high school enrollment in a cross-country regression. Our cross-country data covers 177 countries and the period 1980-2019. To obtain exogenous variation to agricultural mechanization across countries and years, we use the fact that most of the countries rely on imported machines and construct instrumental variable that combines countries' distances from coasts with fluctuations in the international oil prices. The IV strongly predicts variation in agricultural mechanization across country-years. Our cross-country analysis yields results that are very similar (both qualitatively and quantitatively) to the results we obtain from our analysis of Chinese data. Using cross-country data on child labor,

[2] We try to mitigate potential bias due to small sample sizes by weighting our regressions by the sample sizes.

we also document a strong negative correlation between agricultural mechanization and child labor, accounting for level of economic development (GDP per capita).

Overall, we conclude that agricultural mechanization significantly reduces labor supply by 15-19 years-olds and increases their high school enrollment from our analysis of both Chinese data and cross-country data. The results in this study suggest that subsidizing agricultural mechanization could boosts human capital development, besides its direct effect on agriculture. In China, for instance, the governments may improve the effectiveness of its existing policies in human capital development by directing such subsidies to households with school-age children.

This paper directly contributes to limited studies on the effect of adoption of labor-saving 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 papers fills this void by tracing the link between agricultural mechanization, child labor and school enrollment.

This paper is closely related a growing literature on the effect of child labor on school enrollment, academic performance and adulthood income. One strand of this literature studies the effect of expansion of job opportunities in manufacturing and service sectors on children's school enrollment. 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 children 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 closely related paper by Oster and Steinberg (2013) finds that increased return to schooling following India's IT sector boom caused 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). The focus of the current paper is on the effect of decrease in agricultural labor demand due to agricultural mechanization on children's school enrollment. In its focus on labor demand in agriculture, the current paper is more closely related to Bai and Wang (2020) who find that decrease in returns to adult crops (crops intensive in adult labor) reduces educational achievement of children while decrease in the returns to child crops (crops intensive in child labor) has the opposite effect, and Shah and Steinberg (2017) who 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.[3]

Another strand of this literature focuses on the effect of child labor on academic 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 children 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.[4]

The rest of the paper is organized in seven sections. Section 2 describes the data sets. In Section 3 we provide a number of stylized facts about trends in employment and high school enrollment of 15-19-year-olds across four (2000,2005,2010 & 2015) Chinese censuses and mini-censuses. Section 4 presents our theoretical model. Section 5 presents our main empirical analysis. We discuss our robustness exercises in section 6. In Section 7, we tackle a crucial question about to what extent the results we obtain from analysis of our Chinese data apply broadly to developing countries using cross-country data that is comparable to our Chinese micro data. Section 8 concludes the paper.

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

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

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 combine this data with the 10% sample data from 2000 and 2010 rounds of census and 2005 and 2015 rounds of mini-census data to trace cohorts of high school-age children (15-19 year-olds). The combined census and mini-census data give us information on child labor and school enrollment of millions of school-age children 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.

Unit of analysis: China's administrative regions include provinces, prefectures, counties, towns, and villages, ranging from high to low hierarchy.[5] 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 in the censuses are children aged 15-19 and in significant number of counties the number of children in this age bracket are less than 10 while the vast majority of counties have 10 or more children 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 children in the age bracket as importance weights.

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.

[5] 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).

3 Stylized facts

In figures 1-4 we present a series of facts about trends in high school enrollment rate and employment rate across cohorts of children based on the 2000, 2005, 2010, and 2015 censuses and mini censuses.

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 children aged 15-19.

Fact-2: The fraction of high school-aged children in employment decreased significantly over decades. Figure 2 shows that the fraction of 16-year-old children 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 children over decades.

Fact-3: Figures 3-4 show that among 15-19 year-old children 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 children 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 5 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 significantly labor-saving technologies, adoption of these machines would decrease agricultural labor demand and wage, potentially driving children into the labor market to cope with reduced wage income of parents. However, these technologies are also significantly productivity-enhancing and may increase farm profit, thus allowing parents to send their children to school. Below we explore the effect of subsidy to agricultural mechanization on child labor and school enrollment theoretically.

4 Theoretical model

4.1 Main model

Our theoretical model builds on the seminal paper by Basu and Van (1998). We adopt the conventional view in the literature that child labor exists because parents are compelled to send their children 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 children to work. Instead they send them to school. That is, children's leisure or school is a luxury good in household's utility. This is consistent with the fact that children from non-poor households in poor countries rarely work.[6]

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

$$U = (C - c)E \tag{1}$$

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

For later use, we also define the following notations. $L_c^h = n_c - E$ is child labor per household, N is exogenous number of households, $L_c = NL_c^h$ is total child 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, children 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. 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

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

the remaining fraction own land and receive farm profit in addition to labor income. Household consumption is given by:

$$C = w_a + w_c(n_c - E) + R \tag{2}$$

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. To obtain tractability, we assume the farm production function takes the following CRS CES form

$$Y = A\left[\delta K^{\rho} + (1-\delta)(N + \gamma L_c)^{\rho}\right]^{1/\rho} \tag{3}$$

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 child 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.

While we do not impose any restriction at this stage, we are particularly interested in the case where capital is a substitute for labor, i.e., agricultural mechanization is a labor-saving technology. This is in line with our prior information that most of the agricultural machines covered under the subsidy program (such as tractors, combine-harvesters, etc) are labor-saving in nature. This corresponds to $\sigma > 1$ or $\rho > 0$. Moreover, while capital is typically treated as dynamic input in macroeconomic models, here we treat capital as variable input with annualized costs r.

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

$$\pi = Y - w_a N - w_c L_c - (1-s)rK \tag{4}$$

Equilibrium

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

$$L_c = NL_c^h = N\left(\frac{w_c n_c - w_a - R + c}{2w_c}\right) \tag{5}$$

Thus child 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. Wages are determined by marginal products from FOCs with respect to L_a and L_c:

$$w_a = \frac{\partial Y}{\partial L_a} = A(1-\delta)(N+\gamma L_c)^{\rho-1}\left[\delta K^\rho + (1-\delta)(N+\gamma L_c)^\rho\right]^{\frac{1-\rho}{\rho}} \tag{6}$$

$$w_c = \frac{\partial Y}{\partial L_c} = A(1-\delta)\gamma(N+\gamma L_c)^{\rho-1}\left[\delta K^\rho + (1-\delta)(N+\gamma L_c)^\rho\right]^{\frac{1-\rho}{\rho}} = \gamma w_a \tag{7}$$

The FOC with respect to K:

$$\frac{\partial \pi}{\partial K} = A\delta K^{\rho-1}\left[\delta K^\rho + (1-\delta)(N+\gamma L_c)^\rho\right]^{\frac{1-\rho}{\rho}} - (1-s)r = 0 \tag{8}$$

Substituting profit income into the child labor supply condition (Eq. 5):

$$L_c = N\left(\frac{\gamma w_a n_c - w_a - \frac{Y - w_a N - \gamma w_a L_c}{N} + c}{2\gamma w_a}\right) \tag{9}$$

which simplifies to

$$Y = Nc + w_a(Z - N\gamma n_c) \tag{10}$$

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

Using Y and w_a from equations 6 in equation 10 we obtain:

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

Using the above expression for Z, the FOC for K (Eq. 8) can be written as follows :

$$A\delta K^{\rho-1}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}} = (1-s)r \tag{12}$$

Equations 11 and 12 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. The equilibrium values of key variables are given as follows:

1. **Child Labor (L_c)** (assuming interior solution):

$$L_c = \frac{N}{\gamma}\left[\frac{c}{A(1-\delta)}\left(\frac{1-\delta\left[\frac{A\delta}{(1-s)r}\right]^{\frac{\rho}{1-\rho}}}{(1-\delta)^{\frac{1}{\rho}}}\right)\left(\frac{A\delta}{(1-s)r}\right)^{\frac{\rho}{\rho-1}} - \frac{\gamma n_c\left(1-\delta\left[\frac{A\delta}{(1-s)r}\right]^{\frac{\rho}{1-\rho}}\right)}{\delta\left[\frac{A\delta}{(1-s)r}\right]^{\frac{\rho}{1-\rho}}} - 1\right] \tag{13}$$

2. **Capital (K)**:

$$K = Z\left[\frac{(1-\delta)\left[\frac{A\delta}{(1-s)r}\right]^{\frac{\rho}{1-\rho}}}{1-\delta\left[\frac{A\delta}{(1-s)r}\right]^{\frac{\rho}{1-\rho}}}\right]^{1/\rho} \tag{14}$$

3. **Wages**:

$$w_a = A(1-\delta)Z^{\rho-1}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}}, \quad w_c = \gamma w_a \tag{15}$$

4. **Profit**:

$$\pi = Y - w_a N - w_c L_c - (1-s)rK \tag{16}$$

5. **Consumption**:

$$C = \frac{Y}{N} = \frac{A\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{1/\rho}}{N} \tag{17}$$

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 child labor:* $\frac{dL_c}{ds} < 0$
3. *Increases child education enrollment:* $\frac{dE}{ds} > 0$

Proof. Proof is given in the Appendix B. □

The intuition is that when $\sigma > 1$ $(\rho > 0)$, the subsidy generates a strong direct income effect. First, higher s reduces $(1-s)r$, increasing K, Y, R, and reducing L_c. We call this the *direct income effect*. Second, K substitutes L_e, lowering w_c, reducing L_c. That is, labor-saving technology reduces the demand for labor, suppressing wage which decreases child labor. This is the *substitution effect*. However, note also that this decrease in wage pushes households towards poverty, thus generating a negative *indirect income effect*. Nevertheless, the direct income effect and the substitution effect dominate the negative indirect income effect, so that $\frac{dL_c}{ds} < 0$ when $\sigma > 1$. However, if $\sigma < 1$ ($\rho < 0$) the effect of the subsidy on child labor is ambiguous because the income and substitution effects operate in opposing direction. The income effect is still negative, i.e., increase in s reduces L_c. But the *substitution effect* could be positive in the sense that if K complements L_e, higher K due to the subsidy would raise w_c, potentially increasing L_c particularly if the wage increase is not large enough to render adult income sufficient for minimum consumption.

4.2 Extension of the basic model

We now consider an extension of the above model to the case where there are two groups of households: land owners and land-less households. 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 $\alpha = 1$ and detailed derivations are provided in Appendix B. In the current model, agricultural mechanization has different effects on the land owners and land-less households and their children. 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 child 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 child labor, the negative indirect income effect may dominate, causing increase in child labor and decrease in school enrollment. When $\sigma < 1$, the effect of the subsidy on child 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, child labor may decrease. If the complementarity between machine and labor is weak (hence the wage increase is smaller), the subsidy could worsen child labor by encouraging them to join the labor market.

Overall, the link between agricultural mechanization, child labor and school enrollment is theoretically ambiguous. Our results in Proposition 1 present a specific case where agricultural machines are labor-saving and all households receive farm profit in addition to labor income. The next two sections are devoted to testing the empirical relevance of Proposition 1.

5 Empirical analysis

5.1 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. These funds have 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 Column 1 of Table 3. 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 [7]. As an example, all 66 pilot counties in 2004 were located within key grain-producing regions, with subsidies allocated specifically to leading grain farmers [8]. This targeted approach reflected the programs 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.

5.2 Methodology

Our baseline estimation equation is written as follows:

$$y_{ct} = \sum_{h=-a}^{h=b} \tau_h \mathbf{1}(D_{ct} = h) + \gamma_p * t + \gamma_c + \gamma_t + \varepsilon_{ct} \tag{18}$$

where y_{ct} is outcome variable for county c in year $t = 2000, ..., 2015$, which mainly includes secondary school enrollment rate and employment rate of 15-19 year-olds. $D_{ct} = t - G_c$ 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), $G_c = \infty$. γ_c and γ_t are county and year fixed effects capturing, respectively, time-invariant county features such as geographic location and year-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 across provinces. In our setting, the scalars a and b are 5 and 6 respectively. Our choice of the value of $a = 5$ insures that each cohort has at least for years of pre-treatment data ($a = 5$ for counties that received the treatment in 2004). Including further distant outcomes may introduce confounding factors. Our

[7] https://www.ers.usda.gov/webdocs/outlooks/40443/30113_wrs0501_002.pdf?v=6973.9

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

choice of $b = 6$ is motivated similarly. For counties that received treatment in 2009 (which are few), identification comes from comparison with never-treated groups.

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, 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 and the TWFE model would give biased estimates of average treatment effect (Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and SantAnna, 2021; Wooldridge, 2021; Roth et al., 2023; Borusyak et al., 2024). 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 18. 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.

5.3 Main results

5.3.1 High school enrollment and teenagers' labor market participation

Before we present our results on the link between agricultural mechanization and high school enrollment, we first present how high school enrollment and labor market participation are correlated within counties. Table 1 presents the correlation between the fraction of children (ages 15-19) employed and the fraction enrolled in high school. Panel A of the table includes all children aged 15-19 while Panel B restricts estimation to children 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 children in agricultural households relative to the correlation based on the entire sample of children (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 children 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), children 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 1 suggest that labor market participation significantly hinders high school enrollment of children aged 15-19.

5.4 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 2. The table shows the coefficients of dynamic effects estimated from equation 18.

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 2 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 children 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 2 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 children worked without totally altering their employment status. As the scope and intensity of the subsidy grew overtime, it may affect employment status of children as the machines fully replace child labor and children abandon working altogether. In the meantime, the decrease in children's 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 18 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 6-8 present the event-study plots for each of our outcome variables: the stock of agricultural machine, employment rate and high school enrollment rate, respectively.

Figure 6 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 2.

Figure 7 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 8 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 6-8 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 2 against changes in the high school enrollment rate and employment rate of 15-19 year-olds presented in figures 1 and 2. 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 2 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 3), we believe that our results give a reasonable estimate of the magnitude of effect of agricultural mechanization induced by the subsidy program.

5.5 Endogeneity concern

One concern in identification of the causal effect of agricultural mechanization using the subsidy program is that the rollout of this program may not be exogenous. For instance, authorities may favor counties that were already ahead in agricultural mechanization rate as this may signal improved success chance of the program. If these counties are also generally further ahead in other economic outcomes, such as high school enrollment rate, the marginal gain from the subsidy in terms of high school enrollment and reduced child labor could be smaller than if treatment rollout was random.[9] 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

[9]We find suggestive evidence that counties that received treatment earlier had significantly higher agricultural mechanization rate in prior to the commencement of the rollout program, compared to counties that received the subsidy during the latter years of the rollout.

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 3. 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 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 4. 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

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

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 4 are largely in line with our baseline results in Table 2. 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, causing stronger. Table 5 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]

5.6 Mechanism: Income effect

Our empirical results above show that agricultural mechanization decreased labor supply of 15-19 year old children and increased their high school enrollment rate. Our theoretical results suggest that adoption of labor-saving agricultural technology would reduce child labor and increase school enrollment if it significantly raises household income so that households can afford subsistence consumption without the need to send their children to work. We test if this key theoretical mechanism is at work in our setting by investigating the effect of the subsidy rollout on per-capita income of rural households.

The result is presented in Figure 9. The figure shows event-study plot of the effect of subsidy rollout on per-capita income of rural residents (measured in Yuan).

[11] Intuitively, counties that received the treatment in a given year but are not predicted to receive treatment in that 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.

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 results in Figure 9 suggest that the *direct* income effect of the subsidy rollout is quite strong. Such a strong direct income effect is likely to dominate the *indirect* negative income effect attributed to 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 child labor and an increase in high school enrollment following the subsidy program.

6 Robustness: Prefecture-level analysis

One issue in our county-level analysis is that our measurement of high school enrollment rate and employment rate of children aged 15-19 is based on small sample sizes. In particular, for a significant 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:

$$y_{rt} = \beta_0 + \beta_1 m_{rt} + \mathbf{x}'_{rt}\delta + \gamma_v * t + \gamma_r + \gamma_t + \varepsilon_{rt} \tag{19}$$

where y_{rt} is outcome variable for prefecture r in year t which includes mainly secondary school enrollment and fraction of cohorts of children 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 15.[12] 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 child labor and school enrollment in equation 19 is that unobserved factors (such as expected future skill premium) could increase the demand for school enrollment, reducing the amount of child 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.

$$\mathrm{IV}_{rt} = \mathrm{MachineryShare}_{r,1996} \times \mathrm{Log}\ (1{+}\mathrm{Subsidy})_{vt} \tag{20}$$

where $\mathrm{MachineryShare}_{r,1996}$ is the share of agricultural machine stock in China that existed in prefecture r in 1996. $\mathrm{Subsidy}_{vt}$ 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 pre-

[12]Measuring exposure to agricultural mechanization at age 16 gives very similar results.

fectures 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 in the prefectures.

Results: Table 7 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 7 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 8). 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 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 and late enrollment is not uncommon, the vast majority of children make decision to enroll in high school at the age of 16. Thus, it is expected that agricultural mechanization would have stronger effect on children at this critical age than their younger or older cohorts. In Table 8 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 children 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 8 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 8 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.

7 Generalizability: cross-country evidence

Our main analysis above documents strong evidence on how agricultural mechanization reduces child labor and increases high school enrollment in the context of China. Do these results hold more generally across countries? In this section, we seek to answer this crucial question using cross-country panel data covering 177 countries and the period 1980-2019 on agricultural machineries and high school enrollment and data on child labor for 61 countries over recent period (2016-2020). We focus on countries in Africa, Asia, and Latin America, even though we also include estimation results covering all countries in our data for comparison.[13]

We begin by presenting the correlation between agricultural mechanization, and high school enrollment and child labor in figure 10. Agricultural mechanization is measured as log of agricultural machineries (in horsepower) per hectare of farmland. High school enrollment is measured as gross high school enrollment ratio, and child labor is measured as percentage of children aged 5-17 who are engaged on labor activities including paid jobs and domestic chores.

The first panel of figure 10 shows the relationship between agricultural mechanization and high school enrollment. Because both of these variables increase with the level of economic development, we use residuals of these variables after regressing on logs of GDP per capita and population size. We then plot the residuals for the year 2015 (though the figures look very similar across years). The figure shows

[13]We Obtain this data from United States Department for Agriculture (USDA) Economic Research Service processed by Our World in Data. https://ourworldindata.org/grapher/machinery-per-agricultural-land

a clear positive correlation between agricultural mechanization and high school enrollment. While the figure includes countries in Africa, Asia and Latin America only, including all the countries in our data makes the correlation even larger. Middle eastern countries generally tend to have both lower agricultural mechanization rate as well as lower high school enrollment while southern and south-eastern Asian countries have both higher agricultural mechanization and high school enrollment.

The second panel of figure 10 show the relationship between percentage of children engaged in labor work and agricultural mechanization. Data on child labor is available for only 61 countries in our main data. Moreover, this data is available across different years between 2016-2020 for different countries. If a country has data on this variable for multiple years, we use the most recent year value. We then plot this variable against the residual of agricultural mechanization measure (after removing GDP per capita and population size) for the year 2015. The figure shows a clear negative correlation between agricultural mechanization and child labor. African countries in general have higher child employment rate as well as lower agricultural mechanization rate.

Next we present cross-country regression analysis of the relationship between agricultural mechanization and high school enrollment in table 9. For this, we use unbalanced panel data covering 1980-2019. All our regressions include the following control variables: GDP per capita, fertilizer use per hectare and interaction of the rule-of-law index, soil quality index, percent of tropical climate and percent of people with European descent with year dummy as well as country and year fixed effects. Because other factors (such as economic growth) could drive both agricultural mechanization and high school enrollment, thus giving spurious correlation, it is difficult to give causal interpretation to OLS result. To address this, we use the fact that most of the countries in our sample (particularly those in Africa, Asia, and Latin America) rely on imported machines. This allows us to construct exogenous variation in trade costs across countries and years by interacting countries' distance from coasts with international fluctuation in oil prices. We obtain distance from coasts measure from Nunn and Puga (2012) and it varies significantly across countries, and adoption of agricultural machines generally decreases with distance from coasts. Also, there is massive fluctuation in oil prices over our sample period. Our IV is strongly negatively related to agricultural mechanization.[14]

Columns 1-2 in table 9 pool all 177 countries in our data while Columns 3-4 restrict estimation to 109 countries in Africa, Asia, and Latin America. Column 1 shows OLS estimation result where agricultural mechanization is significantly pos-

[14]To improve exogeneity of the IV, we include time-varying control variables such as GDP per capita and fertilizer use per hectare and a host of other time-invariant country features interacted with year dummies. Our identification assumption is that our IV would be exogenous to high school enrollment rate conditional on these control variables.

itively correlated with high school enrollment. Column 2 shows the IV estimation result, which is more than five times larger than the OLS estimate. Column 3 shows similar level of OLS point estimate for our sample of countries in Africa, Asia, and Latin America, while column 4 shows the the IV point estimate for this subsample of countries.

It is worth commenting on the magnitude of the point estimates. The magnitude of these estimates is reasonable given significant variation in both high school enrollment rate and agricultural mechanization across countries and years. For the countries in our sample in columns 3-4 (African Asian and Latin American countries), the 25th and 75th percentiles, respectively, of gross high school enrollment rate are 45% and 96%, while these percentile for log agricultural machineries per farmland are -2.88 and -0.07 across country-year variation. The implied effects of moving from the 25th to 75th percentile of agricultural mechanization based on the point estimates in columns 3-4 is that gross enrollment rate increases by 2.4 and 26 percentage points, respectively, for the OLS and IV estimates. While the IV results look large at first glance, they are not implausible when we take into account the significant variation in the gross enrollment rate in our data. The OLS estimate in particular is very similar to our TWFE estimate in our Chinese data.

8 Conclusions

In developing countries where child labor is widely used in agricultural sector, agricultural mechanization may reduce the demand for child labor. This decrease in demand for child labor would allow children to acquire more years of schooling if the child 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.

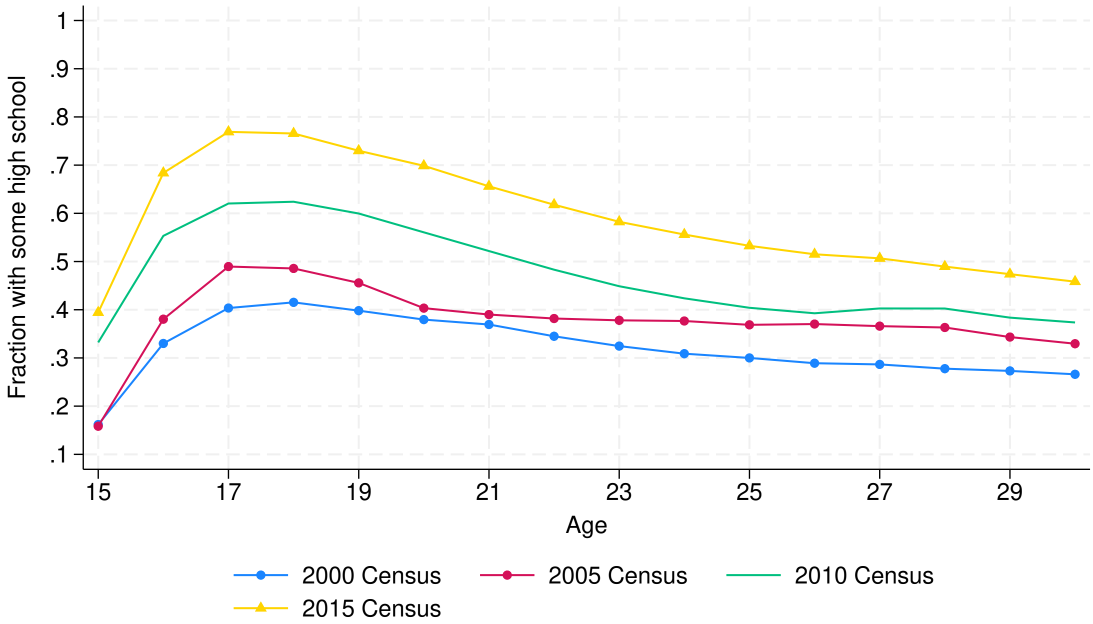
To explore whether this results is driven by specific feature of Chinese economy (such as fast growth) or holds more generally, we compile and analyze data on agricultural mechanization and high school enrollment rate across 177 countries since 1980. Our cross-country analysis yields similar conclusion – countries that adopted labor-saving agricultural machines more intensively experienced growth in high school enrollment rate. We also provide evidence that agricultural mechanization is negatively related to child labor across countries.

Overall, our results in this paper inform policy makers on child 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 children. Such policies could be more effective than child labor laws in reducing child labor use, particularly in agricultural sector where the practice is most common.

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

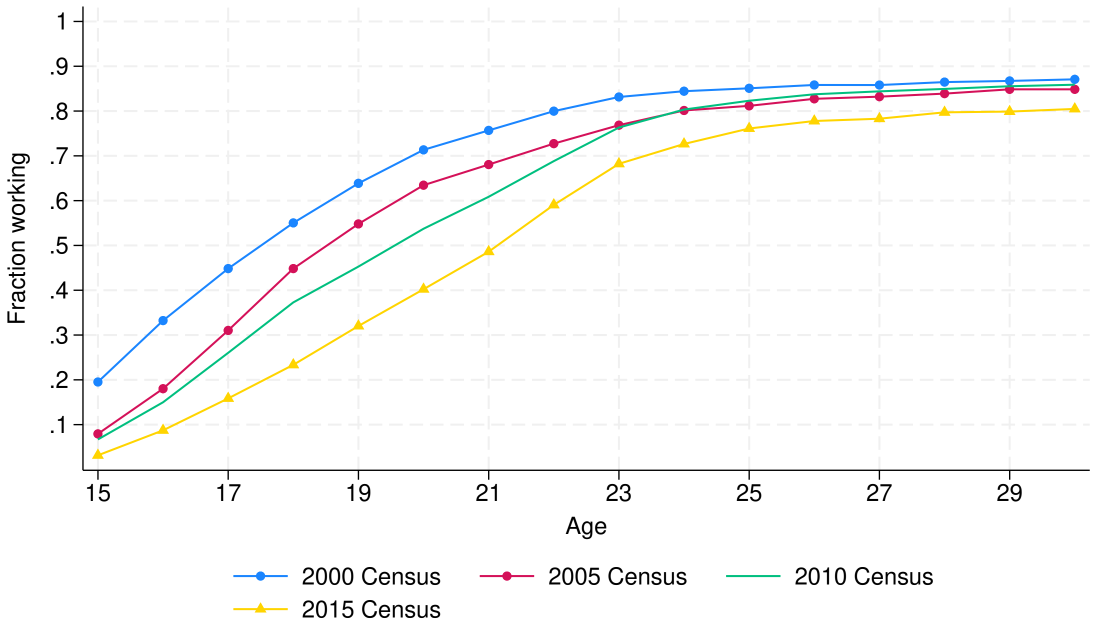
Figures

Figure 1: Fraction with some high school education



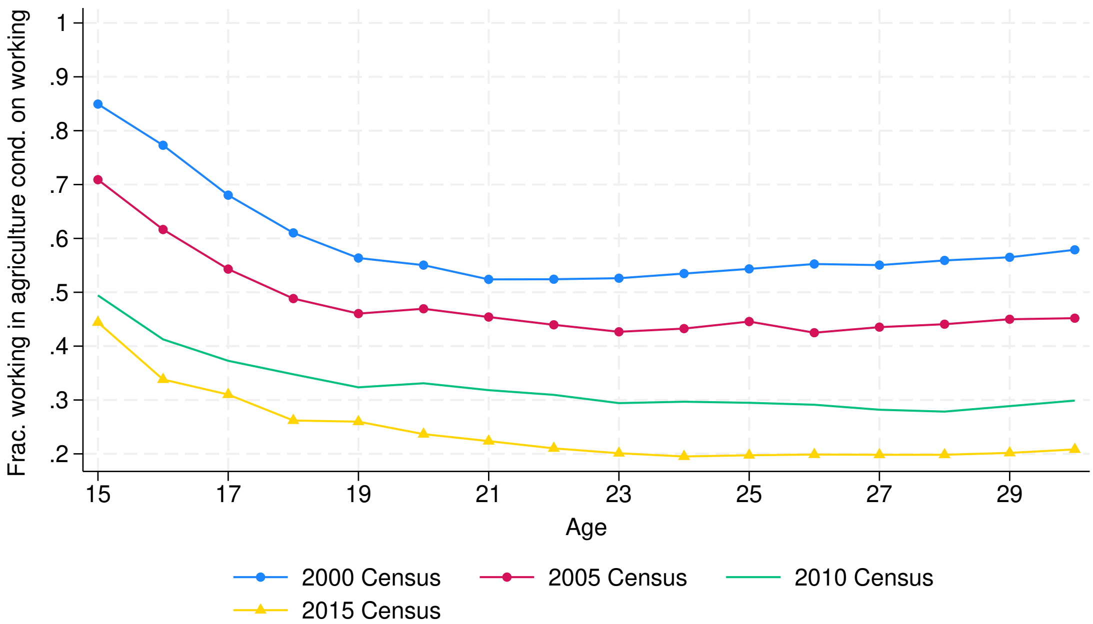
Notes: This figure presents fraction of people aged 15-30 with some high school education, including those enrolled in school.

Figure 2: Fraction working



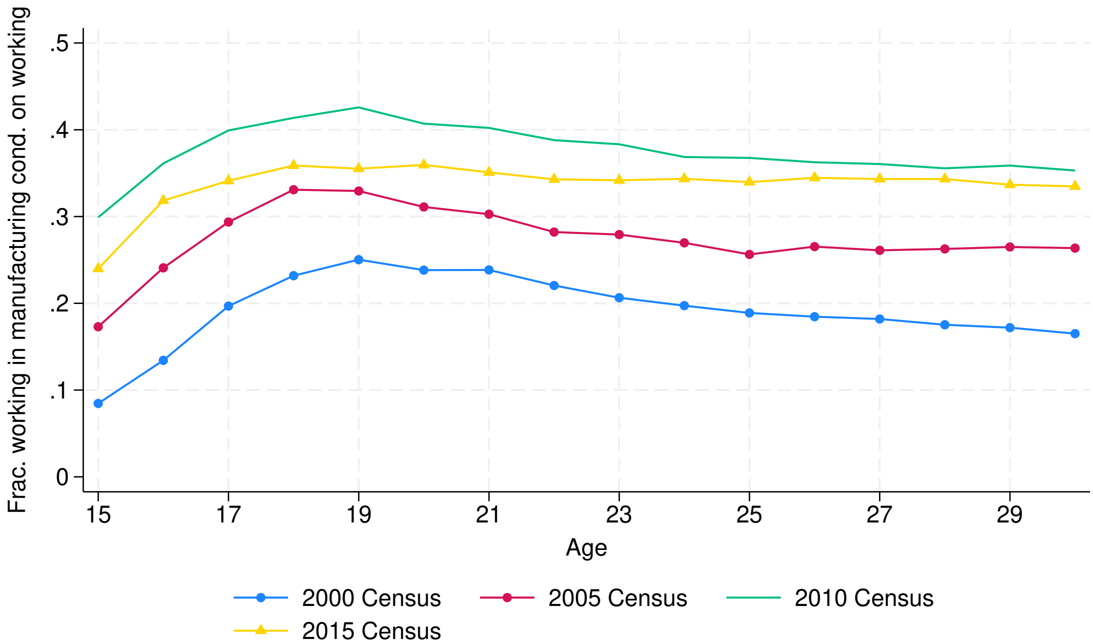
Notes: This figure presents fraction of people 15-30 working by age.

Figure 3: Fraction working in primary sector, conditional on working



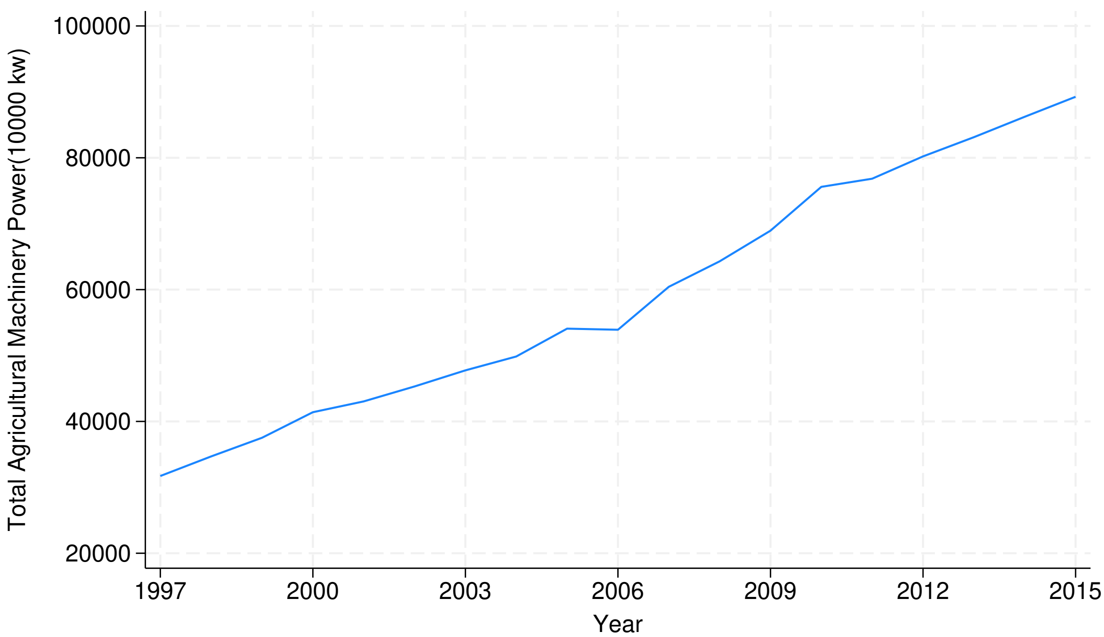
Notes: This figure presents the fraction of those who work who are employed in the primary sector.

Figure 4: Fraction working in secondary sector, conditional on working



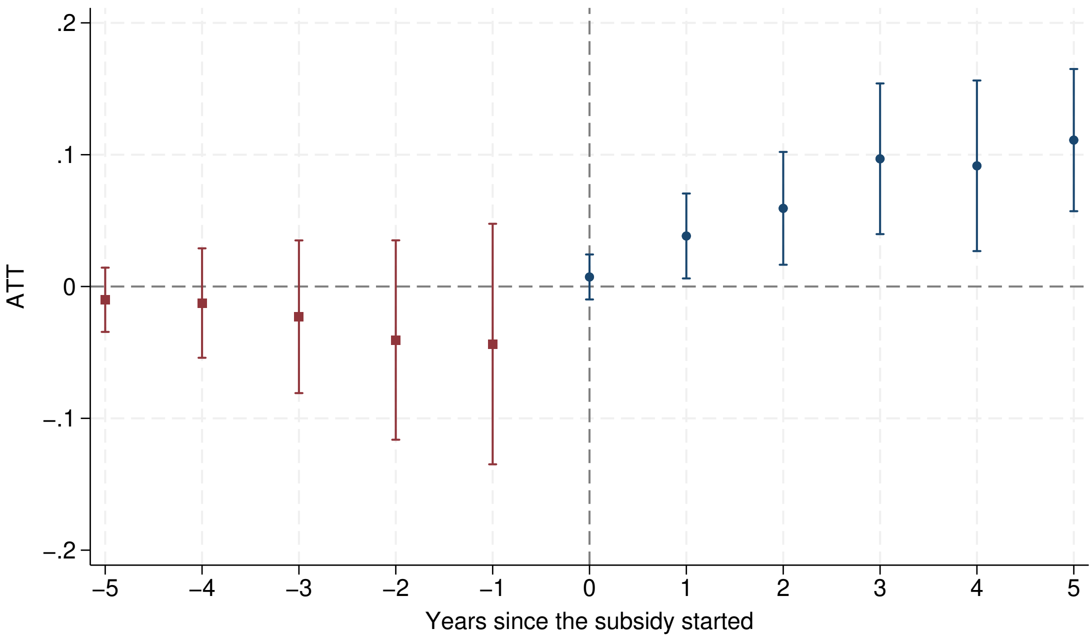
Notes: This figure presents the fraction of those who work who are employed in the secondary sector.

Figure 5: Total agricultural machine stocks over time



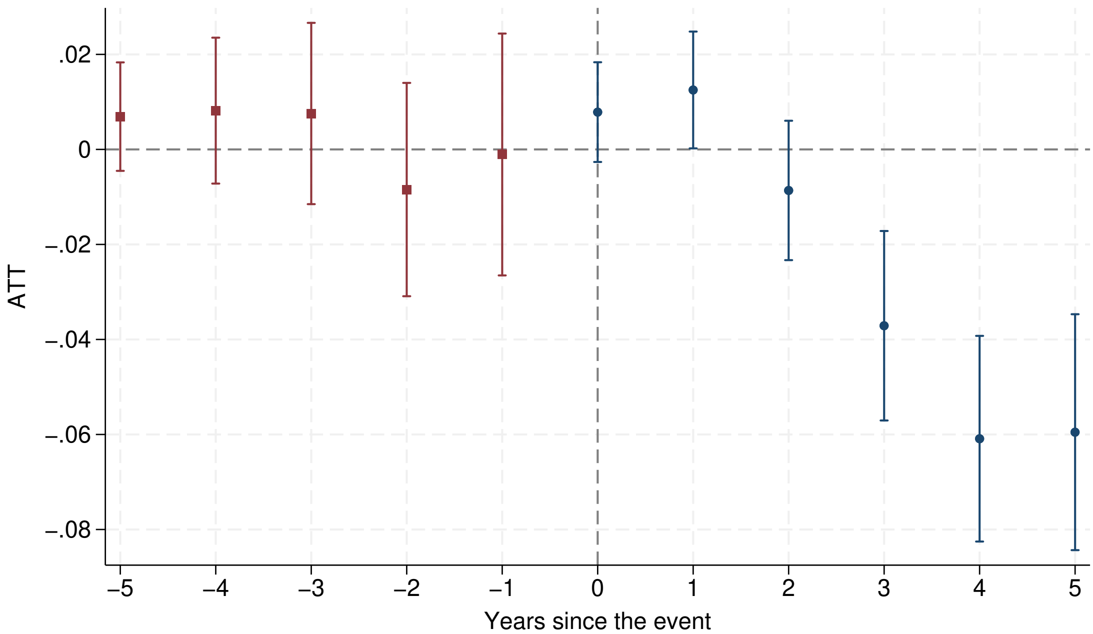
Notes: This figure presents total agricultural machine power (in 10,000KW) over time.

Figure 6: The effect of subsidy on agricultural machine stock (in log units)



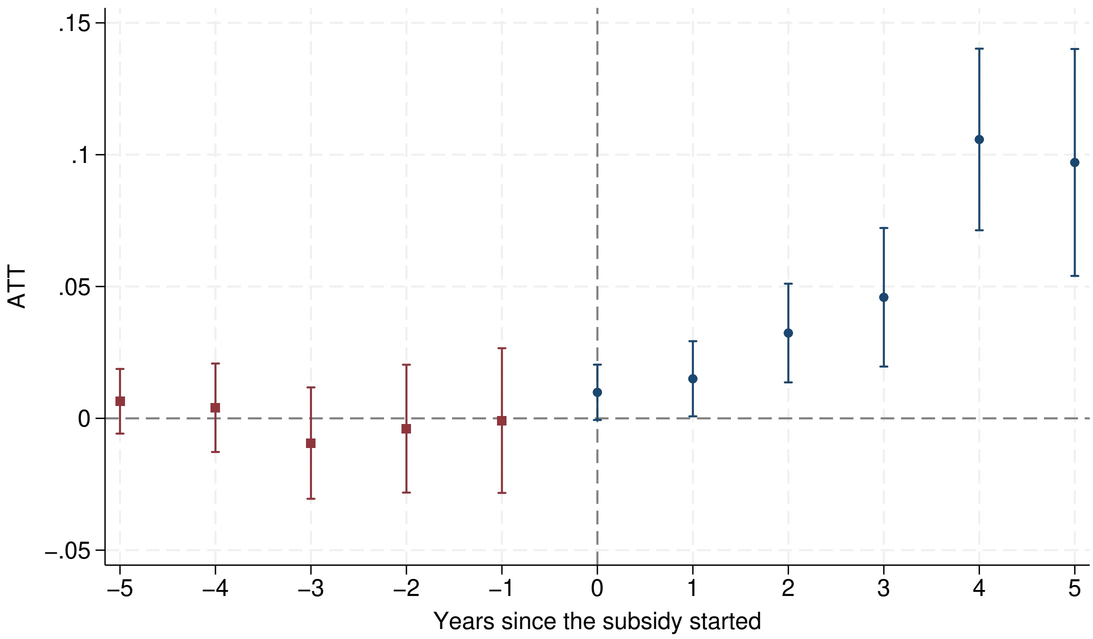
Notes: This figure presents event plot of the effect of the subsidy rollout on the stock of agricultural machine (measured in log units). To create the event study plot, we allow each unit has five years of pre-treatment period to exclude distant past outcomes of units which might be contaminated by confounding factors. Similarly, we trim at six years of post-treatment period. This is because, apart from few counties which never received the treatment, almost all counties received the subsidy between 2004 and 2009. Thus, for counties treated in 2004 a valid control group (not yet treated group) are available only for the years 2004-2009 (i.e. six years of horizon). For counties who received the treatment later, this horizon becomes shorter.

Figure 7: The effect of subsidy on teenage employment rate: event plot



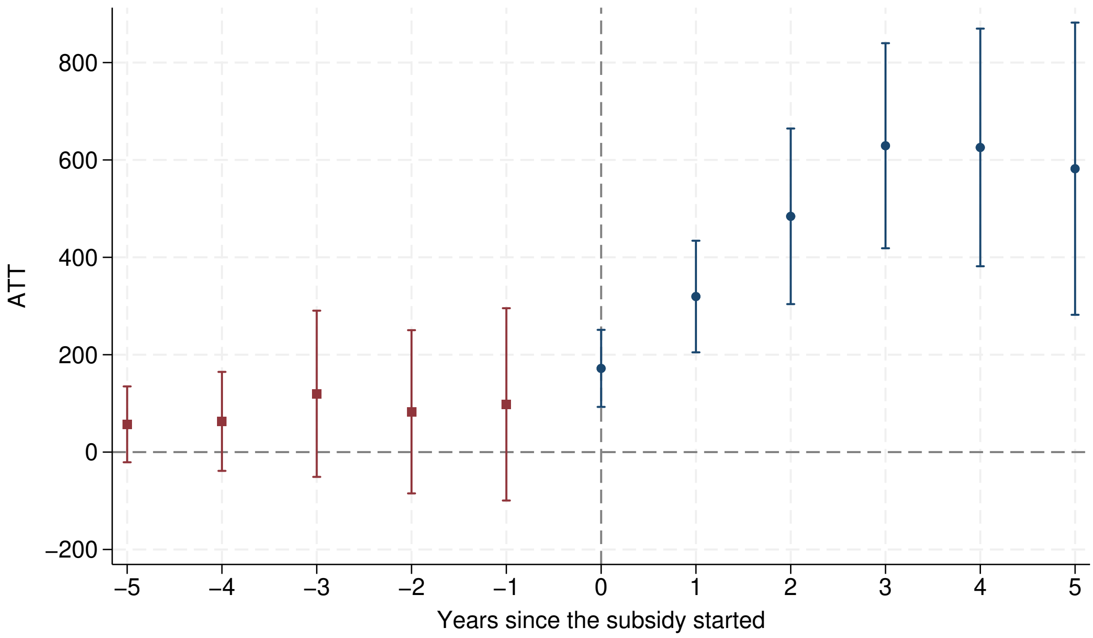
Notes: This figure presents event plot of the effect of the subsidy rollout on teenage employment rate. To create the event study plot, we allow each unit has five years of pre-treatment period to exclude distant past outcomes of units which might be contaminated by confounding factors. Similarly, we trim at six years of post-treatment period. This is because, apart from few counties which never received the treatment, almost all counties received the subsidy between 2004 and 2009. Thus, for counties treated in 2004 a valid control group (not yet treated group) are available only for the years 2004-2009 (i.e. six years of horizon). For counties who received the treatment later, this horizon becomes shorter.

Figure 8: The effect of subsidy on high school enrollment rate



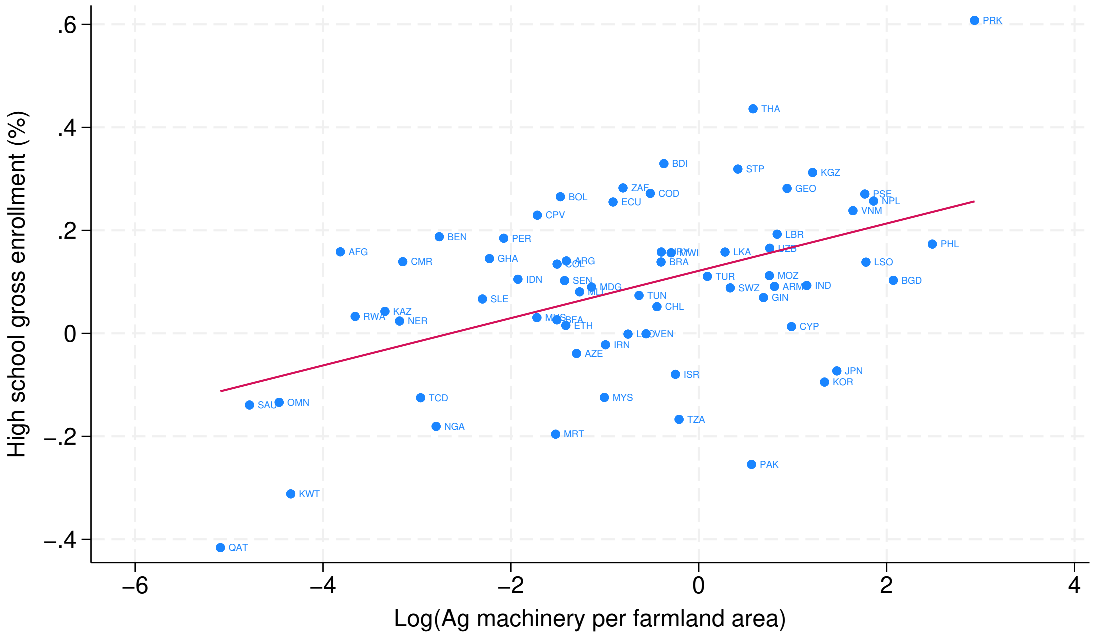
Notes: This figure presents event plot of the effect of the subsidy rollout on high school enrollment. To create the event study plot, we allow each unit has five years of pre-treatment period to exclude distant past outcomes of units which might be contaminated by confounding factors. Similarly, we trim at six years of post-treatment period. This is because, apart from few counties which never received the treatment, almost all counties received the subsidy between 2004 and 2009. Thus, for counties treated in 2004 a valid control group (not yet treated group) are available only for the years 2004-2009 (i.e. six years of horizon). For counties who received the treatment later, this horizon becomes shorter.

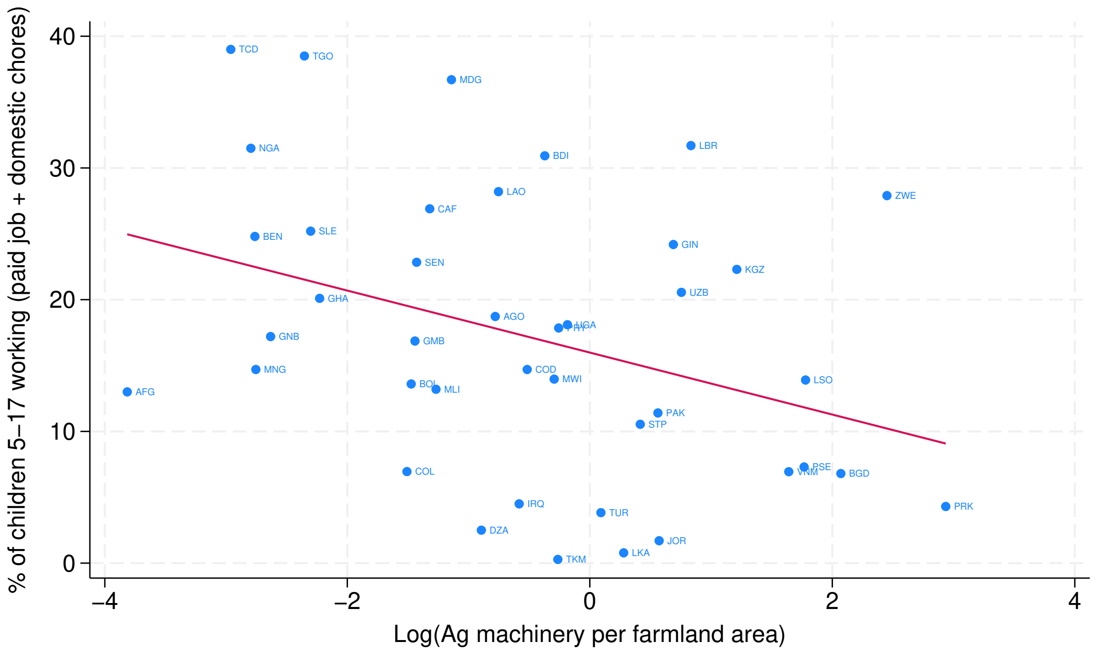
Figure 9: The effect of subsidy on per-capita income of rural residents (measured in Yuan): event plot



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 unit has five years of pre-treatment period to exclude distant past outcomes of units which might be contaminated by confounding factors. Similarly, we trim at six years of post-treatment period. This is because, apart from few counties which never received the treatment, almost all counties received the subsidy between 2004 and 2009. Thus, for counties treated in 2004 a valid control group (not yet treated group) are available only for the years 2004-2009 (i.e. six years of horizon). For counties who received the treatment later, this horizon becomes shorter.

Figure 10: Agricultural machinery, child 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 children 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 children 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 child labor data.

Tables

Table 1: Correlation between high school education 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 2: 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 3: 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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: 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 5: 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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robustness: Prefecture-level results

Table 6: 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 7: The effect 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 and cohort fixed effects. Standard errors clustered at prefecture level are in parenthesis. $MachineryShare_{p,1996}$ th agricultural machineries in prefecture p as a share of the national stock for the year 1996. $Subsidy$ is subsidy (in 10 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 8: The effect 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.

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

Table 9: Agricultural machineries and high school enrollment across countries

	All countries		Countries in Africa, Asia, L. America	
	(1) OLS	(2) IV	(3) OLS	(4) IV
Log machinery per area of cropland	0.010***	0.264***	0.012***	0.129***
	(0.003)	(0.068)	(0.004)	(0.041)
N	4151	4151	2546	2546
First-stage F-stat		23		24

Notes: The dependent variable is gross high school enrollment ratio.The estimation is based on cross-country data since 1980-2019. Columns 1-2 include panel data of 177 countries. Columns 3-4 restrict the estimation to panel data 109 countries in Africa, Asia, and Latin America. All regressions include GDP per capita, fertilizer use per hectare and interaction of the rule-of-law index, soil quality index, percent of tropical climate and percent of people with European descent with year dummy as control variables as well as country and year fixed effects. In columns 2 and 4 we use Log(Distance to coast) $\times$ Log(Oil price), where distance to coast measure is obtained for Nunn and Puga (2012). Robust standard errors in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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.

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

Appendix B Theoretical results

A Proof of Proposition 1

Write the equilibrium conditions 11 and 12 in implicit form:

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

$$F_2(Z,K,s) = A\delta K^{\rho-1}\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-\rho}{\rho}} - (1-s)r = 0 \tag{22}$$

Total differential:

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

Compute partial derivatives:

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

Solving the system:

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

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

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

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 $\frac{dE}{ds} > 0$.

B The case of heterogeneous households

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 child 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:

$$2w_c L_c = N(w_c n_c - w_a + c) - (Y - w_a N - w_c L_c - (1-s) r K) \tag{34}$$

$$Y = Nc + w_a N + w_c L_c + (1-s) r K \tag{35}$$

Firm condition:

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

Define $Z = N + \gamma L_c$, solve implicitly.

Comparative Statics: $\frac{dL_c}{ds}$, $\frac{dE}{ds}$, $\frac{dK}{ds}$ Rewriting the equilibrium conditions in 35 and 36 in implicit form we obtain:

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

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

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

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

- $\frac{\partial F_1}{\partial s} = rK > 0$
- $\frac{\partial F_2}{\partial Z} = A\delta K^{\rho-1}\left(\frac{1-\rho}{\rho}\right)\left[\delta K^\rho + (1-\delta)Z^\rho\right]^{\frac{1-2\rho}{\rho}}(1-\delta)\rho Z^{\rho-1}$ (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 $\sigma < 1$.

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