Agricultural Mechanization and Structural Change

Hundanol Kebede*

May 22, 2026

Abstract

This paper provides causal evidence of the impact of agricultural mechanization on structural change using Chinese county-level data and a large-scale agricultural machinery subsidy program rollout. Mechanization significantly decreased agricultural value-added and employment shares while expanding the secondary sector. This structural shift operates through two distinct channels: large-scale worker emigration and a within-county reallocation toward manufacturing that boosted both the number of industrial firms and their total output. On average, this local sectoral labor reallocation generated a 7% increase in aggregate productivity between 2000 and 2010, though the productivity gains exhibit substantial variation across individual counties.

Keywords: Aggregate productivity, Agricultural mechanization, Economic development, Structural transformation. JEL Codes: J43, O13, O14, O33, O47, Q16

*I would like to thank Sajal Lahiri for his insightful comments and suggestions. I also thank participants of seminar at SIU Carbondale, 2024 Pacific Conference for Development Economics (PacDev), SEA 94th Annual Meetings, and CEA2024 Online Conference for their helpful comments.
Southern Illinois University Carbondale, email: `hundanol.kebede@siu.edu`

1 Introduction

The role of agriculture in the process of economic development is one of the oldest and at the same time less understood topics in development economics. The dominant view is the dual economy view (Lewis, 1951; Ranis and Fei, 1961). According to this view, agriculture in low-income countries is a subsistence sector incapable of being a driving sector for sustained economic growth, and economic development requires reallocation of labor from the agricultural sector where the marginal product of labor is near zero to a modern sector where the combination of labor with capital increases the productivity of labor.[1]

A recent empirical work by Restuccia et al. (2008) shows that the major reason behind low aggregate productivity in poor countries, compared to rich countries, is that the poor countries have higher share of employment in agriculture coupled with low agricultural labor productivity.[2] The implication is that, while improving agricultural productivity gap could close the income gap between rich and poor countries partially, substantial reduction or elimination of the income gap requires reallocation of labor from the less productive agricultural sector to the more productive modern sectors in poor countries.

In the mean time, reallocation of labor from the agricultural sector to the modern sectors remains one of the key developmental challenges in low-income countries. In most countries in sub-Saharan Africa, South Asia and Latin America, between half and three-quarters of the population live on small scale farms. In such countries, structural transformation is not only required to increase aggregate productivity but also that due to increasing population pressure, climate change and environmental degradation agriculture is unlikely to be a sustainable source of livelihood for the mass of the population. This begs the question: How could these countries achieve faster reallocation of labor from agriculture to the modern sectors? The experience from the Green Revolution shows that technological improvements that increase agricultural productivity did not necessarily lead to structural change in many countries (Foster and Rosenzweig, 2004; Moscona, 2019). In this paper, I empirically study the role of a different kind of agricultural technology, i.e., agricultural mechanization, in

[1] A related but slightly different view is that the key to achieving successful industrialization lies in robust agricultural productivity growth Schultz (1953); Nurkse (1953); Rostow (1956). This view became widely adopted in neoclassical models of structural transformation (Kongsamut et al., 2001; Gollin et al., 2002, 2004; Ngai and Pissarides, 2007). However, other scholars such as Matsuyama (1992) argued that the role of agricultural productivity growth in industrialization critically depends on the openness of the economy. In an open economy environment, high agricultural productivity may lock a country into its comparative advantage agricultural sector which could be detrimental to structural change and sustained economic development in the long run.

[2] Adamopoulos and Restuccia (2021) show that such agricultural productivity gap between poor and rich countries cannot be explained by geography and soil quality. If countries produced crops across fields according to their potential yields using the same technology, the agricultural yield gap between rich and poor countries would decrease from 214% to just 5%.

driving structural transformation. Agricultural mechanization is different from the widespread adoption of high yield varieties or chemical fertilizers brought by the Green Revolution in that agricultural mechanization is a labor-saving technological change that could induce a large scale release of surplus labor from agriculture, thus providing the modern sectors with cheap labor.

I leverage county-level panel data that includes a unique measure of agricultural mechanization from China, a country that experienced both rapid rate of agricultural mechanization and dramatic structural transformation over the past three decades. My measure of agricultural mechanization is a county-level annual statistics on the total agricultural machine powers (in Kilowatts) which is obtained by aggregating all the agricultural machine powers used for ploughing, harvesting, threshing, pumping, etc. I combine this dataset with county-level panel data on output and employment disaggregated by sectors and rounds of census data.

Empirical study on the link between agricultural mechanization and structural transformation is complicated by at least two factors. First, data on accurate measure of agricultural mechanization and sectoral measures of economic activities at detailed subnational level is not widely available for most developing countries. Second, even when such data is available, exogenous source of variation to the rate of agricultural mechanization is difficult to find. Specifically, rapid development of the manufacturing sector due to, say, expansion of international trade could increase the demand for agricultural mechanization by drawing workers from agriculture to manufacturing and thus raising the cost of labor to the agricultural sector, causing endogeneity issue.

To address the endogeneity issue, I utilize a shock to the costs of mechanization due to a large-scale agricultural machine subsidy (AMS) program. Starting in 2004, the Chinese government introduced AMS in 66 pilot counties with a goal of ensuring national grain self-sufficiency. The program gradually rollout to more counties across the country, finally reaching near universal coverage by 2009. To identify the causal effect of agricultural mechanization, I use the subsidy program to construct instrumental variable (IV) for variation in the stock of agricultural machinery across counties and years. The subsidy program significantly reduced the net costs of machines born by farmers and spurred its adoption.

Five main results emerge from my empirical analysis. First, agricultural mechanization led to sectoral reallocation of output. Counties that had faster agricultural mechanization rate experienced significant shrinks in the share of agricultural value added (VA) in GDP and an equivalent increase in the share of manufacturing VA in GDP, with little effect on the share of service sector. Second, agricultural mechanization led to reallocation of labor from agriculture to manufacturing and to services (to some extent). Third, counties that experienced faster agricultural mechanization had a significant drop population counts. Fourth, in counties that had faster agricultural mechanization, both the number of industrial enterprises and their output grew significantly. That is, agricultural mechanization concurrently induced migration of population out of the county and fostered significant development of the manufacturing sector within the county.

Finally, I find that within-county reallocation of labor from agriculture to manufacturing and services due to agricultural mechanization contributed significantly to aggregate productivity growth. In an average county, the within-county reallocation of labor led to 6.88% growth in aggregate productivity between 2000 and 2010. However, this average figure masks heterogeneity across counties. Aggregate productivity falls by 3% in a lowest percentile county while it increases by 20% in the top percentile county.

These results are robust to alternative identification strategies. First, as an alternative identification strategy, I use the rollout implementation of the AMS across counties to estimate the causal effects. I obtain similar magnitude of effects on sectoral reallocation in value added and employment. Second, one concern in my identification strategy is that the government subsidies and its rollout implementation across counties are likely not random and could be directed to politically connected counties or to those with labor shortages. To allay this concern, I use machine-learning technique and counties' national rankings in their natural suitability to different major grains to predict the rollout of the subsidy program. This procedure predicts the actual rollout reasonably well, suggesting that the implementation of the subsidy program closely followed its stated goal ensuring national grain self-sufficiency. I use this predicted rollout in place of the actual rollout in my estimation of the causal effect and obtain very similar results.

This paper contributes to empirical studies on the role of agriculture in structural change and economic development. Influential papers by Bustos et al. (2016, 2020) study the effect of agricultural productivity growth due to adoption of genetically engineered soybean seeds (GE soy) in Brazil. GE soy is significantly labor saving because the seeds are herbicide-resistant, which allows for the use of no-tillage farm technique, obviating the need of labor for land preparation and weeding. In Bustos et al. (2016), they show that in regions that adopt the technology agricultural labor shrunk and industrial employment expanded. They contrast this with the adoption of a different technology, a second harvest-season of maize, which is labor intensive (land-augmenting). Regions that adopted this latter technology experienced increase in agricultural labor and decrease in manufacturing employment. In Bustos et al. (2020), they show how the adoption of GE soy increased farm profit and capital accumulation. However, they find that the increased capital did not have significant effect on local structural transformation, instead, the capital was transferred to other regions via bank networks and contributed to structural change in the destination regions. My paper relates to these papers by studying how adoption of labor-saving agricultural machines facilitates structural transformation. The main difference in my paper is that I use a comprehensive measure of agricultural mechanization instead of a technological shock to the production of a single crop.

A closely related literature uses the agricultural productivity shock during the Green Revolution (GR) as a source of variation to study the link between agricultural productivity growth and structural change. Foster and Rosenzweig (2004) find that faster industrial development in India happened in areas with lowest rates of growth in crop yield. Similarly, using the same shock Moscona (2019) finds negative effect of agricultural productivity growth on urbanization and manufacturing development by comparing districts in India and in cross-country regressions.[3] Importantly, the negative effect on manufacturing development is stronger for districts and countries more open to trade. Other studies such as (Gollin et al., 2021; McArthur and McCord, 2017) conduct cross-country analysis using the GR shock and find a positive effect of GR on agricultural productivity, GDP percapita and a negative effects on agricultural share of employment. While cross-country analysis is well-suited to account for national level general equilibrium effects of the shock, it also has its own downsides. In particular, different countries have different economic institutions and economic environments which may fasten or thwart structural change. As long as these same factors may critically influence successful adoption of the GR, it could be difficult to isolate the effect of the GR from these factors.[4]

One potential reason why studies that are based on the GR find inconsistent effect on structural change is that the GR is not necessarily labor-saving. At its core GR includes the adoption of high-yield seed varieties and chemical fertilizers, which significantly increase yield without decreasing labor input. On the contrary, the agricultural shock studied in the current paper (as well as the one in Bustos et al. (2016, 2020)) are labor-saving. In particular, the agricultural mechanization studied in this paper is a canonical case of labor-saving technology where labor inputs required for ploughing, weeding, harvesting and threshing are largely replaced by machine power.

Other studies on the long term effects of agricultural technology shock include (Schmidt et al., 2018; Nunn and Qian, 2011; Andersen et al., 2016; Chen and Kung, 2016; Marden, 2016; Carillo, 2018). These papers mostly study the transformative

[3]Another study that finds null effect of agricultural productivity shock on the development of non-agricultural sector is Hornbeck and Keskin (2015) who explore the long-term effect of a shock to irrigation technology in the post-war era which made the exploitation of ground water for irrigation easier in the regions of Ogallala Aquifer.

[4]See also (von der Goltz et al., 2020; Bharadwaj et al., 2020) for studies on the effects of GR on various development outcomes such as infant mortality.

effects of adoption of some critical crops: potatoes in Nunn and Qian (2011), maize in Chen and Kung (2016), and clover in Schmidt et al. (2018). While adoption of these crops might have significant effect on agricultural production by increasing yields, they are unlikely to be labor saving. A more closely related paper to the current one is Andersen et al. (2016), who study the effect of adoption of heavy plow in medieval Europe.

A bulk of recent studies explore how manufacturing demand shock following China's accession to WTO led to migration, structural change and productivity growth (Tombe and Zhu, 2019; Imbert et al., 2022; Feng et al., 2017). My paper presents evidence that agricultural mechanization serves as a *push factor* which complements the *pull factor* induced by international trade of manufactured products (see for instance Erten and Leight (2021)). Much less attention is give to this push factor in comparison to the pull factor.

The rest of the paper is organized as follows. Section 2 describes the data and provides important definitions and cross-country descriptive results while Section 3 outlines the empirical methodology. Section 4 presents the main results, and is followed by analysis on potential mechanisms and heterogeneous effect of agricultural mechanization across counties in Section 5. Section 6 presents estimation of aggregate productivity growth from sectoral reallocation of labor due to agricultural mechanization. Section 7 concludes the paper.

2 Data and measurement

2.1 Data

I combine data from several sources. My main dataset is county-level panel data covering the period 1997-2015 compiled from official government reports called Annual Provincial Yearbooks. This dataset includes information on sectoral value-added, GDP, and agricultural mechanization rate, among others. The Chinese government collects annual data on agricultural mechanization rate at county, prefecture, province and national levels. Because it is difficult to aggregate machines of different size (e.g., small and large tractors) or different function (e.g., threshers and water pumps), agricultural mechanization is measured in terms of total power of all agricultural machineries in 10,000KW. I use this as a measure of agricultural mechanization.

I combine this dataset with Global Agro-Ecological Zones (GAEZ) agricultural suitability data (Fischer et al., 2021), Global cropland data (Monfreda et al., 2008), and Global irrigation areas data (Nagaraj et al., 2021). The GAEZ data provides potential yields for each crop at detailed geographical unit (9km $\times$ 9km at equator) under low, intermediate and high input scenarios and under rainfed and irrigation farm methods. I use the high-input potential yield scenarios, which is likely to reflect the actual agricultural practice in China during the past three decades. Because farming in China involves both rainfed and irrigation depending on geographic regions, seasons and crop types, I combine the yield estimates under rainfed and irrigation scenarios using the fraction of irrigated land in each county as a weight to obtain a county-level crop potential yield estimates for each county c and crop k combinations. The fraction of irrigated areas is obtained from Nagaraj et al. (2021)[5] . I use the global cropland data to estimate harvested areas in hectare for each county-crop combination. The global cropland data is based on subnational crop production information for the period 1997-2003 and combines crop cover data over these multiple years to give an average harvested area for each crop at spatial resolution of 5 min by 5 min (9km $\times$ 9km at equator).

2.2 Measurement

Structural transformation is defined as reallocation of economic activities across the broad economic sectors agriculture, manufacturing and services and can be measured using changes in employment share, value-added share and consumption shares of these sectors over time (Herrendorf et al., 2014).[6]

My main measures of structural transformation are changes in the value-added shares of primary sector (agriculture), secondary sector (manufacturing and mining) and tertiary sector (services), for which I have county-level annual panel data since 1997. Figure 3 presents trends in the shares of sectoral VA in GDP at national level. These sectoral VA shares in GDP are weighted averages across counties where the weights are county population size in 1990. The figure shows a persistent decrease in the share of VA in primary sector in GDP from 38% in 1997 to 18% in 2015. The figure also shows that the share of secondary sector VA in GDP increased from 35% in 1997 to its highest value of 47.4% in 2013 before slightly decreasing afterwards. The share of service sector VA in GDP increased relatively fast during the late 1990s and post 2010 period, but largely remained flat in between. Note that these average changes mask massive heterogeneity in the trends in the sectoral VA shares in GDP across counties. In some counties, the reallocation of VA production from the primary to the secondary and tertiary sectors is dramatic; in other counties it is relatively small.

I complement my analysis on sectoral reallocation of VA production with data on county level employment shares from the 1982, 1990, 2000, and 2010 censuses, which I use to trace changes in sectoral share of employment over longer period. Figure 4

[5]While Nagaraj et al. (2021) estimate irrigated areas for each year between 2001-2015, there is little variation over time for China. So I use the 2001 estimation in my calculations.

[6]Using data from multiple countries, Herrendorf et al. (2014) show that structural change measures based on employment and value-added shares shows very similar relationship with level of economic development.

presents changes in the sectoral share of employment across census rounds. The figure shows relatively stable employment shares of sectors over the two decades before 2000. However, between 2000 and 2010, the share of employment in the primary sector decreased by about 15 percentage points while the share of employment in the secondary and tertiary sectors increased by about 8 and 7 percentage points, respectively. Again, these average changes in the sectoral employment shares mask substantial heterogeneity across the counties, where some counties experienced significantly larger employment reallocation across sectors than others over the decades.

The two measures of structural change have their own merits, and they complement each other when used together. There are two major advantages of using the value-added shares over the employment shares. The first is the availability of annual panel data on value-added shares but only decennial panel for employment shares. Second, workers, particularly in rural areas, may spend a significant fraction of their time working outside their primary sector of employment. Rural farmers are likely to work in non-agricultural sectors during slack seasons (seasonal migration). Besides seasonal migration, farmers may work in manufacturing or services to earn additional income. This is particularly the case for smallholder farmers with too small plot of land to support their full onfarm employment or generate enough living income. Rozelle et al. (1999) estimate that about 154 million farmers (34% of rural labor force) had some form of off-farm employment in 1995 in China.[7] Guang and Zheng (2005) discuss how Chinese government statistics fails to account for these facts and thus leads to overestimation of employment in the agricultural sector.[8] The value-added shares are not subject to these type of measurement problems. However, the value-added shares have some drawbacks that the employment shares may not. In particular, some scholars (Chen et al., 2019) have argued that statistical data compiled at local government levels are unreliable. This is because local government officials' performances are evaluated based on the economic performance of their jurisdictions and this motivates the officials to inflate certain statistics such as investment and industrial production. However, the employment shares are not subject to such criticism because they come from census data that is managed by the central government, and hence there is no above mentioned incentives to manipulate these measures.

[7] Su et al. (2016) find that the proportion of rural workers employed simultaneously in farm and non-farm sectors is rising due to increasing tendency of rural workers to work in agriculture on part-time basis.

[8] Similarly, while urbanization is used as a proxy measure for structural change in some contexts, it is likely to be misleading in the context of China where rural manufacturing (commonly known as Township and Village Enterprises (TVEs)) is extensive (see Cheng (1996) for instance).

3 Empirical Analysis

3.1 Baseline specification

My baseline estimation equation is written as follows:

$$y_{ct} = \beta_0 + \beta_1 m_{ct} + \mathbf{x}'_{ct}\delta + \gamma_c + \gamma_t + \varepsilon_{ct} \tag{1}$$

where y_{ct} is outcome variable for county c in year t which includes mainly the shares of value-added and employment in the primary, secondary, and tertiary sectors. m_{ct} measures agricultural mechanization rate in county c in year t measured in logs of total agricultural machinery measured in 10,000 kilowatts. This includes all agricultural machines including those used for ploughing, harvesting, threshing, pumping, etc aggregated together. Figure 2 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. Here, β_1 captures the effect of agricultural mechanization on the outcome variables. If agricultural mechanization significantly contributes to structural change, we should see the value-added and employment shares in the primary sector decrease and similar shares in the secondary and/or tertiary sectors increase in counties that adopted mechanization at faster rate than other counties.

The variables $\mathbf{x}_{ct}$ capture demand shock to manufacturing sector due to China's accession to the WTO in December 2001. One of the variables is county-level share of employment in manufacturing interacted with post-2002 dummy variable. The second variable is prefecture-level measure of improved access to U.S. market due to U.S granting Permanent Normal Trade Relation (PNTR) status to China, which become effective in 2002 (see Pierce and Schott (2016)). This later measure captures heterogeneous impact of the granting of PNTR to China across 489 four-digit industries and variation in the level of industrial specialization across Chinese prefectures in 1998.[9]

3.2 The identification challenge

Identification of β_1 in equation 3 is complicated by potential endogeneity of the demand for mechanization. The problem is illustrated in figures 1. Consider a two sector-economy with agriculture and manufacturing sectors (assume that services are included in manufacturing). Suppose there is a positive demand shock to the manufacturing sector (say, due to trade liberalization). The booming manufacturing

[9] Prefecture-level exposure to China's accession to U.S market (granting of PNTR) is calculated as $\text{NTRgap}_r = \sum_j \alpha_{jc}\text{NTRgap}_j$, where NTRgap_j the difference between the non-NTR and NTR tariff rates for industry j; α_{jr} is industry j's employment share in prefecture r in 1998. I include the $Post_{2002} \times \text{NTRgap}_r$ to account for accession to U.S market.

sector would increase labor demand and wage in the manufacturing sector, which induces flow of labor from the agricultural sector to the manufacturing sector. The increase in manufacturing labor demand and the decrease in agricultural labor supply would raise the cost of labor in both sectors.[10] The increase in labor costs induces farmers to mechanize their operation, thus creating an identification challenge.[11]

To address the above identification challenge, I use a shock to the costs of agricultural mechanization induced by a large-scale agricultural machine subsidy (AMS) program. The program commenced in 2004 and is funded mainly by the central government with small contribution from provincial governments. The subsidy amount dramatically increased over years from 10 million USD in 2004 to 3.5 Billion USD in 2015. Approximately 1.7 million rural households benefited from the subsidy which significantly increased farmers' ability to invest in machinery. For instance, an average rural household received 500 RMB in subsidies in 2004, which corresponded to 25% of its annual disposable income per capita. 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 became eligible for a maximum subsidy of 150,000 RMB each, accounting for up to 50% of the costs of the machines. This is a significant shock to the costs of adopting mechanization and this is precisely the shock I exploit to identify the effect of mechanization on sectoral reallocation.

I 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 county's *historical* share of agricultural machine stock in the nation in 1990.

$$\mathrm{IV}_{ct} = \mathrm{MachineryShare}_{c,1990} \times \mathrm{Log}\ (1{+}\mathrm{Subsidy})_{vt} \tag{2}$$

where $\mathrm{MachineryShare}_{c,1990}$ is the share of agricultural machine stock in China that existed in county c in 1990. $\mathrm{Subsidy}_{vt}$ the total amount of subsidy disbursement in province v and year t by both provincial and central governments. The IV predicts growth in agricultural machine stock across counties reasonably well.

It is important to highlight two assumptions behind the above shift-share instrument. First, I rely on the assumption that the "shifts" (subsidy disbursement across provinces) is exogenous to demand for mechanization due to rising labor costs or sectoral reallocation of labor. This is a plausible assumption because the stated goal of the subsidy program was to ensure national grain self-sufficiency by modernizing

[10]Other economic liberalization policies such as FDI liberalization will have similar consequences, by causing faster growth of and increasing labor demand in the manufacturing sector.

[11]See, for instance, Tian et al. (2020) how study how trade induced labor demand in manufacturing affects land rental market and agricultural mechanization in China.

agricultural tools. Below, I provide evidence showing that the actual rollout of the subsidy across counties tightly adheres to this goal. Second, it is unlikely that variation in the machinery subsidy disbursements across provinces and years would affect sectoral reallocation via other mechanism than agricultural mechanization.[12] Hence, this IV is unlikely to violate the exclusion restriction.

3.3 Using staggered rollout of the subsidy program

As a complement to my baseline analysis, I use the staggered rollout of the agricultural machine subsidy program across counties to estimate its causal effect on sectoral reallocation. The subsidy rollout program started in 2004 with 66 pilot counties and gradually 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. 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.

I estimate the following dynamic treatment equation:

$$y_{ct} = \sum_{h=-4}^{h=7} \tau_h \mathbf{1}(D_{ct} = h) + \gamma_p * t + \gamma_c + \gamma_t + \varepsilon_{ct} \tag{3}$$

where c denotes county and t denotes year. $D_{ct} = 0$ represents the year in which the county rolled into the subsidy program. I consider four years of pre-enrollment and seven years of post-enrollment time span.

The advantage of the above dynamic treatment effect over the traditional two-way fixed-effects (TWFE) model is that when treatment effects are heterogeneous across rollout cohorts or time since treatment, the TWFE estimator can produce biased averages of treatment effects on the treated (ATT), as it implicitly assigns heterogeneous—and sometimes negative—weights to different group-time observations. I implement this dynamic treatment effects following the imputation-based approach suggested by Borusyak et al. (2024).

[12]One obvious concern here is that production of agricultural machines increases the demand for labor in manufacturing. However, production of agricultural machineries is a very small share of the manufacturing sector and highly geographically concentrated to invalidate this assumption. Moreover, some of the popular agricultural machineries adopted during our sample period were imported (mainly from Japan).

4 Results

4.1 Baseline result

OLS results: I first present the OLS estimation result of sectoral reallocation of VA production in Panel A of table 1 to facilitate comparison with the IV results. The first column in Panel A shows negative effect of agricultural mechanization on the share of agricultural VA in GDP. One log point increase in agricultural machines power decreases the share of agricultural VA in GDP by 1.4 percentage points. Column 2 of Panel A reports a positive effect of agricultural mechanization on the share of manufacturing VA in GDP where one log point increase in agricultural machine power increases share of manufacturing VA in GDP by nearly 1.1 percentage points. The last column of Panel A reports no significant effect on share of services VA in GDP. Overall, the OLS results suggest that agricultural mechanization contributed significantly to structural transformation in China. However, the magnitude of these OLS estimates is likely to be biased due to the endogeneity issues discussed in the previous section as well as measurement problems in agricultural mechanization. Next, I discuss how using the IV strategy affects the estimated effects.

IV results: Panel B of table 1 reports the IV results. Column 1 shows that one log point in crease in agricultural machine power resulted in 3.9 percentage points decrease in the share of agricultural VA in GDP. Column 2 shows that the share manufacturing VA in GDP increased by 3.5 percentage points following one log point increase in agricultural machine power. Column 3 shows a null effect on the share of services VA in GDP. The first-stage F-stat of 107 reported in the last row of Panel B suggests that my IV is strong. Table A.1 reports the first-stage regression results. Th IV strongly predicts variation in agricultural mechanization.

Overall, the IV estimation results show stronger effect of agricultural mechanization on sectoral reallocation of economic activity. More specifically, agricultural mechanization led to 3.9 percentage point decrease in the share of agriculture VA and 3.4 percentage point increase in the share of manufacturing VA, with no significant effect on services share of VA. That is, most of the sectoral reallocation in response to agricultural mechanization occurred from agriculture to manufacturing. This is consistent with the conventional view that the immediate destination of most of the workers who leave the agricultural sector tends to be secondary sectors such as manufacturing and construction, which tend to require less skills compared to services.

4.2 Results based on subsidy rollout

The results for the dynamic treatment effects based on rollout of agricultural machine subsidy program are presented in Figures 5-7.

Figure 5 presents the effect of the subsidy program on the stock of agricultural machinery at county level. The figure shows that enrollment into the subsidy program significantly increased the stock of agricultural machinery in counties. The stock of agricultural machines in a county increased by 5% after three years of enrollment into the subsidy program and by 11% after seven years of enrollment. The gradual increase in the estimated effects is attributed to expansion in the scope of the subsidy program in its coverage of different machine types and increased take up by farmers. These results show that the subsidy program had a meaningful effect on the agricultural mechanization overtime.

Figure 6 presents the effect of the subsidy program on the agricultural value-added share. Counties that enroll to the subsidy program experience a decrease in the agricultural value-added as a share of their GDP. This effect becomes statistically significant only three years after enrollment into the subsidy program and the effect becomes stronger over time. Seven years after introduction of the subsidy program, VA share of the agricultural sector decreases by 2.5 percentage points.

Figure 7 presents the effect of the subsidy program on the manufacturing value-added share. This effect becomes positive and statistically significant after three years. The effect peaks at nearly 5.8 percentage points six years after a county's admission into the subsidy program.

Overall, the dynamic effect results from the rollout of the subsidy program strongly support the baseline result that agricultural mechanization led to reallocation of economic activity from agriculture to manufacturing. As I discuss below, the magnitudes of the estimated effects are comparable across different estimation strategies followed.

Discussion: It is worth commenting on the size of the estimated effects. Taking the point estimates in from the IV estimation, one log point increase in agricultural machine power (measured in 10,000KW) resulted in about 4 percentage point decrease in the share of agricultural VA in GDP and almost an equivalent increase in the share of manufacturing VA in GDP. Over my sample period 1997-2015, the median (across counties) agricultural machine power increased by nearly 1 log points (from 2.48 in 1997 to 3.53 in 2015). Thus the above point estimates reflect the effect of agricultural mechanization in a median county. Over the same period, the share of agricultural VA in GDP decreased by 22 percentage points (from 40% in 1997 to 18% in 2015) while the share of manufacturing VA in GDP increased by 12 percentage points (from 32% in 1997 to 44% in 2015)[13], in a median county. Thus, my IV estimates in Panels B of Table 1 suggest that agricultural mechanization alone accounts for close to 20 percent of the observed decrease in the share of agricultural VA in GDP in a median county and a quarter of the increase in share of manufacturing VA in GDP over the sample period.[14]

4.3 Robustness

The stated goal of the subsidies was to ensure grain self-sufficiency by modernizing agricultural tools. In line with this, the counties selected for the pilot program of AMS rollout were typically located in highly grain producing areas. If the government subsidies were disproportionately allocated to counties where rural wage is high due to migration of agricultural labor, using subsidies as an instrument would not resolve the endogeneity concern.

To address this issue, I predict the rollout of the subsidy program across counties based on the counties' natural agricultural productivity based on GAEZ data (Fischer et al., 2021). This data allows to construct yield measure for each county for each of the main grains under a high input scenario and under two alternative farming techniques: rainfed and irrigation. I construct the counties' national ranking in their yield for maize, wheat, and rice. This gives six different national rankings of a county, i.e., in rainfed-maize, irrigation-maize, rainfed-wheat, irrigation-wheat, rainfed-rice and irrigation-rice. I then use a non-parametric random forest classification model to predict the rollout of subsidy using the above rankings of counties. The model predicts the year when a county would enroll into the subsidy program based on the county's national rankings in each of the above six rankings and choice of parameters (tree depth and leaf length). This gives *predicted* rollout, which is equivalent to the first-stage fitted value in 2SLS procedure. The procedure strongly predicts the rollout of the subsidy program (see Table A.2). This suggests that any concern of diversion of subsidy towards high wage counties or towards politically favored areas is minimal.

I then use this *predicted* rollout in our "second-stage" regression, in place of the actual rollout.[15]. The results are presented in Figures A.1-A.3. Figure A.1 shows

[13] The share of manufacturing VA in GDP peaked in 2012, reaching 47%, and continued to shrink afterwards.

[14] Note that these projections should be interpreted cautiously. First, the reported median changes in sectoral VA shares and agricultural machinery mask significant heterogeneity across counties. Second, the point estimates are strictly speaking valid for small changes in the independent variable and using them to project the effect of large change in the independent variable may lead to predictions that are outside the range of the dependent variable in the sample.

[15] 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

the effect on the stock of agricultural machines. The figure closely resembles those based on *actual* rollout of the subsidy program. Figures A.2 and A.3 present the effect of value-added shares of primary and secondary sectors. These figures also closely resemble their counterparts based on actual subsidy rollout. Overall, the *predicted* rollout of the subsidy program based on counties' national rankings in their suitability to grain production closely mimics the actual rollout, suggesting the government's adherence to the stated goal of the subsidy program, i.e., ensuring national grain self-sufficiency. The fact that the subsidy rollout is driven by counties' natural agricultural suitability, rather than local labor market or other economic feature, significantly allays the endogeneity concerns.

4.4 Sectoral employment reallocation

The theoretical literature discussed in section 1 suggests that agricultural mechanization leads to reallocation of labor force from the agriculture to the manufacturing and service sectors. This could mean either workers are switching sectors in their original location or they are migrating to a new location and a new sector. I explore the empirical content of this prediction by looking at how sectoral shares of employment change within a county and how county demographic characteristics change across decades between 1990-2010.

I first use county-level panel data on agricultural employment and rural population for the period 2000-2012 to estimate the baseline regression (equation 3). My data does not include rural employment in non-agricultural sectors nor the total employment. Data on some counties is also incomplete. Table 2 reports the effect of agricultural mechanization on log agricultural employment and agricultural employment as a share of rural population. The IV estimation results show that agricultural employment significantly decreases both in logs and as a share of rural population. One log point increase in the stock of agricultural machines decreased agricultural employment by 4.8% and agricultural employment as a share of rural population decreased by 2.1 percentage points.

To further strengthen the analysis on changes in sectoral employments, I combine county-level census data for the 1990, 2000, and 2010 census rounds, from which I calculate sectoral employment shares. I estimate the following stacked difference across decades:

$$\Delta Y_{cd} = \alpha_0 + \alpha_1 \Delta m_{cd} + \Delta \mathbf{x}'_{cd}\delta + \gamma_c + \gamma_d + \varepsilon_{cd} \tag{4}$$

where ΔY_{cd} change in percentage share of employment in a sector (for each of the primary, secondary and tertiary sectors), γ_c is county fixed-effects, and γ_d is decade

well without overfitting (Belloni et al., 2012).

(census-round) fixed effects. $\mathbf{x}_{cd}$ is a vector of control variables accounting for the demand shock to manufacturing sector due to China's accession to WTO discussed under equation 3.

I first estimate the above regression using OLS. Results are reported in panel A of Table 3. It shows that employment in primary sector decreases by 1.44 percentage points and employment in the secondary sector increases by 1.3 percentage points following one log point increase in agricultural machine power.

In panel B, I estimate the above regression using average land gradient as an instrument for change in agricultural mechanization between 2000 and 2010. Because land gradient is time-invariant, this estimation uses only crossectional variation. The key idea here that agricultural mechanization is significantly more costly in areas with steeper slope, particularly above 15^o (see appendix B for details of the technical arguments and the construction of the data). Thus, agricultural mechanization rate expected to be significantly slower in counties with steeper terrain. I find that slope is strongly negatively correlated with change in agricultural machine stock across counties between 2000 and 2010. Panel B of table 3 presents the IV estimation results. The results show that agricultural mechanization decreases employment share of the primary sector by 6 percentage points, increases the employment shares of secondary by 3 percentage points and increases the employment shares of tertiary sector by approximately 2 percentage points. The first-stage F-stat reported at the bottom of the table shows that my IV is strong.

Overall, the results in Table 3 clearly show that reallocation of workers from the primary (agricultural) sector to the secondary (manufacturing) sector *within a county* is an important mechanism through which the agricultural mechanization contributed to structural transformation.

5 Evidence on mechanisms

5.1 Within-county reallocation vs migration

The above discussions highlight how the agricultural mechanization led to reallocation of VA and employment from the primary to the secondary sector. The decrease in the employment share of agriculture and the increase in the employment share of manufacturing could be caused by: (i) reallocation of labor from agriculture to manufacturing *within* a county, and/or (ii) migration of surplus agricultural labor out of the county and hence change in the composition of labor.

Table 2 shows that agricultural employment decreases both in levels and as a share of rural population in response to mechanization. The decrease in agricultural employment could either be absorbed into manufacturing sector within the counties or migrate out. In the case of migration, we should see a decrease in the population size (of migration age) in counties with faster rate of agricultural mechanization.

To investigate this, I explore how county populations for different age groups evolve over decades by combining county demographic data for the 2000 and 2010 censuses. I run similar specifications as equation 4 using changes between 2000 and 2010. I use counties' land gradient to instrument for change in agricultural mechanization. The results are presented in Table 4. Panel A of the table shows that the agricultural mechanization decreases population counts. Counties that experienced faster agricultural mechanization have seen decreases in their total population counts. The decrease in population size is significant and largely similar across different age groups. As a result, there is modest change in the age composition of the counties' population following agricultural mechanization. An exception is statistically significant but small decreases in the percentage of population between ages 30-39 and above 64 age.

Overall, the results in tables 2 and 4 suggest that agricultural mechanization has decreased agricultural employment and induced significant migration of people.

5.2 Further evidence on mechanisms

The above analysis shows that agricultural mechanization led to decrease in the share of agriculture and increase in the share of manufacturing in both VA production and employment. The decrease in agricultural employment could lead to shrinking agricultural production, thus increasing the share of manufacturing mechanically. Here, I rule out this possibility by showing that the agricultural mechanization in a county not only increased agricultural output but also led to expansion of manufacturing within the county.

Table 5 presents the estimation results. I explore the effect of agricultural mechanization on grain production, the number of industrial enterprises and industrial production within the counties. These later two variables are based on survey of industrial enterprises with annual main business revenue of 5 million yuan or above (i.e., they do not include small enterprises, which are perhaps more likely to be located in rural areas). Panels A and B report results based on alternative IVs. Column 1, in both panels, shows that agricultural mechanization led to significant increase in grain production. The estimated elasticity of grain production with respect to agricultural machineries is 0.27. This implies that the emigration of active age workers did not hamper agricultural production, implying that the agricultural machineries replaced the workers. This is consistent with the hypothesis that the agricultural mechanization is labor-saving technology. Column 2 estimates the effect of agricultural mechanization on the number of industrial enterprises in the county. The estimates in both panels show the elasticity of number of industrial enterprises with respect to agricultural mechanization of 0.7-0.76. Column 3 repeats similar estimation now using output of industrial enterprises (deflated using CPI). The estimates across both panels show elasticity of industrial output with respect to agricultural mechanization of about 2.3. The results in columns 2 and 3 imply that agricultural mechanization in a county led to expansion of manufacturing production within the county.

Overall, the results in table 5, together with the above analyses, clearly show that agricultural mechanization resulted in not only expansion of both agricultural and manufacturing production within the counties but also caused emigration of surplus labor out of the counties. Thus, the increase in manufacturing share of VA is not caused by shrink in the agricultural VA but by a faster expansion of the manufacturing sector within the counties. Moreover, the increase in manufacturing share of employment is not totally caused by change in worker composition due to emigration of agricultural workers. Instead, it is partially driven by workers switching sectors within their own counties.

6 The productivity gain from sectoral reallocation

My goal in this section is to quantify the productivity gain from reallocation of workers from the primary to the secondary sector within a county in response to agricultural mechanization.[16] This analysis is related to McCaig and Pavcnik (2018) who estimate the aggregate productivity gain due to worker reallocation from the informal to formal sector in response to export demand shock in Vietnam. The key difference in my analysis is that I estimate the productivity gains at subnational (county) level. This empirical exercise requires county-level estimates of labor reallocation from the primary to the secondary sectors (which can be inferred from the regression results in table 3) and county-level measure of sectoral productivity gap between the primary and secondary sectors. I use value-added per worker in each sector as a measure of sectoral productivity and I combine county-level sectoral employment data from rounds of census data with county-level sectoral value-added data from provincial yearbook, to calculate VA per worker in each sector for the years 2000 and 2010 to measure productivity in the sector.

Let county-level aggregate productivity T (in logs) is given by the weighted average of sectoral VA per worker where the weights are employment shares of the

[16]Because I do not have data on migration between counties, I cannot quantify the effect of sectoral reallocation of workers that happens due to workers migrating out of their counties. However, this channel is likely to be very important since migration in response to agricultural mechanization is quantitatively significant (particularly for people aged 20-29) and it is highly likely that migrant workers switch sectors more often than those who stay in their counties.

sectors:

$$T = S^p T^p + S^s T^s + S^t T^t \tag{5}$$

where T^p, T^s and T^t are log of value-added per worker in the primary, secondary and tertiary sectors, and S^p, S^s and S^t are employment shares of these sectors. Productivity growth between years 2000 and 2010 is given by:

$$\begin{aligned} \Delta T = S_0^p \Delta T^a + S_0^s \Delta T^s + S^t \Delta T^t \\ + \Delta S^p T_0^p + \Delta S^s T_0^s + \Delta S^t T_0^t \end{aligned} \tag{6}$$

where ΔX denotes changes in variable X between years 2000 and 2010, and 0 subscript denotes value of the variable in 2000.

From equation 6, the total productivity gain from reallocation of workers across sectors is given by $\Delta S^p T_0^p + \Delta S^s T_0^s + \Delta S^t T_0^t$. My goal is to quantify the productivity gain from within-county reallocation of labor from the primary to secondary and tertiary sectors due to agricultural mechanization. From the IV estimation results (Panel B) in table 3, the share of labor in primary sector decreased by 0.06, the share of employment in secondary and tertiary sectors increased by 0.03 and 0.022, respectively. The productivity gain from reallocation of labor from primary to secondary sector is given as $\Delta S^s(T_0^s - T_0^p)$. Likewise, the productivity gain from reallocation from primary to tertiary sector is given by $\Delta S^t(T_0^t - T_0^p)$. The changes in shares of employment in secondary and tertiary sectors due to agricultural mechanization can be calculated for each county as $\widehat{\Delta S_c^s} = 0.03 \times \Delta \text{logAg.Mech}_c$ and $\widehat{\Delta S_c^t} = 0.022 \times \Delta \text{logAg.Mech}_c$, respectively. I first estimate the productivity gains in each county as $\widehat{\Delta S_c^s}(T_{0,c}^s - T_{0,c}^p) + \widehat{\Delta S_c^t}(T_{0,c}^t - T_{0,c}^p)$. I then calculate aggregate productivity gain from the reallocation by taking weighted average across the counties where the weights are counties' share of national employment $\sum_c [\widehat{\Delta S_c^s}(T_{0,c}^s - T_{0,c}^p) + \widehat{\Delta S_c^t}(T_{0,c}^t - T_{0,c}^p)] \times \theta_c$ where θ_c is the employment share in county c.

The results are reported in Table 6. Column 1 reports the sectoral productivity gap (log of ratio of value-added productivity in the secondary sector to the value-added productivity in the primary sector) in the year 2000. It shows that the sectoral productivity gap varies widely across counties. In few counties, it is negative implying that the agricultural sector is more productive than the manufacturing sector. Column 2 presents productivity gap between tertiary and primary sectors, which is significant but not as large as productivity gap between secondary and primary sectors. Consequently, the gain from reallocation from primary to tertiary sector contributes less to the aggregate productivity gain. Columns 3-6 report: overall productivity growth ΔT, productivity growth due to sectoral productivity growth $S_0^p \Delta T^a +$

$S_0^s \Delta T^s + S_0^t \Delta T^t$, productivity growth due to between sector reallocation $\Delta S^p T_0^p + \Delta S^s T_0^s + \Delta S^t T_0^t$, and productivity growth due to reallocation from the primary to secondary and tertiary sectors due to agricultural mechanization $\widehat{\Delta S_c^s}(T_{0,c}^s - T_{0,c}^p) + \widehat{\Delta S_c^t}(T_{0,c}^t - T_{0,c}^p)$. Panel A reports summary statistics of these estimates across counties while Panel B reports the national aggregate using the employment shares of counties as weights.

Column 3 shows significant difference in aggregate productivity growth between 2000 and 2010 across counties, ranging from 51% in the lowest percentile counties to 286% in the highest percentile counties while the average county experienced a growth of 148.5%. Column 4 shows that most of the aggregate productivity growth is attributed to productivity growth in each of the sectors. In an average county, out of 148.5% growth in aggregate productivity, 120% of it was caused by growth in productivity in the primary, secondary and tertiary sectors. The remaining growth in aggregate productivity of counties is caused by reallocation of labor across sectors within the counties. This is reported in column 5 and it is evident that within-county reallocation of labor accounts for smaller share (roughly 28%) of aggregate productivity growth in the counties. In some counties, reallocation of labor actually decreased aggregate productivity. Column 6 reports how much of the productivity growth due to sectoral reallocation of labor within counties is attributed to agricultural mechanization. Aggregate productivity growth due to reallocation of labor induced by agricultural mechanization significantly varies across counties, ranging from -2.9% in the lowest percentile counties to 19.6% in the highest percentile counties. In an average county, agricultural mechanization led to 4.8% aggregate productivity growth between 2000 and 2010.

Panel B reports the country level aggregate. Aggregate productivity increased by 145% at national level, of which 119% is attributed to growth within each sector and the remaining 26% caused by reallocation across sectors. Sectoral reallocation due to agricultural mechanization accounts for 6.9% of the overall growth. That is, about a fifth of growth due to sectoral reallocation is attributed to agricultural mechanization.

Note that this exercises do not take into account sectoral reallocation of workers due to migration. Because migrant workers are more likely to switch sectors (since most of the migrations are rural-urban) it is likely that such migrations could contribute significantly to aggregate productivity growth. In this sense, my above estimates about the aggregate productivity growth due to sectoral reallocation induced by agricultural mechanization (column 6) could be interpreted as a lower bound of the gain from overall reallocation induced by mechanization. Another limitation of this exercises is that it does not account for worker heterogeneity. It is likely that workers who move from agriculture to manufacturing or services are relatively more educated or have some attributes that makes them different from those who stay in agriculture. However, this is unlikely to have significant effect on the above analysis (see, for instance, Herrendorf and Schoellman (2018); Vollrath (2014)).

7 Conclusion

In this paper, I study how agricultural mechanization could be a driving factor for structural transformation using a uniquely comprehensive measure of the stock of agricultural machinery at detailed geographic unit, spanning over two decades, from China.

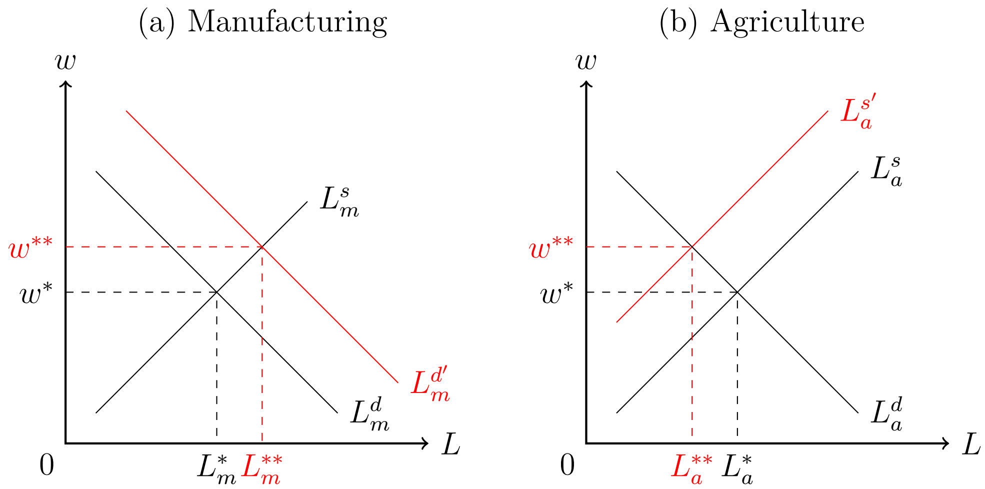
The main empirical challenge in studying the effect of agricultural mechanization on structural transformation is endogeneity problem: agricultural mechanization could be both the driver of structural change by releasing surplus labor from agriculture and be driven by manufacturing/service sector development which may increase rural wages by drawing rural labor to these sectors. I address this endogeneity problem by using a large-scale subsidy program to adoption of mechanization and variation in the steepness of terrain across counties.

I find that agricultural mechanization led to significant reallocation of labor and value-added production from the primary sector towards mainly secondary sector. It led to not only out-migration of productive-age population but also caused significant expansion of manufacturing sector within the counties.

I quantify the aggregate productivity gain from within-county reallocation of labor at both county level and national level. I find that the effect on aggregate productivity significantly varies across counties. On average, the within-county reallocation of labor due to mechanization led to about 7% growth in aggregate productivity at national level between 2000 and 2010. An important avenue for future studies is to quantify the aggregate productivity gain from inter-regional reallocation of labor and economic activities due to agricultural mechanization.

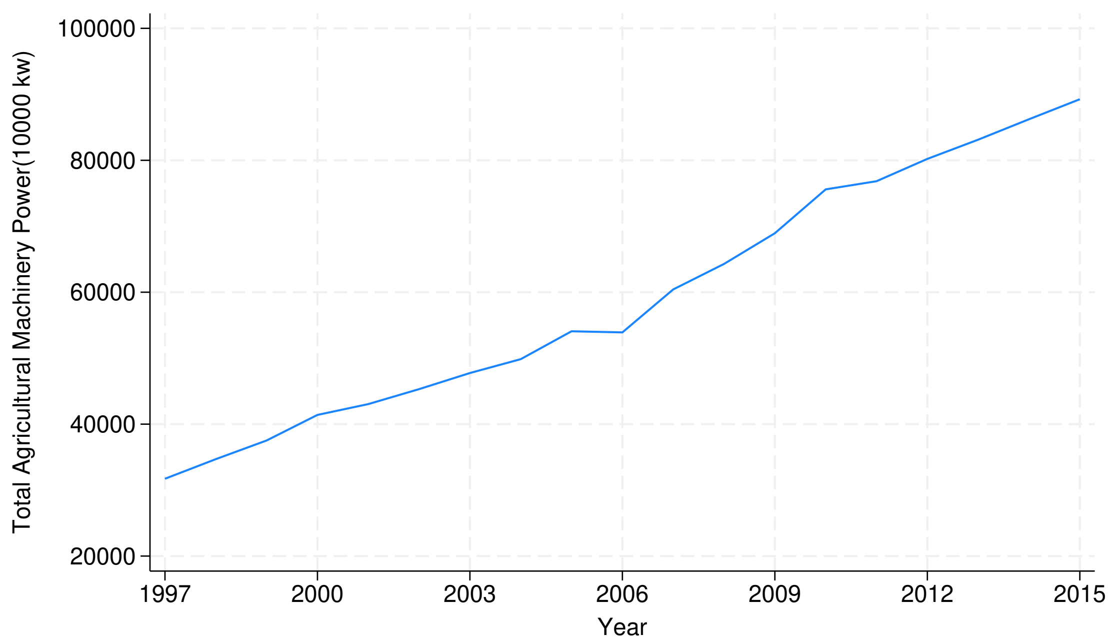
Figures

Figure 1: The effect of manufacturing demand shock



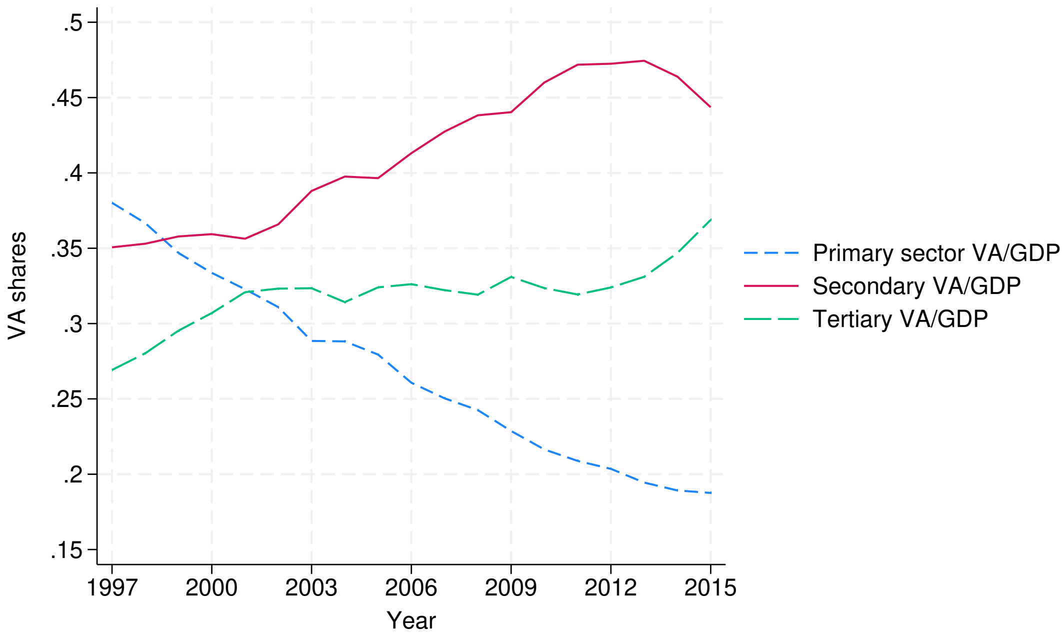
Notes: A positive demand shock to the manufacturing sector increases manufacturing labor demand and increases manufacturing wage. This induces worker migration from agriculture to manufacturing, which decreases labor supply in agriculture. Wage increases in both sectors.

Figure 2: Total agricultural machine stocks over time



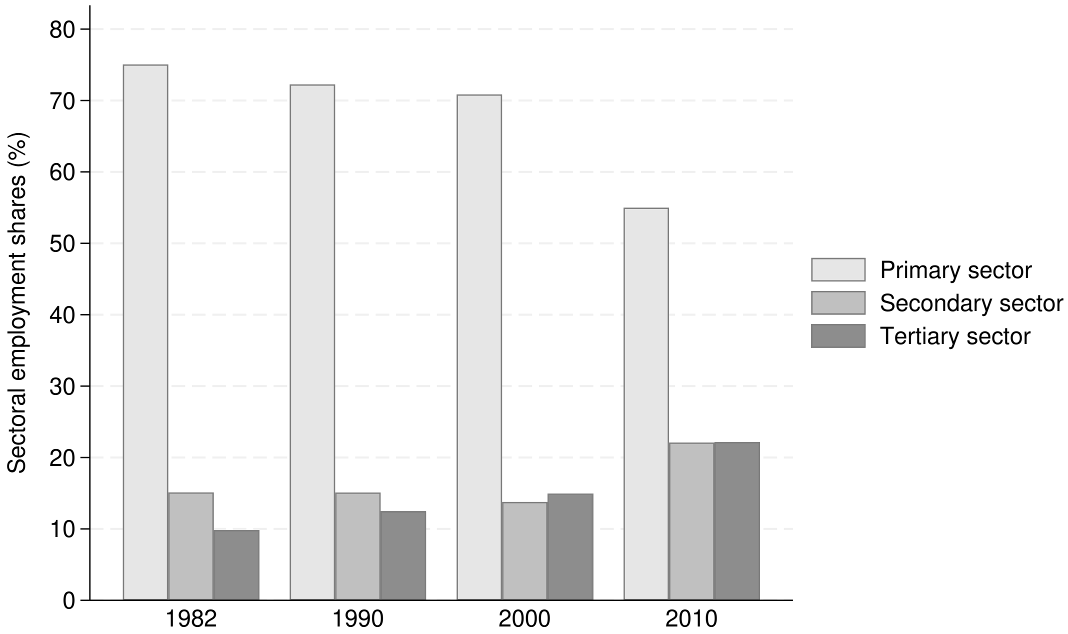
Notes: This figure presents total agricultural machine power (in 10,000KW) over time.

Figure 3: Trends in sectoral VA shares in GDP



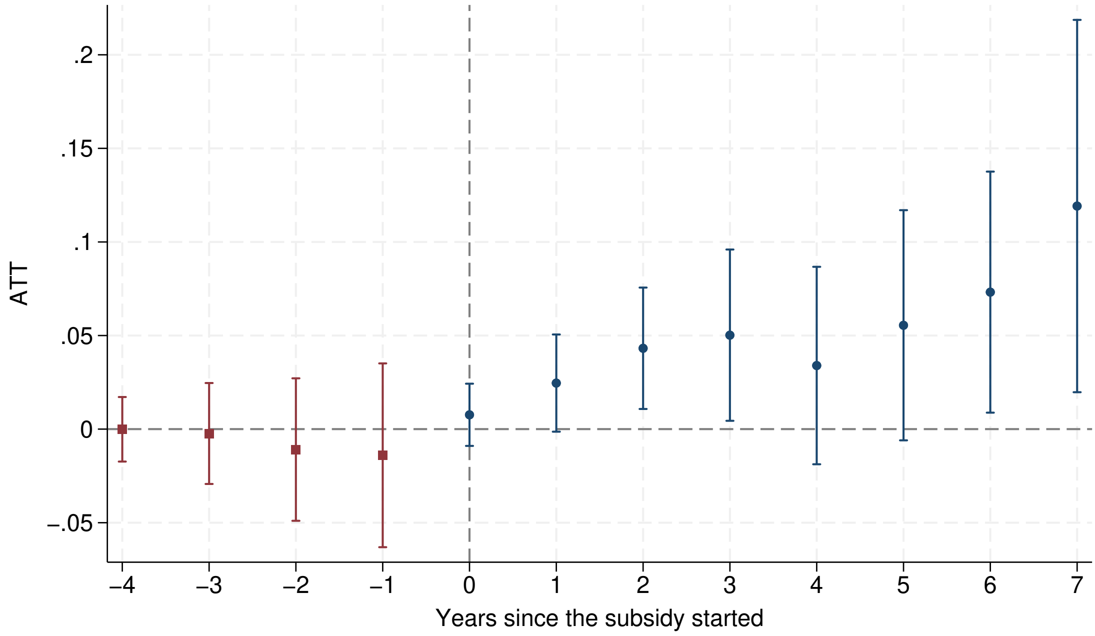
Notes: The vertical axis measures the share in GDP of value added in primary, secondary and tertiary sectors. These shares are weighted average across counties where the weights are counties' population in 1990 census. The primary sector includes agriculture, forestry, animal husbandry and fishery. The secondary sector includes manufacturing, mining and quarrying, construction, and production and supply of electricity and gas. The tertiary sector includes all the other industries (services).

Figure 4: Sectoral shares of employment over decades



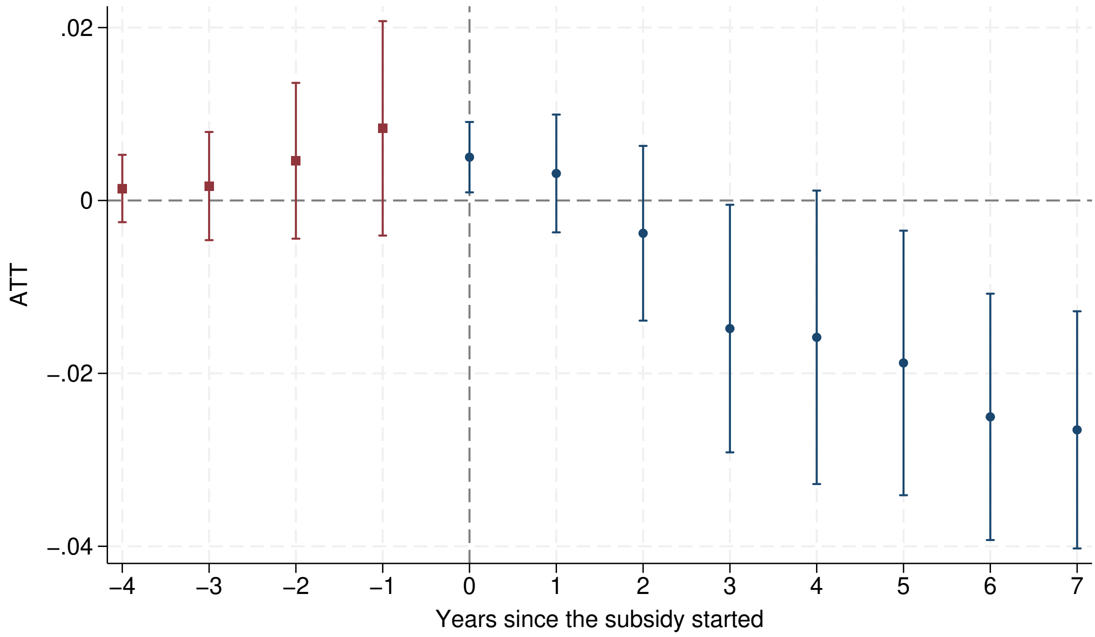
Notes: This figure presents the employment shares of the primary, secondary and tertiary sectors across census years. These shares are weighted average across counties where the weights are counties' total employments in each census. The primary sector includes agriculture, forestry, animal husbandry and fishery. The secondary sector includes manufacturing, mining and quarrying, construction, and production and supply of electricity and gas. The tertiary sector includes all the other industries (services).

Figure 5: The effect of agricultural machine subsidy on the stock of agricultural machines



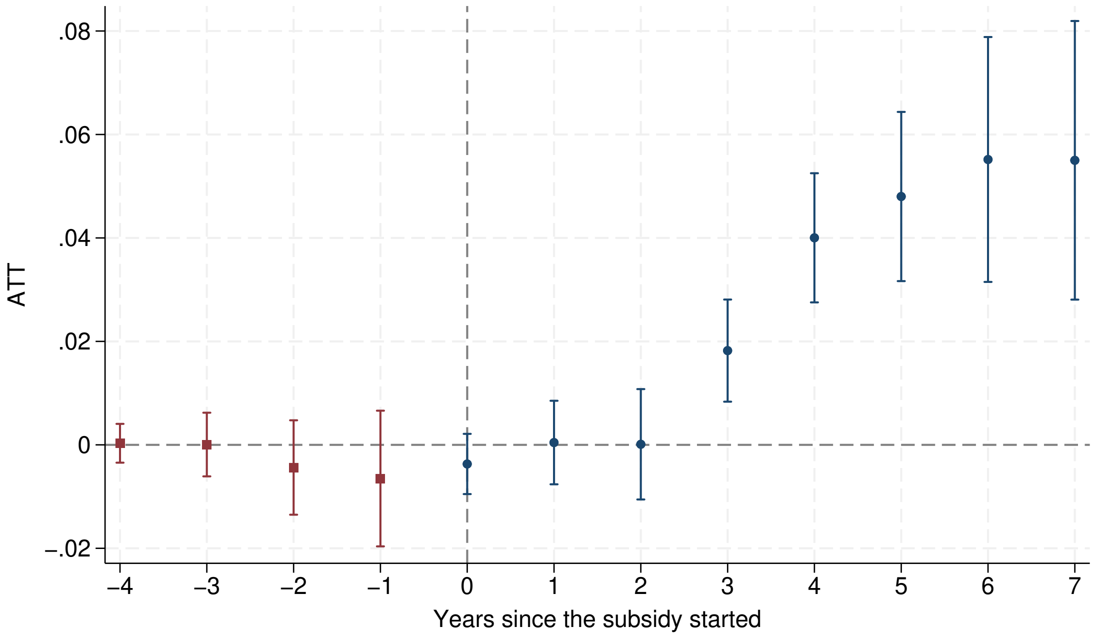
Notes: This figure presents event study plot of the effect of agricultural machines subsidy on the stock of agricultural machines.

Figure 6: The effect of agricultural machine subsidy on agricultural VA



Notes: This figure presents event study plot of the effect of agricultural machines subsidy on agricultural value added share.

Figure 7: The effect of agricultural machine subsidy on manufacturing VA



Notes: This figure presents event study plot of the effect of agricultural machines subsidy on manufacturing value added share.

Tables

Table 1: The effect of agricultural mechanization on sectoral share of VA: main result

	(1) VA prim/GDP	(2) VA sec/GDP	(3) VA ter/GDP
		Panel A: OLS	
Log Ag.machinery	-0.014***	0.011**	0.003
	(0.003)	(0.004)	(0.003)
R-squared	0.902	0.846	0.704
Observations	24834	24834	24834
		Panel B: IV	
Log Ag.machinery	-0.039**	0.035**	0.003
	(0.018)	(0.015)	(0.009)
N	24834	24834	24834
First-stage F-stat	107	107	107

Notes: All regressions include county and year fixed effects and Post 2002 dummy interacted with Prefecture-level NTR gap. Standard errors are clustered at county level. The estimation includes data from 1997-2015. The IV is constructed as $\text{MachineryShare}_{c,1990} \times \text{Subsidy}_{pt}$ * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: The effect of agricultural mechanization on agricultural employment

	(1) Log employment	(2) Share of rural pop	(3)
	Panel A: OLS		
Log Ag.machinery	0.055***	-0.003	
	(0.018)	(0.003)	
R-squared	0.930	0.724	
Observations	20028	20015	
	Panel B: IV		
Log Ag.machinery	-0.048**	-0.021***	
	(0.022)	(0.007)	
N	20028	20015	
First-stage F-stat	161	161	

Notes: All regressions include county and year fixed effects and Post 2002 dummy interacted with Prefecture-level NTR gap. Standard errors are clustered at county level. The estimation includes data from 2000-2012. The IV is constructed as $\text{MachineryShare}_{c,1990} \times \text{Subsidy}_{pt}$ * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: The effect of agricultural mechanization on sectoral share of employment

	(1) Δ % Primary	(2) Δ % Secondary	(3) Δ % Tertiary
		Panel A: OLS	
Δ Log Ag.machinery	-1.437***	1.303***	0.245
	(0.368)	(0.243)	(0.191)
N	3972	3972	3972
R^2	0.638	0.688	0.515
		Panel B: IV- Slope	
Δ Log Ag.machinery	-6.099***	3.025**	2.188**
	(2.047)	(1.396)	(1.032)
N	1918	1918	1918
First-stage F-stat	51	51	51

Notes: The estimation is based on county-level data of stacked first difference across the 1990, 2000, and 2010 census rounds. Panel A regressions include county and decade fixed effects and standard errors are clustered at county level. Panel B regressions are based on decadal change in county employment shares between 2000 and 2010 censuses and the counties' slope is used to instrument for changes in agricultural mechanization between 2000 and 2010. The panel B regressions also include a host of time-invariant county characteristics including distance to major city and distance to port and province fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: The effect of agricultural mechanization on county demographic features

	(1) ΔPop	(2) ΔBelow 14	(3) Δ15-19	(4) Δ20-29	(5) Δ30-39	(6) Δ40-64	(7) Δabove 64
	Panel A: Log Population Size						
Δ Log Ag.machinery	-0.564***	-0.500***	-0.495***	-0.588***	-0.661***	-0.534***	-0.701***
	(0.098)	(0.105)	(0.116)	(0.109)	(0.104)	(0.101)	(0.103)
N	1917	1918	1918	1918	1918	1918	1918
First-stage F-stat	64	64	64	64	64	64	64
	Panel B: Percentage composition						
Δ Log Ag.machinery	.	1.355*	0.615	-0.762	-1.107***	0.265	-0.842***
		(0.736)	(0.439)	(0.593)	(0.421)	(0.490)	(0.228)
N		1917	1917	1917	1917	1917	1917
First-stage F-stat		64	64	64	64	64	64

Notes: The estimation is based on county-level data of changes between 2000 and 2010 census rounds. Land gradien
an instrument for agricultural mechanization. All regressions include province fixed effects. Robust standard errors in
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Mechanisms: The effect of agricultural mechanization on agricultural and manufacturing productions (IV estimation)

	(1) Log Grain production (10000 tons)	(2) Log Number of Industrial Enterprises	(3) Log Output of Industrial Enterprises
Log Ag. Machinery	0.227***	0.268**	0.251**
	(0.064)	(0.119)	(0.112)
N	24547	24735	24732
First-stage F-stat	109	107	107

Notes: All regressions include county and year fixed effects and Post 2002 dummy interacted with manufacturing share of county employment in 1990 and Prefecture-level NTR gap. Standard errors are clustered at county level. Data for grain production covers the period 1997-2016. Data for Industrial enterprises covers 1996-2010 for output and 2000-2010 for number of enterprises. The data on number and output of industrial enterprises is based on survey of industrial enterprises with annual main business revenue of 5 million yuan or above. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

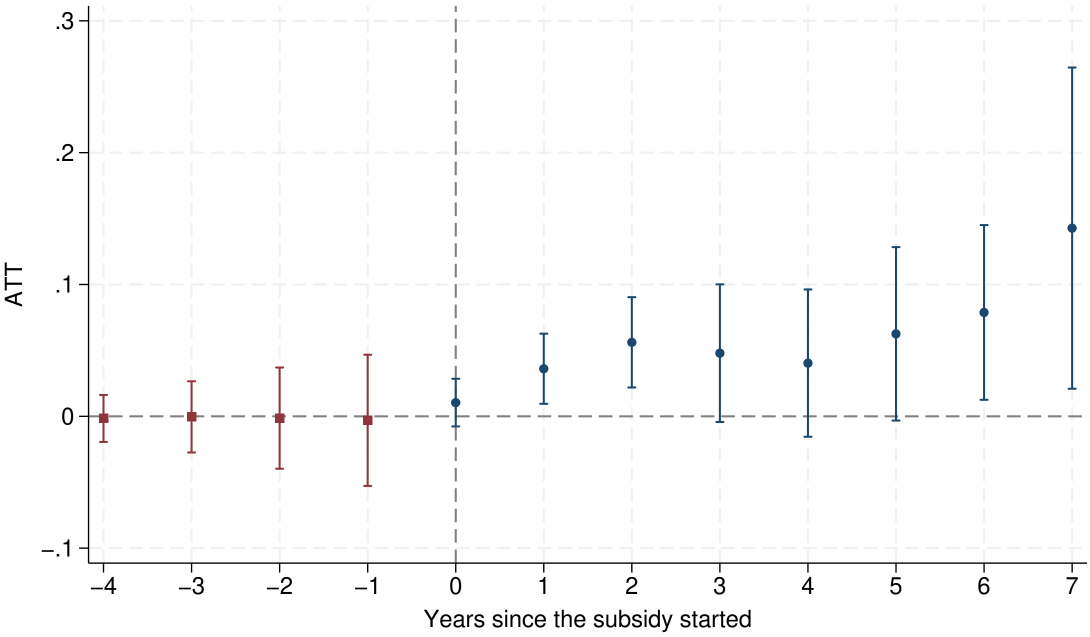
Table 6: Decomposing productivity growth between 2000 and 2010

	(1) Log second-primary productivity gap (2000)	(2) Log tertairy-primary productivity gap (2000)	(3) Total productivity growth	(4) Growth due to growth in each sector	(5) Growth due to overall sectoral reallocation	(6) Growth due to sectoral reallocation induced by agri. mechan.
Panel A: County-level productivity gains						
p1	-0.35	-0.36	51.20	40.97	-35.59	-2.90
p5	0.88	0.50	83.67	66.42	-13.38	-0.03
p10	1.26	0.85	98.10	80.71	-4.31	1.09
p25	1.77	1.30	120.32	99.16	8.81	3.48
p50	2.33	1.74	144.93	115.61	24.52	6.01
mean	2.31	1.68	148.53	119.99	27.98	6.47
p75	2.87	2.13	170.42	135.85	44.53	9.20
p90	3.44	2.47	203.74	162.81	66.14	12.06
p95	3.79	2.71	227.17	185.95	84.56	14.28
p99	4.50	3.16	286.27	236.13	124.81	19.57
Panel B: Aggregate productivity gains						
National aggregate	2.37	1.81	145.05	118.89	26.12	6.88

Notes: This table decomposes growth in productivity (value-added per worker) between 2000 and 2010. Panel A repo results for county-level exercises. Panel B reports the national aggregate result, which is obtained by aggregating countie the national employment shares as weights. Log productivity gaps in the first and second columns are calculated as log ratio of value-added per worker in the secondary and tertiary sectors to value-added per worker in the primary sector, year 2000.

Appendix A Additional results

Figure A.1: The effect of agricultural machine subsidy on the stock of agricultural machines



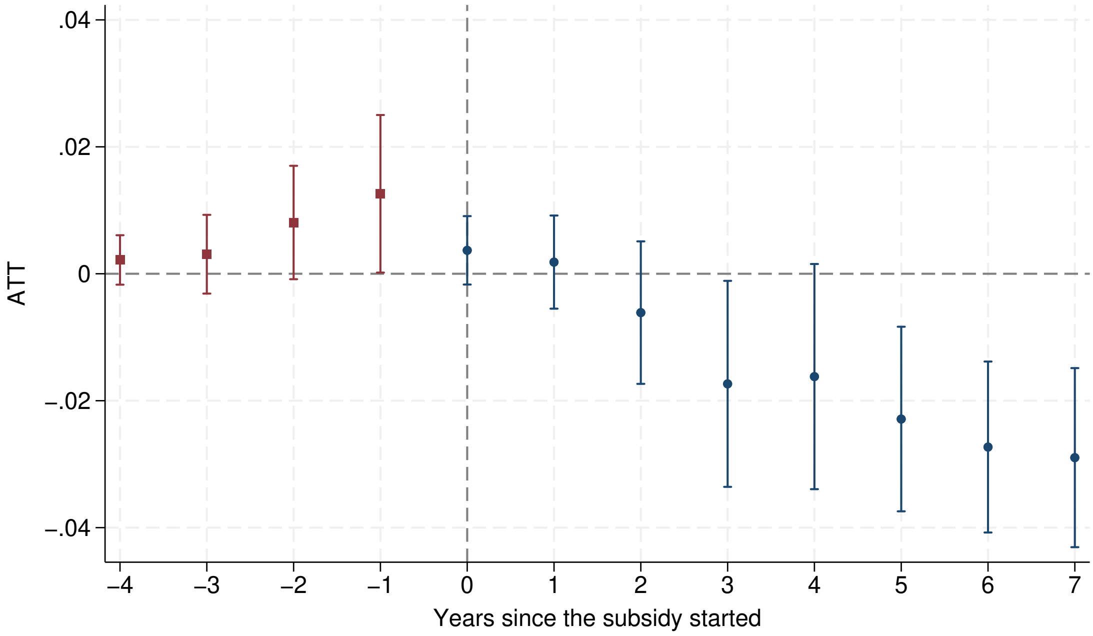
Notes: This figure presents event study plot of the effect of agricultural machines subsidy on the stock of agricultural machines using *predicted* rollout of the subsidy program.

Table A.1: First-stage regressions

	(1) Log Ag. Mach	(2) Log Ag. Mach
MachineryShare $_{c,1990}$ * Subsidy$_{pt}$	3.476***	6.687***
	(0.515)	(0.747)
R-squared	0.946	0.959
Observations	25126	25126

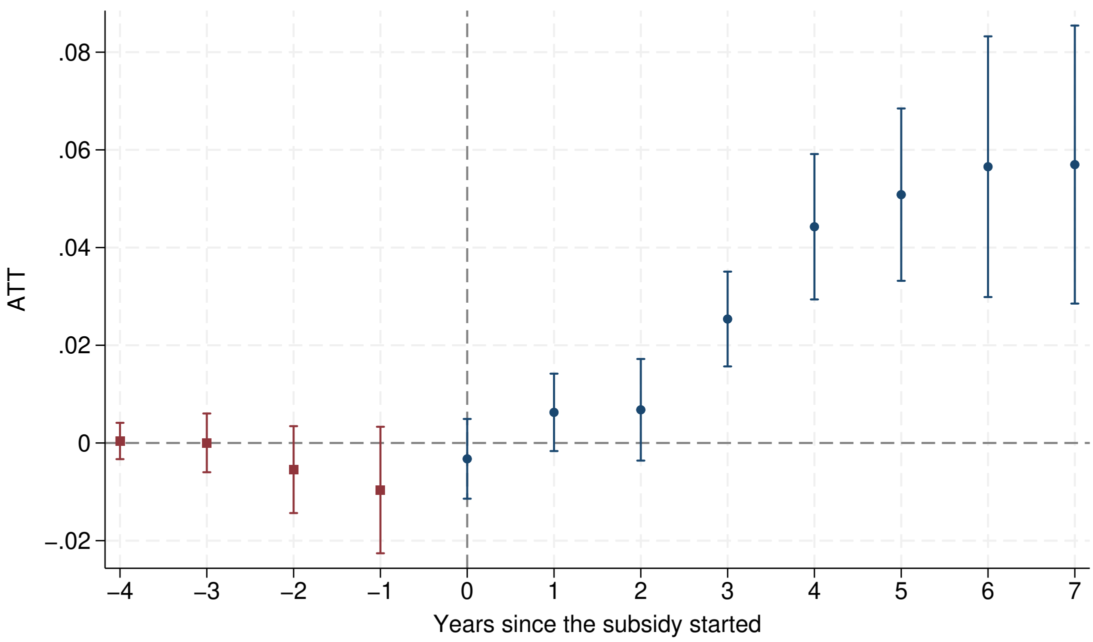
Notes: All regressions include county and year fixed effects. Standard errors are clustered at county level. The estimation includes county level data from 1997-2015. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.2: The effect of agricultural machine subsidy on agricultural VA



Notes: This figure presents event study plot of the effect of agricultural machines subsidy on agricultural value added share using *predicted* rollout of the subsidy program.

Figure A.3: The effect of agricultural machine subsidy on manufacturing VA



Notes: This figure presents event study plot of the effect of agricultural machines subsidy on manufacturing value added share using *predicted* rollout of the subsidy program.

Table A.2: 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.

Appendix B Construction of land gradient as IV

In this section, I exploit plausibly exogenous variation in agricultural mechanization rates across counties driven by variation in the steepness of farmlands across counties.

The steepness of agricultural land is a crucial factor that affects the costs of mechanization, with the cost of mechanization sharply increasing on farmlands steeper than 15^o. Moreover, fuel costs account for significant fraction of the costs of agricultural mechanization. Zhang et al. (2017) find that fuel costs account for nearly 30% of the operation costs of agricultural mechanization services in China. In particular, higher fuel prices raise the costs of mechanization relatively more on steeper farmlands than flat ones. There are a number of reasons for this.

First, farming a steep terrain requires specialized equipments with additional features for stability and traction which increases the prices of the machines. Moreover, because of these additional features and the technical requirement that these equipments need to be heavier to be used on steep terrain (to avoid rollovers), they are also relatively less fuel efficient. Second, tractors and harvesters need increased engine load to climb and work on steeper slopes due to the added gravitational resistance. This increased workload leads to higher fuel consumption as the engine works harder to maintain speed and perform harvesting operations. Third, ploughing/harvesting on hills often requires frequent adjustments and maneuvers to maintain stability and prevent slippage or rollover. These additional movements contribute to higher fuel consumption as the vehicle accelerates and decelerates more frequently. Fourth, farming on steep hills may require more time to complete compared to flat terrain, especially if the machine needs to navigate complex terrain or work at reduced speeds for safety reasons. Extended operating time translates to increased fuel consumption over the duration of the ploughing/harvesting process. Fifth, operating machinery on steep slopes can accelerate wear and tear on components such as brakes, transmissions, and tires. Increased maintenance requirements, including more frequent replacements and repairs, contribute to higher overall costs.

To construct an instrumental variable that utilizes the above technical details, I use Digital Elevation Model (DEM) to calculate the average land gradient in each Chinese county. Consistent with the technical prediction, I find that, crossectionally, counties with high average slope experienced significantly lower agricultural mechanization. I instrument between decade changes in agricultural mechanization within a county by the counties' average land slope. I consider both changes between 2000 and 2010 as it is the period of rapid mechanization induced by government subsidies.

References

Adamopoulos, T. and Restuccia, D. (2021). Geography and Agricultural Productivity: Cross-Country Evidence from Micro Plot-Level Data. *The Review of Economic Studies*, 89(4):1629–1653.

Andersen, T. B., Jensen, P. S., and Skovsgaard, C. V. (2016). The heavy plow and the agricultural revolution in medieval europe. *Journal of Development Economics*, 118:133–149.

Belloni, A., Chen, D., Chernozhukov, V., and Hansen, C. (2012). Sparse models and methods for optimal instruments with an application to eminent domain. *Econometrica*, 80(6):2369–2429.

Bharadwaj, P., Fenske, J., Kala, N., and Mirza, R. A. (2020). The green revolution and infant mortality in india. *Journal of Health Economics*, 71:102314.

Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting Event-Study Designs: Robust and Efficient Estimation. *The Review of Economic Studies*, page rdae007.

Bustos, P., Caprettini, B., and Ponticelli, J. (2016). Agricultural productivity and structural transformation: Evidence from brazil. *American Economic Review*, 106(6):1320–65.

Bustos, P., Garber, G., and Ponticelli, J. (2020). Capital Accumulation and Structural Transformation. *The Quarterly Journal of Economics*, 135(2):1037–1094.

Carillo, M. (2018). Agricultural policy and long-run development: evidence from mussolini's battle for grain. Mpra paper, University Library of Munich, Germany.

Chen, S. and Kung, J. (2016). Of maize and men: the effect of a new world crop on population and economic growth in china. *Journal of Economic Growth*, 21(1):71–99.

Chen, W., Chen, X., Hsieh, C.-T., and Song, Z. (2019). A forensic examination of china's national accounts. Working Paper 25754, National Bureau of Economic Research.

Cheng, H. (1996). Chapter 11 promoting township and village enterprises as a growth strategy in china. In *Inflation and Growth in China*, page ch013. International Monetary Fund, USA.

Erten, B. and Leight, J. (2021). Exporting Out of Agriculture: The Impact of WTO Accession on Structural Transformation in China. *The Review of Economics and Statistics*, 103(2):364–380.

Feng, L., Li, Z., and Swenson, D. L. (2017). Trade policy uncertainty and exports: Evidence from china's wto accession. *Journal of International Economics*, 106:20–36.

Fischer, G., Nachtergaele, F., van Velthuizen, H., Chiozza, F., Francheschini, G., a. H. M., Muchoney, D., and Tramberend, S. (2021). Global agro-ecological zone v4 – model documentation. Technical report, FAO IIASA.

Foster, A. D. and Rosenzweig, M. R. (2004). Agricultural productivity growth, rural economic diversity, and economic reforms: India, 1970–2000. *Economic Development and Cultural Change*, 52(3):509–542.

Gollin, D., Hansen, C. W., and Wingender, A. M. (2021). Two blades of grass: The impact of the green revolution. *Journal of Political Economy*, 129(8):2344–2384.

Gollin, D., Parente, S., and Rogerson, R. (2002). The role of agriculture in development. *American Economic Review*, 92(2):160–164.

Gollin, D., Parente, S. L., and Rogerson, R. (2004). Farm work, home work and international productivity differences. *Review of Economic Dynamics*, 7(4):827–850.

Guang, L. and Zheng, L. (2005). Migration as the second-best option: Local power and off-farm employment. *The China Quarterly*, (181):22–45.

Herrendorf, B., Rogerson, R., and Ákos Valentinyi (2014). Chapter 6 - growth and structural transformation. In Aghion, P. and Durlauf, S. N., editors, *Handbook of Economic Growth*, volume 2 of *Handbook of Economic Growth*, pages 855–941. Elsevier.

Herrendorf, B. and Schoellman, T. (2018). Wages, human capital, and barriers to structural transformation. *American Economic Journal: Macroeconomics*, 10(2):1–23.

Hornbeck, R. and Keskin, P. (2015). Does agriculture generate local economic spillovers? short-run and long-run evidence from the ogallala aquifer. *American Economic Journal: Economic Policy*, 7(2):192–213.

Imbert, C., Seror, M., Zhang, Y., and Zylberberg, Y. (2022). Migrants and firms: Evidence from china. *American Economic Review*, 112(6):1885–1914.

Jat, R. (2024). *Sufficient Instruments Filter*. PhD thesis, UCR.

Kongsamut, P., Rebelo, S., and Xie, D. (2001). Beyond balanced growth. *The Review of Economic Studies*, 68(4):869–882.

Lewis, A. (1951). The principles of economic planning. *American Political Science Review*, 45(2).

Marden, S. (2016). The agricultural roots of industrial development: 'forward linkages' in reform era china. Working paper series, Department of Economics, University of Sussex Business School.

Matsuyama, K. (1992). Agricultural productivity, comparative advantage, and economic growth. *Journal of Economic Theory*, 58(2):317–334.

McArthur, J. W. and McCord, G. C. (2017). Fertilizing growth: Agricultural inputs and their effects in economic development. *Journal of Development Economics*, 127:133–152.

McCaig, B. and Pavcnik, N. (2018). Export markets and labor allocation in a low-income country. *American Economic Review*, 108(7):1899–1941.

Monfreda, C., Ramankutty, N., and Foley, J. A. (2008). Farming the planet: 2. geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles*, 22(1).

Moscona, J. (2019). Agricultural development and structural change, within and across countries. Technical report.

Nagaraj, D., Proust, E., Todeschini, A., Rulli, M. C., and D'Odorico, P. (2021). A new dataset of global irrigation areas from 2001 to 2015. *Advances in Water Resources*, 152:103910.

Ngai, L. R. and Pissarides, C. A. (2007). Structural change in a multisector model of growth. *American Economic Review*, 97(1):429–443.

Nunn, N. and Qian, N. (2011). The Potato's Contribution to Population and Urbanization: Evidence From A Historical Experiment*. *The Quarterly Journal of Economics*, 126(2):593–650.

Nurkse, R. (1953). *Problems of Capital Formation in Underdeveloped Countries*. Oxford University Press.

Pierce, J. R. and Schott, P. K. (2016). The surprisingly swift decline of us manufacturing employment. *American Economic Review*, 106(7):1632–62.

Ranis, G. and Fei, J. C. H. (1961). A theory of economic development. *The American Economic Review*, 51(4):533–565.

Restuccia, D., Yang, D. T., and Zhu, X. (2008). Agriculture and aggregate productivity: A quantitative cross-country analysis. *Journal of Monetary Economics*, 55(2):234–250.

Rostow, W. W. (1956). The take-off into self-sustained growth. *The Economic Journal*, 66(261):25–48.

Rozelle, S., Guo, L., Shen, M., Hughart, A., and Giles, J. (1999). Leaving china's farms: Survey results of new paths and remaining hurdles to rural migration. *The China Quarterly*, (158):367–393.

Schmidt, T. D., Jensen, P. S., and Naz, A. (2018). Agricultural productivity and economic development: the contribution of clover to structural transformation in denmark. *Journal of Economic Growth*, 23(4):pp. 387–426.

Schultz, T. (1953). *The Economic Organization of Agriculture*. McGraw-Hill.

Su, W., Eriksson, T., Zhang, L., and Bai, Y. (2016). Off-farm employment and time allocation in on-farm work in rural china from gender perspective. *China Economic Review*, 41:34–45.

Tian, Y., Xia, J., and Yang, R. (2020). Trade-induced urbanization and the making of modern agriculture. Discussion Papers 2020-16, University of Nottingham, GEP.

Tombe, T. and Zhu, X. (2019). Trade, migration, and productivity: A quantitative analysis of china. *American Economic Review*, 109(5):1843–72.

Vollrath, D. (2014). The efficiency of human capital allocations in developing countries. *Journal of Development Economics*, 108:106–118.

von der Goltz, J., Dar, A., Fishman, R., Mueller, N. D., Barnwal, P., and McCord, G. C. (2020). Health impacts of the green revolution: Evidence from 600,000 births across the developing world. *Journal of Health Economics*, 74:102373.

Zhang, X., Yang, J., and Thomas, R. (2017). Mechanization outsourcing clusters and division of labor in chinese agriculture. *China Economic Review*, 43:184–195.