Industrializing Agriculture: Structural Transformation and Sugarcane in São Paulo*

Francisco Costa† Francisco Luis Lima‡ Letícia Nunes§

February 28, 2025

Abstract

Agricultural mechanization and environmental regulations reshape labor markets, but their effects on industrialization remain unclear. This paper studies the rapid adoption of mechanical harvesting in the sugarcane industry in São Paulo, Brazil, between 2000 and 2010 following a law banning pre-harvest burning. Using land slope as an instrument for mechanization, we find that mechanization reduced agricultural employment and increased manufacturing jobs. However, labor reallocation occurred only in agriculture-related industries, not broadly across sectors. A one-standard-deviation increase in mechanization raised employment in linked manufacturing industries by 3.5 percentage points, primarily unskilled labor. This shift generated substantial local economic benefits: household incomes rose 19 percent and poverty fell 14 percent. These findings challenge the view of structural transformation as a shift from agriculture to diverse industries. Instead, labor-saving technology in farming strengthens sectoral linkages, deepening the agro-industrial economy rather than diversifying it. Our results also highlight how environmental regulation can shape industrialization by driving sectoral labor reallocation.

*We would like to thank Sam Bazzi, Martin Fiszbein, Jason Garred, Namrata Kala, Marcelo Sant'Anna, Edson Severnini, and seminar participants at EPGE, NEUDC, Jobs and Development Conference (World Bank), LCM Conference (FEA-USP), SBE, REAP Meeting, VII CAEN-EPGE Meeting. We gratefully thank the financial support from Rede de Pesquisa Aplicada FGV and CAPES/Brasil (Grant #001).

†FGV EPGE. E-mail: francisco.costa@fgv.br.

‡Banco ABC Brasil.

§Insper. E-mail: LeticiaFCN@insper.edu.br.

1 Introduction

Structural transformation — the reallocation of labor from agriculture to manufacturing — is central to economic development (Lewis et al., 1954; Kuznets, 1957). In particular, agricultural productivity gains have been pointed as the main driver of industrialization (Rosenstein-Rodan, 1943; Clark, 1967; Mellor, 1995; Gollin et al., 2021). However, evidence from within and across countries points to mixed effects of agricultural productivity on long-term development (Matsuyama, 1992; Moscona, 2019). Today, with automation and offshoring reshaping industrialization, agriculture with agroindustry offers a viable path for growth and poverty reduction (Mellor, 1995; World Bank, 2008; De Janvry and Sadoulet, 2020). For example, agriculture has fomented industrialization in countries like Brazil in the last decades (Bustos et al., 2016). While much is known about structural transformation broadly, less is understood about its composition: who moves and where.

This paper shows that structural transformation driven by agricultural productivity shifts labor only to sectors linked to agriculture, not broadly across the economy. We document that agricultural mechanization frees unskilled labor and expands production, but reallocation is sector-specific, moving labor into industries downstream or upstream from agriculture. This process, in turn, fosters broader local development.

We study the effect of sugarcane harvest mechanization in São Paulo, Brazil, on structural transformation. Sugarcane is the world's largest crop by production quantity, cultivated on about 27 million hectares in more than 90 countries, with a worldwide harvest of 2 billion tons in 2023 (FAOSTAT). Brazil is the largest producer, and São Paulo state accounts for over two-thirds of its production. The state alone produces as much sugarcane as India, the world's second-largest producer (Walter et al., 2014).

We exploit the rapid adoption of mechanical harvesting in São Paulo between 2000 and 2010 to estimate its impact on local structural transformation. Until the early 2000s, sugarcane was manually harvested after pre-harvest straw burning, which released pollutants that caused respiratory diseases (Rangel and Vogl, 2019). Due to public health concerns, São Paulo passed a law in 2002 to phase out pre-harvest burning by 2021. In 2006, a new regulation moved the deadline to 2014. The ban made traditional manual methods nonviable (Novaes et al., 2007). This effectively forced a shift to mechanical harvesting using combine harvesters, which do not require burning. Mechanization requires fewer workers per area harvested, constituting a labor-saving technology (similar to the new soy seeds in Bustos et al., 2016). Before 2002, mechanical harvesting was minimal, but the sector mechanized rapidly soon after. Mechanization doubled from 30 percent in 2006 to 60 percent in 2012.[1]

[1]The first year we can measure mechanization adequately with GIS data is 2006.

We use remote sensing data on sugarcane planting and harvesting at 30 meters resolution (CANASAT/INPE) to measure harvest mechanization in each plot of land in the state. We then create a mechanization index at the municipality level, measuring the share of sugarcane fields that adopted mechanical harvesting by 2010. Using the 2000 and 2010 Demographic Census from the Brazilian Institute of Geography and Statistics (IBGE), we estimate how mechanization affected the labor market across municipality-level sectors.

We propose an instrumental variable strategy to identify the causal effect of mechanization on structural transformation. An instrument for mechanization is necessary because labor market trends and mechanization could be endogenous. For example, local government subsidies to the sugarcane industry or changes in labor regulations could drive both. We instrument for mechanization using the land slope of sugarcane-planted areas at baseline. Mechanization is cheaper on flatter land (Moraes et al., 2015), so producers on steep terrain adopt it more slowly or switch crops. We show that slope negatively correlates with mechanization across all specifications and has explanatory power.[2] Our exclusion restriction assumes that land slope affects labor markets only through mechanization. Supporting this, we show that until 2006, sugarcane expansion was similar across slope levels, suggesting no systematic preference for flatter land. We also examine the relationship between mechanization between 2000 and 2010 and changes in agricultural outcomes between 1991 and 2000, the decade before mechanization. We find no systematic differences in pre-trends.

We find that sugarcane mechanization triggered structural transformation by shifting labor from agriculture to manufacturing. A one-standard-deviation increase in mechanization reduced agricultural employment by 3 percentage points and increased manufacturing employment by 3.5 percentage points. These effects explain over 75 percent of observed sectoral shifts from 2000 to 2010. Mechanization primarily displaced unskilled agricultural workers to manufacturing, increasing the skilled-unskilled ratio in agriculture by 25 percent, while the skill composition in manufacturing remained unchanged. These results align with standard structural transformation models, where labor-saving technological change in agriculture drives structural transformation (Bustos et al., 2016; Gollin et al., 2021).

Agricultural mechanization channeled workers specifically toward industries linked to agriculture rather than driving broad industrial growth. Using Brazilian input-output tables from IBGE, we classify industries as linked to agriculture if they operate upstream or downstream of the sector. We find that a one-standard-deviation increase in mechanization raised employment in linked manufacturing industries by 3.5 percentage points but had no

[2]The Montiel-Pflueger F statistic (Olea and Pflueger, 2013) ranges from 33.91 to 46.16. To address potential weak instrument concerns as in Lee et al. (2022), all inference is based on weak-instrument-robust confidence intervals (Anderson and Rubin, 1949).

effect on non-linked manufacturing. In services, linked industries saw positive but statistically insignificant effects, while non-linked services remained unaffected. Mechanization did not alter the skill composition of any industry, linked or not. These results indicate that mechanization reinforced linkages between agriculture and manufacturing, expanding the agro-industrial supply chain rather than triggering broad structural change.

One explanation for industrialization concentrated within the agricultural supply chain is that industries downstream from agriculture benefited from cheaper, larger-scale agricultural inputs, while upstream industries benefited from larger local demand (e.g., Caselli and Coleman II, 2001; Acemoglu and Guerrieri, 2008; Jones, 2011; Cai and Li, 2019). Our results confirm that mechanization expanded sugarcane production by increasing the share of cultivated land allocated to the crop. A one-standard-deviation increase in mechanization increased the share of agricultural land dedicated to sugarcane by 18.6 percentage points, representing 72 percent of the average expansion during 2000-2010. Mechanization likely displaced other agricultural activities while potentially increasing the total cultivated area (as in Hess et al., 2021; Carreira et al., 2024), though estimates for the total planted area are positive but statistically insignificant.

Agricultural mechanization produced substantial economy-wide benefits beyond sector-specific employment shifts. A one-standard-deviation increase in mechanization raised household income per capita by 19 percent relative to the average growth in the period and reduced poverty rates by 14 percent relative to the baseline. Labor market improvements extended to reduced unemployment and child labor, although these point estimates are noisy.

Related Literature and Contributions. A long-standing view in development economics holds that agricultural productivity growth is a precondition for industrialization and economic growth. Classical models show that rising agricultural productivity releases labor from farming, increases food supply, and creates demand for manufactured goods, driving structural transformation (Lewis et al., 1954; Kuznets, 1957). Historical evidence from the British Industrial Revolution and Green Revolution confirms that agricultural improvements preceded industrial development (Rosenstein-Rodan, 1943; Clark, 1967; Mellor, 1995; Carillo, 2020; Gollin et al., 2021). A skeptical view counters that agricultural productivity growth can hinder industrialization by reinforcing comparative advantage in agriculture, especially in open economies (Matsuyama, 1992). Evidence shows that positive spillovers from agriculture to non-agricultural sectors often fail to materialize locally (Foster and Rosenzweig, 2004; Hornbeck and Keskin, 2015; Moscona, 2019).

Recent work reconciles these views by showing that productivity effects of labor reallocation depend on the factor intensity of productivity gains (Bustos et al., 2016), the skill

composition of displaced workers and receiving firms (Bustos et al., 2019), and the relative factor intensity of expanding sectors and cross-sectoral spillovers (Caselli and Coleman II, 2001; Acemoglu and Guerrieri, 2008; Caunedo and Kala, 2021).

Our first contribution is to show the *composition* of structural transformation caused by labor-saving technology adoption. Our findings reveal that mechanization expanded agricultural production and freed unskilled labor, which flowed specifically to industries downstream or upstream from the agricultural sector. This pattern of industrialization differs from classic structural transformation, where labor reallocates broadly across the economy. Instead, mechanization strengthened sectoral linkages, reinforcing the agro-industrial supply chain rather than driving manufacturing-wide structural transformation.

Another dimension of structural transformation concerns its environmental implications (Jayachandran, 2022; Barrett et al., 2023) and how environmental regulation shapes industrial dynamics (Hsiang et al., 2019). A standing debate contrasts environmental policy as a drag on economic growth against the idea that regulation can catalyze productivity-enhancing innovation (Porter and Van der Linde, 1995; Shapiro and Walker, 2018). While some studies find environmental restrictions worsen firms and workers' conditions (Berman and Bui, 2001; Greenstone, 2002; Greenstone et al., 2012; Walker, 2011, 2013), others argue regulatory pressure drives industrial upgrading and accelerates transition to cleaner, more productive industries (Harrison et al., 2015; Tanaka et al., 2014; Metcalf and Stock, 2020; Lu and Pless, 2024).

Our second contribution is to examine the implication of environmental regulations for the workforce through the lens of structural transformation in low- and middle-income countries (LMICs). We examine the broader economic effects of labor reallocation following the adoption of technology required by environmental regulations. In LMICs, pushing workers out of traditional, low-productivity agriculture may benefit the local economy by inducing technological upgrading and triggering structural transformation. Unlike previous studies focusing on manufacturing sectors in developed economies, we show that environmental regulation targeted at the traditional agricultural sector can generate positive effects for local workers and broader local economic gains.

2 Background

This section discusses the sugarcane industry in São Paulo, focusing on two key aspects: harvesting technology and labor markets.

Sugarcane in São Paulo. According to the Food and Agriculture Organization (FAO), in 2023, sugarcane was cultivated on about 27 million hectares across more than 90 countries, with a global harvest of 2 billion tons. Brazil is the largest producer, accounting for over a third of worldwide production (Walter et al., 2014). São Paulo is responsible for more than two-thirds of national production in Brazil. If treated as an independent producer, it would rank as the world's second-largest producer according to the Brazilian Sugarcane Industry Union (UNICA).

In 2003, sugarcane production occurred in 393 of São Paulo's 645 municipalities, concentrated in the state's central and northern regions. Sugarcane occupied over XX30% of agricultural land in producing municipalities, with some regions reaching XX80% of farmland.

Sugarcane Industry. Sugarcane is a semi-perennial crop, with the harvesting season in São Paulo running from April to December. After harvest, it is transported to a nearby mill. Since sugars in the cane deteriorate quickly, mills are typically located within 40 km of the fields to minimize losses (Sant'Anna, 2024). At the mill, sugarcane can be processed into sugar or ethanol, with most modern mills capable of producing both.

Harvesting Technologies. Two main methods dominate sugarcane harvesting: traditional and mechanical. Traditional harvesting involves pre-harvest field burning and manual labor, while mechanical harvesting uses combine harvesters without burning.

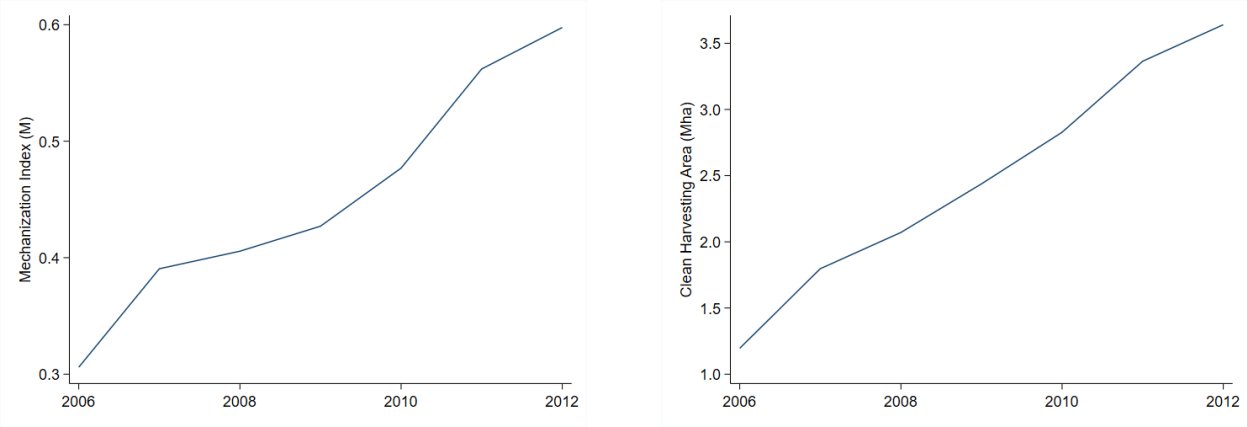
Traditional harvesting employs fire to clear fields of straw and weeds and deter dangerous animals before manual cutting. This burning releases substantial pollutants (Macedo et al., 2008), causing respiratory diseases (Cançado et al., 2006; Dominici et al., 2014; Rangel and Vogl, 2019), and contaminating soil and groundwater (SGPR, 2009). Traditional harvesting in Brazil primarily creates unskilled, temporary jobs.

Mechanical harvesting eliminates the need for pre-harvest burning. The combine harvester processes the straw, making the technology less polluting than traditional methods. It is capital-intensive and exhibits returns to scale. Industry estimates suggest one harvester replaces about eighty workers (SGPR, 2009). Despite higher productivity, producers often prefer traditional harvesting due to available low-wage seasonal labor.

Adopting mechanical harvesting requires a workforce with specialized skills, including machine operators and mechanics, who are scarce in many rural areas (Moraes et al., 2015). The key for our identification is that terrain slope affects mechanization costs, with flatter land being more suitable for combine harvesters. Thus, it is cheaper to use mechanical harvesting on flatter land.

The State Plan to Halt Pre-Harvest Burning. In 2002, São Paulo passed a law to phase out pre-harvest burning by 2021 for most producing areas (State Law 11,241). The stated goals of this law were to reduce respiratory diseases and mitigate climate impacts. This effectively required a shift to mechanical harvesting, as banning pre-harvest burning made the traditional methods nonviable (Novaes et al., 2007). In 2006, a Cooperation Protocol between the state and the Organization of Sugarcane Producers accelerated the phase-out timeline to 2014 and established clean sugarcane certification. In 2012, the Brazilian New Forest Code banned the use of fire in sugarcane harvesting in the country.

Mechanical harvesting adoption in São Paulo was limited before the 2002 burning ban. The adoption of mechanical harvesting accelerated after the 2006 Cooperation Protocol. As Figure 1a shows, by 2006, just over 30% of sugarcane harvesting was mechanical without the use of fire, and by 2012, it had reached over 60%.[3] Figure 1b shows that the sugarcane area using mechanical harvesting grew three-fold between 2006 and 2012. The speed of adoption varied across municipalities due to differences in land suitability, firm-level investment decisions, and enforcement of environmental regulations. Due to cheaper adoption costs, flat areas mechanized earlier, while steeper terrains remained reliant on manual harvesting for longer (SGPR, 2009). Figure 2a shows adoption offer time by terrain slope. This variation in adoption timing allows us to study how the shift from manual to mechanical harvesting affected local labor markets.



(a) Share of Area (b) Total Area

Figure 1: Adoption of Mechanical Harvesting in Sugarcane Over Time

Notes: These figures present the adoption of mechanical harvesting in sugarcane plantations over the years. Source: CANASAT.

[3]As we explain in the following section, 2006 and 2012 are the first and last years we have remote sensing data on sugarcane harvesting by technology used.

Local Labor Markets. Agriculture and services each employ about 40% of sugarcane-producing municipalities' local workforce, with manufacturing accounting for 10%. Most workers are unskilled, with only 30% having at least a high school degree. The figure is even lower in agriculture, where only 20% of permanent workers have completed high school. Farms using traditional harvesting rely primarily on unskilled, seasonal workers. Furthermore, the sugarcane sector has a history of poor labor conditions, with reports of criminal recruitment, exploitative working conditions, inadequate housing, high accident rates, deaths from exhaustion, and child labor (SGPR, 2009).

Mechanical harvesting has shifted labor demand toward skilled workers like machine operators, mechanics, and engineers (Moraes et al., 2015). In 2009, UNICA, the federal government, and the National Confederation of Agricultural Workers (CONTAG) signed the National Agreement to Improve Sugarcane Working Conditions aimed to improve labor practices and support workers displaced by mechanization.

Thus, environmental and labor regulations accelerated mechanization, affecting labor demand through two channels. First, mechanization reduces the need for workers to harvest a given area, leading to structural transformation (Bustos et al., 2016). Second, the technology shift increases the relative demand for skilled over unskilled agricultural workers, potentially impacting the broader local economy.

3 Data

This study relies on multiple data sources, including census data, remote sensing information on sugarcane production, land characteristics, and administrative records. Below, we describe each dataset and its role in the analysis.

Labor Market and Demographics. The Brazilian Institute of Geography and Statistics (IBGE)'s Demographic Census data from 1991, 2000, and 2010 provide our core labor market variables. We restrict the sample to the working-age population – i.e., individuals aged 18-60. We aggregate the data at the municipality level using IBGE-provided sampling weights. For 1991, we used area estimates based on Administrative Minimum Comparable Areas (AMC).

We classify individuals based on their reported employment sector in the previous week using CNAE 1.0 two-digit codes to analyze sectoral employment composition. We define three broad economic sectors: agriculture (codes 01–05), manufacturing (codes 15–37), and services (codes 40–74, 80–94). For each municipality, we compute employment shares as the number of workers in each sector divided by the working-age population and the unskilled employment share within each sector.

To study skill distribution, we classify individuals as skilled if they have at least a high school degree and unskilled otherwise. As a robustness check, we consider two alternative definitions: (i) skilled workers as those with a college degree, and (ii) skilled workers as those with at least a middle school degree. In addition, we calculate the illiteracy rate and the ratio of skilled to unskilled workers at the municipality level.

The census also provides demographic variables. We compute the share of the working-age population living in rural areas and estimate population density by dividing the population's natural logarithm by the municipality's land area.

Industry Linkages. We use Brazilian input-output tables from IBGE (2000) to identify industries based on their linkages to agriculture. This dataset classifies 55 industries, which we merge with the census using CNAE 1.0 codes. We define an industry as upstream of agriculture if more than 0.1% of its output is sold to the agricultural sector and as downstream if more than 0.1% of its inputs come from agriculture. Industries that do not meet either criterion are classified as non-linked. As a robustness check, we also apply a 1% threshold for linkages.

Sugarcane Production and Mechanization Data. We measure sugarcane cultivation and harvesting methods using high-resolution remote sensing data from CANASAT, a program developed by Brazil's National Institute for Space Research (INPE). CANASAT applies digital interpretation of Landsat 5 satellite images at 30-meter resolution to provide annual pixel-level information on sugarcane planted area and harvesting methods (Aguiar et al., 2009, 2011). The dataset covers only São Paulo, preventing us from extending the analysis to other states.

The CANASAT-Planted Area dataset identifies pixels cultivated with sugarcane at the start of each harvest season between 2003 and 2012. The CANASAT-Harvest dataset, developed to support the enforcement of the 2006 Cooperation Protocol, classifies harvested areas according to whether they were subject to pre-harvest burning (traditional harvesting) or mechanized harvesting (without burning). This classification is available for each harvest season between 2006 and 2012.

To quantify the adoption of mechanization at the municipality level, we construct a *mechanization index* that captures the share of sugarcane-planted pixels in 2003 that had transitioned to mechanical harvesting by 2010, the latest census year available:

$$M_j \equiv \frac{\sum_{i \in I_j} \left(m_{i(j),2010} - m_{i(j),2000} \right)}{\sum_{i \in I_j} a_{i(j),2003}} \tag{1}$$

where $a_{i(j),2003}$ equals one if pixel i in municipality j was cultivated with sugarcane in 2003, I_j is the set of such pixels, and $m_{i(j),t}$ equals one if pixel i in municipality j was mechanically harvested in year t. Because CANASAT does not provide data before 2003, we use 2003 as the baseline for the planted area. Likewise, since georeferenced data on harvesting methods is unavailable before 2006, we assume no mechanical harvesting in 2000, setting $m_{i(j),2000} = 0$ for every pixel. As a robustness check, we construct an alternative baseline assuming that mechanization levels in 2000 were the same as in 2006, i.e., $m_{i(j),2000} = m_{i(j),2006}$.

Table 1: Summary Statistics of Agriculture and Economy-wide Variables

	PAM			Economy-wide Effects			
	Total Planted Area (1)	Sugarcane Planted Area (%) (2)	Sugarcane Productivity (3)	Household Income PC (4)	Poverty (< 1.2 MW) (5)	Unemployment Rate (16+) (6)	Child Labor Rate (10-15) (7)
Panel A: 2000							
mean	13260.043	42.855	67820.893	547.386	0.384	0.116	0.137
s.d.	(15318.090)	(31.508)	(27404.623)	(156.812)	(0.113)	(0.038)	(0.048)
Panel B: Δ 2010-2000							
mean	4398.779	25.862	16161.982	171.016	-0.194	-0.057	-0.055
s.d.	(7826.134)	(26.727)	(31360.270)	(92.744)	(0.083)	(0.034)	(0.047)

Notes: This table displays the agriculture, land use, and economy-wide effects variables summary statistics – mean and standard deviations (in parenthesis). The unit of observation is the municipality (N = 393).

Land Characteristics. To assess the suitability of land for mechanization, we use high-resolution topographic data from TOPODATA, based on the Shuttle Radar Topography Mission (SRTM). The dataset provides elevation and slope information at one-arcsecond resolution. We overlay this data with CANASAT sugarcane fields to compute the average slope of sugarcane-producing plots (i.e., $i \in I_j$) in each municipality.

We also measure land suitability for technological change using potential sugarcane yield estimates from the FAO-GAEZ database. This dataset provides simulated yields under different input scenarios. We compute the difference between potential yields under high-input and low-input conditions to construct a municipality-level measure of suitability for mechanization. We use GIS road maps from Brazil's Ministry of Transportation to approximate market access. We compute the average distance from sugarcane fields to the nearest road in each municipality.

Socioeconomic and Agricultural Data. We incorporate additional municipal controls from various sources. We extract municipality-level statistics on household income per capita, unemployment, child labor, and poverty rates using DATASUS/TabNet software.

We use the Municipal Agricultural Survey (PAM/IBGE) for additional agricultural statistics. This dataset provides annual data on total planted area, sugarcane area, yields, and the cultivation of other crops. Information is collected through surveys conducted by IBGE agents, with accuracy checks ensuring inter-annual consistency. This data, however, is not georeferenced.

4 Empirical Strategy

In this section, we describe our empirical strategy. We first present our main regression specification and discuss potential identification issues. We then propose an instrumental variable strategy to address these issues.

We estimate the effects of mechanization at the municipality level on local labor market dynamics between 2000 and 2010, $\Delta Y_j \equiv Y_{j,2010} - Y_{j,2000}$. We estimate the following regression:

$$\Delta Y_j = \alpha + \beta M_j + X_j'\gamma + \varepsilon_j \tag{2}$$

where M_j is the mechanization index defined in equation (1). The coefficient of interest, β, captures the effect of mechanization in the sugarcane sector on labor market outcomes. Tables 2 and 3 report summary statistics of all dependent variables. The error term, ε_j, captures unobserved municipality-level shocks. Following Bustos et al. (2016) and Abadie et al. (2023), we use heteroskedasticity-robust standard errors.

Different specifications include a set of controls, X_j, to address identification concerns. To allow for different labor market trends across municipalities, we control for the rural population share in 2000, population density in 2000, log labor force in 2000, and log sugarcane planted area in 2003. Higher education levels may facilitate technology adoption and affect labor markets, so we control for the shares of illiterate and skilled workers in 2000. To account for the role of infrastructure and agricultural conditions, we control for distance to roads and potential sugarcane yield. Table A1 shows control variables' descriptive statistics.

Even with these controls, estimates from equation 2 may suffer from endogeneity if labor market trends influence mechanization. For example, local government subsidies to the sugarcane industry or changes in labor regulations could drive both mechanization and labor outcomes. To address this, we propose an instrumental variable strategy to identify the causal effect of mechanization on structural transformation.

Table 2: Summary Statistics of Structural Transformation Variables

	Agricultural	Manufacturing sector			Services sector		
	sector	All	Linked	Non-linked	All	Linked	Non-linked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: 2000							
Employment share	0.164	0.107	0.083	0.025	0.241	0.149	0.092
	(0.089)	(0.061)	(0.053)	(0.021)	(0.074)	(0.050)	(0.031)
Unskilled employment share	0.190	0.109	0.086	0.024	0.211	0.135	0.076
	(0.100)	(0.064)	(0.056)	(0.021)	(0.068)	(0.048)	(0.029)
Skilled-unskilled workers ratio	0.129	0.406	0.395	0.534	0.643	0.605	0.773
	(0.079)	(0.209)	(0.268)	(0.525)	(0.218)	(0.319)	(0.380)
Panel B: Δ 2010-2000							
Employment share	-0.036	0.046	0.045	0.001	0.031	0.016	0.015
	(0.053)	(0.055)	(0.053)	(0.014)	(0.036)	(0.028)	(0.021)
Unskilled employment share	-0.028	0.039	0.041	-0.002	0.008	0.001	0.006
	(0.065)	(0.059)	(0.058)	(0.014)	(0.038)	(0.030)	(0.022)
Skilled-unskilled workers ratio	0.181	0.435	0.412	0.696	0.563	0.566	0.540
	(0.126)	(0.457)	(0.439)	(1.078)	(0.282)	(0.392)	(0.518)

Notes: This table displays the labor market outcomes summary statistics – mean and standard deviations (in parenthesis). The unit of observation is the municipality (N = 393).

4.1 Instrumental Variable

We use the land slope of sugarcane-planted areas in 2003 as an instrument for the adoption of mechanical harvesting. The rationale for this instrument is that mechanization is cheaper on flatter land (Moraes et al., 2015), so producers on steep terrain adopt it more slowly. Our estimates capture a (local) causal effect of mechanization on labor market outcomes if: (i) slope is correlated with mechanization, and (ii) slope is uncorrelated with the error term, ε_j, in equation (2). In other words, land slope must predict mechanization but have no direct impact on labor markets except through mechanization.

We assess assumption (i). Figure 2a shows mechanical harvesting adoption (relative to 2006) by land slope over time. We can see mechanization increased faster in flatter areas, consistent with lower mechanical harvesting costs.

We test assumption (i) directly by estimating the first-stage regression:

$$M_j = \alpha_0 + \lambda S_j + X_j'\gamma_0 + \epsilon_j \tag{3}$$

where S_j is the average slope of sugarcane pixels in 2003, our instrument. Table 4 presents the first stage results. As expected, slope negatively correlates with mechanization, robust across all specifications. The Montiel-Pflueger F statistic (Olea and Pflueger, 2013) ranges from 33.91 to 46.16, indicating strong instrument relevance. To address weak instrument concerns

Table 3: Summary Statistics of Agriculture and Economy-wide Variables

	PAM			Economy-wide Effects			
	Total Planted Area (1)	Sugarcane Planted Area (%) (2)	Sugarcane Productivity (3)	Household Income PC (4)	Poverty (< 1.2 MW) (5)	Unemployment Rate (16+) (6)	Child Labor Rate (10-15) (7)
Panel A: 2000							
mean	13260.043	42.855	67820.893	547.386	0.384	0.116	0.137
s.d.	(15318.090)	(31.508)	(27404.623)	(156.812)	(0.113)	(0.038)	(0.048)
Panel B: Δ 2010-2000							
mean	4398.779	25.862	16161.982	171.016	-0.194	-0.057	-0.055
s.d.	(7826.134)	(26.727)	(31360.270)	(92.744)	(0.083)	(0.034)	(0.047)

Notes: This table displays the agriculture, land use, and economy-wide effects variables summary statistics – mean and standard deviations (in parenthesis). The unit of observation is the municipality (N = 393).

as in Lee et al. (2022), we report weak-instrument-robust confidence intervals (Anderson and Rubin, 1949).

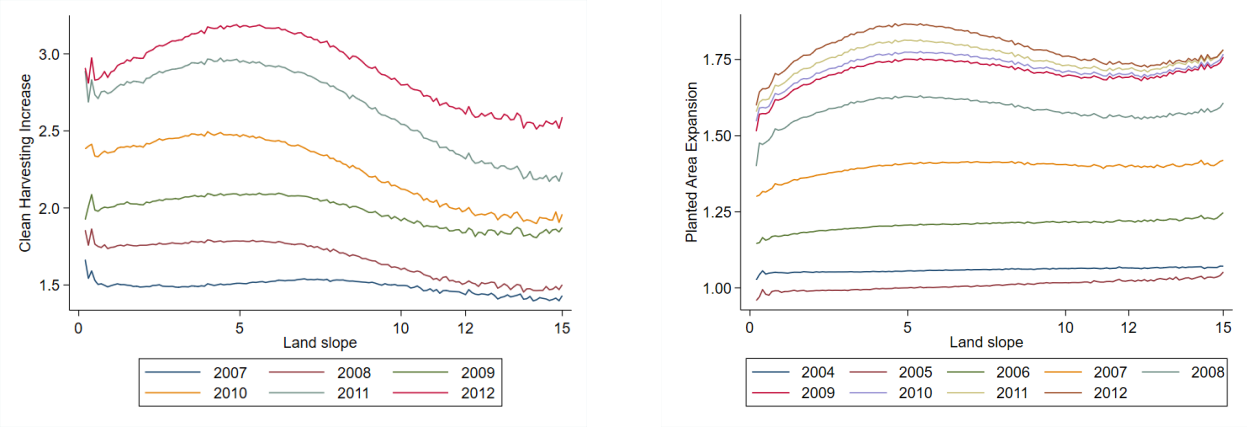
To assess assumption (ii), we test whether sugarcane expansion favored flatter terrain. If producers preferred flatter land for expansion, slope might correlate with factors beyond mechanization. Figure 2b shows sugarcane expansion (relative to 2003) by land slope. Before 2006, expansion patterns were similar across slope levels, suggesting no systematic preference for flatter land. This indicates that land slope did not drive sugarcane expansion until the Cooperation Protocol was signed. For further reassurance, the next section presents placebo tests to examine whether technology adoption in the 2000s was correlated with pre-trends in agricultural and sugarcane-planted areas.

5 Results

5.1 Agriculture and Land Use

Before examining the broader economic effects of agricultural mechanization, we first assess its direct impact on sugarcane production. Table 5 presents the estimated effects of mechanization on land use and productivity. The evidence shows mechanization expanded the scale of sugarcane production, increasing the share of cultivated land allocated to the crop. Column 1 reports the OLS estimates. Panels A and C show mechanization had a positive but statistically non-significant correlation with the total planted area and sugarcane productivity. In Panel B, we find mechanization is correlated with the expansion of the sugarcane planted area.

Columns 2–7 report the instrumental variable estimates. The IV results in Panel B



(a) Mechanical Harvesting vs. Slope

(b) Planted Area vs. Slope

Figure 2: Sugarcane Mechanical Harvesting by Land Slope Over Time

Notes: Figure (a) presents mechanical harvesting in year t divided by mechanical harvesting in 2006 per pixel's land slope. Figure (b) presents planted area in year t divided by planted area in 2003 per pixel's land slope. We drop pixels with a slope greater than 15% due to a long tail with few observations.

confirm that mechanization substantially increased sugarcane production. The estimates remain stable and statistically significant across specifications that progressively control for education levels (column 3), population density (column 4), distance to roads (column 5), and soil suitability (column 6). The preferred specification (column 7) in Panel B shows that a one standard deviation increase in mechanization (0.193) led to an 18.6 percentage point increase in the share of agricultural land planted with sugarcane between 2000 and 2010 [=0.193 $\times$ 96.43]. This effect is economically large, corresponding to 72 percent of the average increase in sugarcane cultivation during this period.

Mechanization may have displaced other agricultural activities. While the share of agricultural land growing sugarcane increased, mechanization did not significantly affect the total planted area. The point estimates in Panel A are positive across all specifications but statistically insignificant at conventional levels. However, their magnitude is economically relevant: a one-standard-deviation increase in mechanization is associated with a 536-hectare increase in the total planted area [= 0.193 $\times$ 2,781.98], about 12 percent of the average agricultural expansion during the period.

Mechanization also appears to have increased sugarcane productivity, measured as output per hectare. The results in Panel C indicate that a one-standard-deviation increase in mechanization raised sugarcane yield by 9,507 tons per hectare [= 0.193 $\times$ 49,261.27]. However, these estimates are sensitive to specification choices and not always statistically significant (columns 2–7). This suggests that mechanization primarily reallocated land and labor rather than immediately improving farm-level efficiency.

Table 4: First-Stage Results

	Dep. Var.: Mechanization Index (M_j)					
	(1)	(2)	(3)	(4)	(5)	(6)
Slope (S_j)	-0.035***	-0.036***	-0.034***	-0.036***	-0.038***	-0.037***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Standard controls	Y	Y	Y	Y	Y	Y
Education		Y				Y
Population density			Y			Y
Distance to roads				Y		Y
Soil suitability					Y	Y
1st Stage (MP F-stat.)	37.37	37.60	33.91	39.57	46.16	41.95

Notes: This table reports the first-stage estimates of land slope on mechanical harvesting adoption, captured by λ in equation (3). All regressions control for the rural population share in 2000, log labor force in 2000, and log sugarcane-planted area in 2003. Education controls include the shares of illiterate and skilled workers in 2000. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane comes from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

To validate our identification strategy, we examine pre-existing trends in agricultural outcomes. Column 8 reports the IV estimates of the relationship between mechanization between 2000 and 2010 and changes in agricultural outcomes between 1991 and 2000, the decade before mechanization. We find no systematic differences in pre-trends: the coefficients are small and insignificant, suggesting that municipalities that mechanized more in the 2000s followed similar paths in agricultural expansion in the previous decade. For example, the pre-trend coefficient for the sugarcane planted area is 19.26, compared to the treatment effect of 96.43 in our preferred specification. This supports the exclusion restriction of our instrumental variable strategy, indicating that the relationship between land slope and mechanization adoption does not simply reflect other potential confounding factors that would lead to differential pre-existing trends in sugarcane expansion.

In sum, the findings in Table 5 validate two key assumptions: (i) mechanization expanded sugarcane production by increasing the planted area, and (ii) there is no evidence of pre-trends that would violate the exclusion restriction of our instrument.

Table 5: Results – Agriculture and Land Use

	Δ2010 − 2000							Δ2000 − 1991
	OLS	IV	IV	IV	IV	IV	IV	Pre-trend
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Total Planted Area								
Mechanization Index (M_j)	1502.08	10084.10	5754.55	4425.24	8603.57	9810.42	2781.98	5147.45
	(2496.09)	(6759.85)	(6743.75)	(6557.16)	(6411.50)	(6701.29)	(6538.54)	(5379.05)
		[-4101.77, 25340.60]	[-8931.57, 20440.70]	[-11412.30, 17666.50]	[-4851.28, 22566.10]	[-4252.54, 24934.70]	[-12492.80, 15985.60]	[-5714.76, 16861.60]
Panel B: Share of Sugarcane in Total Planted Area (%)								
Mechanization Index (M_j)	30.99***	127.11***	108.78***	112.80***	120.95***	117.45***	96.43***	19.26
	(7.81)	(23.58)	(21.54)	(23.00)	(22.15)	(21.47)	(19.53)	(17.36)
		[86.97, 191.52]	[70.39, 164.22]	[70.00, 172.00]	[81.47, 179.72]	[79.20, 172.71]	[58.54, 143.59]	[-13.05, 59.81]
Panel C: Sugarcane Productivity								
Mechanization Index (M_j)	12980.23	79221.33**	61542.91*	67276.66*	78690.06**	65464.91**	49261.27	-7801.69
	(10674.35)	(33847.90)	(32717.96)	(35742.61)	(32920.18)	(30255.34)	(31064.08)	(5562.50)
		[148.62, 147572.00]	[-17481.10, 125021.00]	[-21883.30, 136623.00]	[4391.59, 145168.00]	[-5215.16, 124165.00]	[-28228.10, 107071.00]	[-21677.30, 2109.48]
Standard controls	Y	Y	Y	Y	Y	Y	Y	Y
Education			Y				Y	Y
Population density				Y			Y	Y
Distance to roads					Y		Y	Y
Soil suitability						Y	Y	Y
1st Stage (MP F-stat.)		37.56	39.11	36.34	39.79	46.37	44.52	45.06

Notes: This table reports estimates of mechanical harvesting adoption on agriculture and land use from PAM, captured by β in equation (2). Column 1 presents OLS estimates, while columns 2–8 present 2SLS estimates, using sugarcane field slope as an instrument for mechanical harvesting. Column 8 tests for pre-trends and reports outcomes from 1991–2000. Regressions 1–7 control for the rural population share in 2000, log labor force in 2000, and log sugarcane-planted area in 2003. Education controls include the shares of illiterate and skilled workers in 2000. Population density is measured in 2000. Regression 8 controls for the rural population share in 1991, log labor force in 1991, and log sugarcane-planted area in 2003, with education and population density controls measured in 1991. Distance to roads is in logs. Soil suitability for sugarcane comes from GAEZ/FAO. The unit of observation is the municipality ($N = 393$) for regressions 1–7 and the AMC ($N = 352$) for regression 8. Heteroskedasticity-robust standard errors are in parentheses. The Anderson-Rubin confidence interval is in brackets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5.2 Structural Transformation

Mechanization in agriculture often triggers structural transformation by shifting labor away from farming toward industry and services. Table 6 presents the estimated effects of sugarcane mechanization on employment shares across sectors. The results indicate a large and systematic labor reallocation, consistent with standard structural transformation patterns documented in the literature (e.g., Bustos et al., 2016).

Panel A of Table 6 shows that mechanization reduced the agricultural employment share. The preferred IV estimate (column 7) suggests that a one-standard-deviation increase in mechanization lowered agricultural employment by 3.03 percentage points [$= 0.193 \times 0.157$], accounting for 84 percent of the sector's total employment decline between 2000 and 2010. In contrast, Panel B shows a corresponding increase in manufacturing employment, with a one-standard-deviation increase in mechanization raising the sector's employment share by 3.45 percentage points [$= 0.193 \times 0.179$], explaining 75 percent of its observed growth. Meanwhile, Panel C finds no significant effects on the services sector.

To understand how mechanization reshaped labor demand, we turn to Table 7. The primary driver of structural transformation appears to be a decline in unskilled employment in agriculture. Panel A of Table 7 shows that mechanization significantly increased the skilled-unskilled employment ratio in agriculture. The preferred IV estimate (column 7) suggests that a one-standard-deviation increase in mechanization raised the skilled-unskilled ratio by 25 percent relative to the average change over the period [$= 0.193 \times 0.234 \,/\, 0.181$]. Table A2 further shows that the decline in the use of unskilled workers in agriculture largely explains the observed decline in agricultural employment.[4]

In contrast, worker composition in manufacturing and services remained unchanged. Panel B of Table 7 shows that the increase in manufacturing employment did not alter the sector's skill distribution, suggesting that displaced agricultural workers were absorbed into existing roles. Panel C finds no effect on the skill composition of the services sector.

In sum, Tables 6 and 7 provide strong evidence that mechanization drove structural transformation by displacing unskilled agricultural workers into manufacturing.

5.3 Linked Industries

Taken together, the results so far align with standard structural transformation models, where labor-saving technological change in agriculture releases workers who transition into industry (Bustos et al., 2016). However, the fact that only the manufacturing sector ab-

[4]Tables A3 and A4 confirm the robustness of these findings under alternative definitions of skilled and unskilled workers.

Table 6: Results – Employment Share

	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Agricultural sector							
Mechanization Index (M_j)	0.005	-0.173***	-0.171***	-0.185***	-0.172***	-0.146***	-0.157***
	(0.017)	(0.056)	(0.054)	(0.061)	(0.055)	(0.051)	(0.053)
		[-0.345, -0.086]	[-0.331, -0.088]	[-0.381, -0.091]	[-0.336, -0.087]	[-0.295, -0.063]	[-0.314, -0.075]
Panel B: Manufacturing sector							
Mechanization Index (M_j)	-0.009	0.183***	0.179***	0.190***	0.181***	0.178***	0.179***
	(0.017)	(0.058)	(0.056)	(0.062)	(0.057)	(0.054)	(0.055)
		[0.093, 0.364]	[0.093, 0.354]	[0.099, 0.395]	[0.094, 0.354]	[0.095, 0.342]	[0.098, 0.352]
Panel C: Services sector							
Mechanization Index (M_j)	0.018	0.033	0.041	0.045	0.034	0.022	0.037
	(0.011)	(0.035)	(0.035)	(0.036)	(0.034)	(0.032)	(0.033)
		[-0.034, 0.119]	[-0.027, 0.127]	[-0.022, 0.142]	[-0.032, 0.115]	[-0.041, 0.097]	[-0.025, 0.121]
Standard controls	Y	Y	Y	Y	Y	Y	Y
Education			Y				Y
Population density				Y			Y
Distance to roads					Y		Y
Soil suitability						Y	Y
1st Stage (MP F-stat.)		37.37	37.60	33.91	39.57	46.16	41.95

Notes: This table reports estimates of mechanical harvesting adoption on employment share by sector (as indicated in the Panels), captured by β in equation (2). Column 1 presents OLS estimates, while columns 2–7 present 2SLS estimates, using sugarcane field slope as an instrument for mechanical harvesting. All regressions control for the rural population share in 2000, log labor force in 2000, and log sugarcane-planted area in 2003. Education controls include the shares of illiterate and skilled workers in 2000. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane comes from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. The Anderson-Rubin confidence interval is in brackets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

sorbed labor suggests that the reallocation was not a broad shift across sectors but rather a targeted expansion of industrial employment linked to agricultural mechanization. Table 8 investigates this channel by distinguishing between industries linked to agriculture – those that use agricultural inputs in production – and non-linked industries.

Panel A of Table 8 shows that mechanization increased employment in manufacturing industries linked to agriculture. The preferred IV estimate (column 7) suggests that a one-standard-deviation increase in mechanization raised the employment share of linked manufacturing industries by 3.51 percentage points [$= 0.193 \times 0.182$], explaining 78 percent of their observed growth. In contrast, Panel B shows negative point estimates and no significant effect on non-linked manufacturing industries, indicating that mechanization did not drive a broad industrial expansion.

A similar pattern emerges in services. Panel C shows positive but statistically insignificant point estimates for employment gains in services industries linked to agriculture. In contrast, Panel D finds no effect on non-linked service industries, with point estimates sub-

Table 7: Results – Skilled-unskilled ratio

	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Agricultural sector							
Mechanization Index (M_j)	0.027	0.267**	0.234**	0.319***	0.264**	0.225**	0.234**
	(0.039)	(0.113)	(0.114)	(0.120)	(0.111)	(0.107)	(0.112)
		[0.057, 0.558]	[0.022, 0.526]	[0.115, 0.655]	[0.058, 0.550]	[0.026, 0.493]	[0.034, 0.532]
Panel B: Manufacturing sector							
Mechanization Index (M_j)	0.084	-0.304	-0.140	-0.264	-0.306	-0.370	-0.194
	(0.112)	(0.327)	(0.338)	(0.338)	(0.322)	(0.303)	(0.313)
		[-1.197, 0.253]	[-1.009, 0.488]	[-1.188, 0.338]	[-1.186, 0.242]	[-1.173, 0.145]	[-1.000, 0.388]
Panel C: Services sector							
Mechanization Index (M_j)	0.089	0.116	0.154	0.128	0.103	0.111	0.143
	(0.103)	(0.266)	(0.273)	(0.274)	(0.263)	(0.256)	(0.268)
		[-0.484, 0.674]	[-0.441, 0.748]	[-0.490, 0.702]	[-0.491, 0.634]	[-0.447, 0.649]	[-0.441, 0.726]
Standard controls	Y	Y	Y	Y	Y	Y	Y
Education			Y				Y
Population density				Y			Y
Distance to roads					Y		Y
Soil suitability						Y	Y
1st Stage (MP F-stat.)		37.37	37.60	33.91	39.57	46.16	41.95

Notes: This table reports estimates of mechanical harvesting adoption on skilled-unskilled workers ratio by sector (as indicated in the Panels), captured by β in equation (2). Column 1 presents OLS estimates, while columns 2–7 present 2SLS estimates, using sugarcane field slope as an instrument for mechanical harvesting. All regressions control for the rural population share in 2000, log labor force in 2000, and log sugarcane-planted area in 2003. Education controls include the shares of illiterate and skilled workers in 2000. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane comes from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. The Anderson-Rubin confidence interval is in brackets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

stantially smaller in magnitude than those in Panel C and often opposite in sign. This suggests that linked services may have benefited from mechanization to some extent, even if the estimates lack statistical precision.

Table 9 further examines whether mechanization altered worker composition in linked sectors. Panel A shows that linked manufacturing industries absorbed displaced agricultural workers without significantly changing their skill distribution, reinforcing the idea that these industries primarily expanded by hiring unskilled workers released from agriculture. In contrast, Panels B and C show no significant changes in the skill composition of non-linked manufacturing or service sectors, further ruling out a broad labor market shift beyond agriculture.

These findings suggest that mechanization reinforced linkages between agriculture and manufacturing.[5] The employment gains were concentrated in industries downstream from

[5]Table A5 and A6 confirm that these results are robust to an alternative definition of linked sectors,

Table 8: Results – Employment share in linked industries

	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Linked manufacturing sector							
Mechanization Index (M_j)	-0.009	0.190***	0.182***	0.198***	0.188***	0.185***	0.182***
	(0.016)	(0.057)	(0.054)	(0.061)	(0.056)	(0.053)	(0.054)
		[0.102, 0.368]	[0.098, 0.348]	[0.108, 0.399]	[0.102, 0.358]	[0.103, 0.341]	[0.103, 0.351]
Panel B: Non-linked manufacturing sector							
Mechanization Index (M_j)	-0.001	-0.010	-0.007	-0.010	-0.009	-0.008	-0.007
	(0.005)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
		[-0.036, 0.017]	[-0.034, 0.021]	[-0.038, 0.018]	[-0.035, 0.016]	[-0.032, 0.017]	[-0.034, 0.020]
Panel C: Linked services sector							
Mechanization Index (M_j)	0.018**	0.039	0.038	0.046*	0.039	0.031	0.036
	(0.008)	(0.026)	(0.025)	(0.027)	(0.025)	(0.024)	(0.024)
		[-0.009, 0.106]	[-0.009, 0.101]	[-0.002, 0.121]	[-0.008, 0.104]	[-0.014, 0.090]	[-0.009, 0.097]
Panel D: Non-linked services sector							
Mechanization Index (M_j)	-0.001	-0.006	0.003	-0.001	-0.005	-0.009	0.002
	(0.007)	(0.024)	(0.024)	(0.025)	(0.023)	(0.022)	(0.023)
		[-0.057, 0.045]	[-0.047, 0.056]	[-0.055, 0.054]	[-0.055, 0.045]	[-0.057, 0.038]	[-0.046, 0.054]
Standard controls	Y	Y	Y	Y	Y	Y	Y
Education			Y				Y
Population density				Y			Y
Distance to roads					Y		Y
Soil suitability						Y	Y
1st Stage (MP F-stat.)		37.37	37.60	33.91	39.57	46.16	41.95

Notes: This table reports estimates of mechanical harvesting adoption on employment share by linked sector (as indicated in the Panels), captured by β in equation (2). Column 1 presents OLS estimates, while columns 2–7 present 2SLS estimates, using sugarcane field slope as an instrument for mechanical harvesting. All regressions control for the rural population share in 2000, log labor force in 2000, and log sugarcane-planted area in 2003. Education controls include the shares of illiterate and skilled workers in 2000. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane comes from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. The Anderson-Rubin confidence interval is in brackets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

agriculture, which benefited from cheaper, larger-scale agricultural inputs. This pattern is distinct from standard structural transformation (e.g., Matsuyama, 1992), where labor shifts broadly from agriculture into manufacturing and services. Instead, mechanization industrialized the agricultural sector's supply chain by strengthening its connections to agro-industrial manufacturing.

5.4 Economy-wide Effects

We now assess whether this transformation had broader local economic effects. Table 10 examines the impact of mechanization on key economy-wide outcomes, including household income, poverty, unemployment, and child labor.

applying a 1% threshold for linkages instead of 0.1%.

Table 9: Results – Skilled-unskilled ratio in linked industries

	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Linked manufacturing sector							
Mechanization Index (M_j)	0.225*	-0.195	-0.030	-0.125	-0.195	-0.224	-0.042
	(0.135)	(0.394)	(0.375)	(0.413)	(0.390)	(0.360)	(0.360)
		[-1.177, 0.538]	[-0.934, 0.697]	[-1.156, 0.677]	[-1.168, 0.531]	[-1.093, 0.446]	[-0.882, 0.684]
Panel B: Non-linked manufacturing sector							
Mechanization Index (M_j)	-0.680*	-0.130	-0.484	-0.119	-0.102	-0.349	-0.579
	(0.354)	(1.072)	(1.057)	(1.105)	(1.063)	(0.981)	(0.998)
		[-2.635, 2.036]	[-3.038, 1.568]	[-2.789, 2.201]	[-2.501, 2.129]	[-2.641, 1.633]	[-3.068, 1.358]
Panel C: Linked services sector							
Mechanization Index (M_j)	0.137	0.302	0.312	0.312	0.288	0.297	0.303
	(0.157)	(0.305)	(0.366)	(0.318)	(0.301)	(0.309)	(0.361)
		[-0.340, 0.991]	[-0.456, 1.138]	[-0.355, 1.054]	[-0.345, 0.944]	[-0.352, 0.995]	[-0.454, 1.117]
Panel D: Non-linked services sector							
Mechanization Index (M_j)	0.228	-0.207	-0.062	-0.176	-0.205	-0.165	-0.044
	(0.214)	(0.484)	(0.482)	(0.491)	(0.471)	(0.446)	(0.459)
		[-1.413, 0.732]	[-1.189, 0.912]	[-1.402, 0.777]	[-1.342, 0.709]	[-1.208, 0.702]	[-1.116, 0.883]
Standard controls	Y	Y	Y	Y	Y	Y	Y
Education			Y				Y
Population density				Y			Y
Distance to roads					Y		Y
Soil suitability						Y	Y
1st Stage (MP F-stat.)		37.37	37.60	33.91	39.57	46.16	41.95

Notes: This table reports estimates of mechanical harvesting adoption on skilled-unskilled workers ratio by linked sector (as indicated in the Panels), captured by β in equation (2). Column 1 presents OLS estimates, while columns 2–7 present 2SLS estimates, using sugarcane field slope as an instrument for mechanical harvesting. All regressions control for the rural population share in 2000, log labor force in 2000, and log sugarcane-planted area in 2003. Education controls include the shares of illiterate and skilled workers in 2000. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane comes from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. The Anderson-Rubin confidence interval is in brackets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Mechanization increased household income per capita and reduced poverty. The preferred IV estimate in Panel A of Table 10 shows that a one-standard-deviation increase in mechanization raised household income per capita by 32.4 BRL [$= 0.193 \times 167.954$]. The income gain is substantial, accounting for 19 percent larger income growth than average. Similarly, Panel B shows that mechanization significantly reduced poverty rates, with a one-standard-deviation increase in mechanization lowering the share of individuals living below 1.2 minimum wages by 2.7 percentage points [$= 0.193 \times 0.270 \,/\, 0.384$], or 14 percent of the baseline poverty rate (38.4%). These findings suggest that the industrialization of agriculture generated income gains beyond the directly affected sectors.

Mechanization also lowered adult unemployment by 24 percent of the baseline unemployment rate (11.6%). Panel C shows that a one-standard-deviation increase in mechanization

Table 10: Results – Economy-wide outcomes

	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Household income per capita							
Mechanization Index (M_j)	1.488	151.342**	154.861*	184.838**	150.552**	148.767**	167.954**
	(31.786)	(73.681)	(79.428)	(78.939)	(72.980)	(68.749)	(77.932)
		[8.388, 329.305]	[0.758, 346.703]	[37.935, 394.254]	[8.958, 326.821]	[15.384, 309.372]	[22.925, 362.354]
Panel B: Poverty (< 1.2 MW)							
Mechanization Index (M_j)	-0.009	-0.327***	-0.288***	-0.323***	-0.316***	-0.304***	-0.270***
	(0.022)	(0.081)	(0.073)	(0.084)	(0.079)	(0.073)	(0.068)
		[-0.582, -0.202]	[-0.510, -0.175]	[-0.599, -0.201]	[-0.556, -0.195]	[-0.522, -0.191]	[-0.476, -0.165]
Panel C: Unemployment Rate (16+)							
Mechanization Index (M_j)	-0.034***	-0.140***	-0.145***	-0.149***	-0.136***	-0.141***	-0.146***
	(0.010)	(0.032)	(0.033)	(0.035)	(0.031)	(0.030)	(0.033)
		[-0.236, -0.091]	[-0.244, -0.093]	[-0.262, -0.095]	[-0.225, -0.086]	[-0.229, -0.091]	[-0.246, -0.095]
Panel D: Child Labor Rate (10-15)							
Mechanization Index (M_j)	0.005	-0.090*	-0.086	-0.090*	-0.085*	-0.088*	-0.083
	(0.016)	(0.052)	(0.054)	(0.054)	(0.051)	(0.049)	(0.051)
		[-0.236, -0.005]	[-0.238, 0.006]	[-0.249, -0.002]	[-0.224, 0.002]	[-0.222, -0.004]	[-0.223, 0.004]
Standard controls	Y	Y	Y	Y	Y	Y	Y
Education			Y				Y
Population density				Y			Y
Distance to roads					Y		Y
Soil suitability						Y	Y
1st Stage (MP F-stat.)		37.52	37.66	34.04	39.78	46.46	42.14

Notes: This table reports estimates of mechanical harvesting adoption on economy-wide outcomes (as indicated in the panels), captured by β in equation (2). Column 1 presents OLS estimates, while columns 2–7 present 2SLS estimates, using sugarcane field slope as an instrument for mechanical harvesting. All regressions control for the rural population share in 2000, log labor force in 2000, and log sugarcane-planted area in 2003. Education controls include the shares of illiterate and skilled workers in 2000. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane comes from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. The Anderson-Rubin confidence interval is in brackets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

lowered the unemployment rate by 2.82 percentage points [$= 0.193 \times 0.146$]. These findings indicate an overall improvement in labor market conditions.

Finally, Panel D examines the effects of mechanization on child labor, which is often used in traditional sugarcane harvesting. While the point estimates suggest a decline in the share of children aged 10–15 engaged in labor, the results are noisier and not always statistically significant. A one-standard-deviation increase in mechanization is associated with a 1.6 percentage point reduction in child labor [$= 0.193 \times 0.083$], but confidence intervals remain wide. This suggests that while mechanization may have helped reduce child labor – possibly by raising household incomes and decreasing reliance on child workers – the effect is less precisely estimated than other economic indicators.

In sum, these results indicate that the industrialization of agriculture had meaningful

positive effects on broader economic outcomes. Higher household incomes, lower poverty, and reduced unemployment suggest that mechanization-driven structural transformation was not merely a sectoral reallocation but a process that broadly improved local economic conditions.

6 Conclusion

This paper shows that agricultural mechanization triggers structural transformation through a specific pathway: labor reallocation to industries directly linked with agriculture. Sugarcane harvest mechanization in São Paulo reduced agricultural employment and increased manufacturing jobs, but only in sectors connected to agriculture through input-output relationships. This selective reallocation pattern explains why agricultural productivity growth sometimes fails to generate economy-wide industrialization.

Our findings reconcile competing views on agricultural development's role in structural transformation. While mechanization pushed workers out of farming, these workers moved primarily to industries upstream or downstream from agriculture rather than diversifying broadly across manufacturing. This pattern strengthens agro-industrial linkages rather than transforming the entire industrial structure. Despite reduced agricultural employment, the economic benefits remain substantial: higher household incomes, lower poverty rates, and expanded agricultural production.

Environmental regulation catalyzed this transformation by making pre-harvest burning nonviable and effectively mandating mechanical harvesting. Unlike concerns that environmental restrictions impede economic development, our results show that regulation can trigger technological upgrading that benefits local economies while reducing pollution. This suggests an important complementarity between environmental and development policies in contexts where regulation drives the adoption of more advanced technologies. These findings highlight how carefully designed environmental policies can shape sectoral reallocations that support ecological and economic objectives.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge. 2023. "When Should You Adjust Standard Errors for Clustering?" *The Quarterly Journal of Economics*, 138(1): 1–35.

Acemoglu, Daron, and Veronica Guerrieri. 2008. "Capital deepening and nonbalanced economic growth." *Journal of political Economy*, 116(3): 467–498.

Aguiar, Daniel A de, Bernardo FT Rudorff, Marcos Adami, and Yosio E Shimabukuro. 2009. "Imagens de Sensoriamento Remoto no Monitoramento da Colheita da Cana-de-açúcar." *Engenharia Agrícola*, 29: 440–451.

Aguiar, Daniel Alves, Bernardo Friedrich Theodor Rudorff, Wagner Fernando Silva, Marcos Adami, and Marcio Pupin Mello. 2011. "Remote Sensing Images in Support of Environmental Protocol: Monitoring the Sugarcane Harvest in São Paulo State, Brazil." *Remote Sensing*, 3(12): 2682–2703.

Anderson, Theodore W, and Herman Rubin. 1949. "Estimation of the Parameters of a Single Equation in a Complete System of Stochastic Equations." *The Annals of Mathematical Statistics*, 20(1): 46–63.

Barrett, Christopher B, Ariel Ortiz-Bobea, and Trinh Pham. 2023. "Structural transformation, agriculture, climate, and the environment." *Review of Environmental Economics and Policy*, 17(2): 195–216.

Berman, Eli, and Linda T. M. Bui. 2001. "Environmental regulation and labor demand: evidence from the South Coast Air Basin." *Journal of Public Economics*, 79(2): 265–295.

Bustos, Paula, Bruno Caprettini, and Jacopo Ponticelli. 2016. "Agricultural Productivity and Structural Transformation. Evidence from Brazil." *American Economic Review*, 106(6): 1320–1365.

Bustos, Paula, Juan Manuel Castro-Vincenzi, Joan Monras, and Jacopo Ponticelli. 2019. "Industrialization without innovation." National Bureau of Economic Research.

Cai, Jie, and Nan Li. 2019. "Growth through inter-sectoral knowledge linkages." *The Review of Economic Studies*, 86(5): 1827–1866.

Cançado, José ED, Paulo HN Saldiva, Luiz AA Pereira, Luciene BLS Lara, Paulo Artaxo, Luiz A Martinelli, Marcos A Arbex, Antonella Zanobetti, and Alfesio LF Braga. 2006. "The impact of sugar cane-burning emissions on the respiratory system of children and the elderly." *Environmental health perspectives*, 725–729.

Carillo, Mario F. 2020. "Agricultural Policy and Long-Run Development: Evidence from Mussolinis Battle for Grain." *The Economic Journal*. ueaa060.

Carreira, Igor, Francisco Costa, and Joao Paulo Pessoa. 2024. "The deforestation effects of trade and agricultural productivity in Brazil." *Journal of development economics*, 167: 103217.

Caselli, Francesco, and Wilbur John Coleman II. 2001. "The US structural transformation and regional convergence: A reinterpretation." *Journal of political Economy*, 109(3): 584–616.

Caunedo, Julieta, and Namrata Kala. 2021. "Mechanizing Agriculture." National Bureau of Economic Research.

Clark, Colin. 1967. "The Conditions of Economic Progress."

De Janvry, Alain, and Elisabeth Sadoulet. 2020. "Using Agriculture for Development: Supply-and Demand-side Approaches." *World development*, 133: 105003.

Dominici, Francesca, Michael Greenstone, and Cass R Sunstein. 2014. "Particulate matter matters." *Science*, 344(6181): 257.

Foster, Andrew D, and Mark R Rosenzweig. 2004. "Agricultural Productivity Growth, Rural Economic Diversity, and Economic Reforms: India, 1970-2000." *Economic Development and Cultural Change*, 52(3): 509–42.

Gollin, Douglas, Casper Worm Hansen, and Asger Mose Wingender. 2021. "Two Blades of Grass: The Impact of the Green Revolution." *Journal of Political Economy*, 129(8): 2344–2384.

Greenstone, Michael. 2002. "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures." *Journal of Political Economy*, 110(6): 1175–1219.

Greenstone, Michael, John A List, and Chad Syverson. 2012. "The effects of environmental regulation on the competitiveness of US manufacturing." National Bureau of Economic Research.

Harrison, Ann, Benjamin Hyman, Leslie Martin, and Shanthi Nataraj. 2015. "When do Firms Go Green? Comparing Price Incentives with Command and Control Regulations in India." w21763.

Hess, Simon, Dany Jaimovich, and Matthias Schündeln. 2021. "Environmental Effects of Development Programs: Experimental Evidence from West African Dryland Forests." *Journal of Development Economics*, 153: 102737.

Hornbeck, Richard, and Pinar Keskin. 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.

Hsiang, Solomon, Paulina Oliva, and Reed Walker. 2019. "The distribution of environmental damages." *Review of Environmental Economics and Policy*.

Jayachandran, Seema. 2022. "How economic development influences the environment." *Annual Review of Economics*, 14(1): 229–252.

Jones, Charles I. 2011. "Intermediate goods and weak links in the theory of economic development." *American Economic Journal: Macroeconomics*, 3(2): 1–28.

Kuznets, Simon. 1957. "Quantitative Aspects of the Economic Growth of Nations: II. Industrial Distribution of National Product and Labor Force." *Economic Development and Cultural Change*, 5(S4): 1–111.

Lee, David S, Justin McCrary, Marcelo J Moreira, and Jack Porter. 2022. "Valid t-ratio Inference for IV." *American Economic Review*, 112(10): 3260–3290.

Lewis, William Arthur, et al. 1954. "Economic Development With Unlimited Supplies of Labour."

Lu, Yangsiyu, and Jacquelyn Pless. 2024. "Greening to Grow: Evidence from Environmental Regulation and Industrial Firm Productivity in China." *Available at SSRN 5014283*.

Macedo, Isaias C, Joaquim EA Seabra, and João EAR Silva. 2008. "Green house gases emissions in the production and use of ethanol from sugarcane in Brazil: The 2005/2006 averages and a prediction for 2020." *Biomass and Bioenergy*, 32(7): 582–595.

Matsuyama, Kiminori. 1992. "Agricultural Productivity, Comparative Advantage, and Economic Growth." *Journal of Economic Theory*, 58(2): 317–334.

Mellor, John W. 1995. "Agriculture on the Road to Industrialization."

Metcalf, Gilbert E, and James H Stock. 2020. "Measuring the macroeconomic impact of carbon taxes." Vol. 110, 101–106, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Moraes, Márcia Azanha Ferraz Dias, Fabíola Cristina Ribeiro Oliveira, and Rocio A Diaz-Chavez. 2015. "Socio-economic Impacts of Brazilian Sugarcane Industry."

Environmental Development, 16: 31–43.

Moscona, Jacob. 2019. "Agricultural Development and Structural Change Within and Across Countries." *Report, MIT.[1486].*

Novaes, José Roberto Pereira, et al. 2007. "Jovens migrantes canavieiros: entre a enxada e o facão." *Relatório de estudo desenvolvido para a pesquisa Juventude e integração sul-americana: caracterização de situações-tipo e organizações juvenis, realizada pelo Ibase e pelo Instituo Pólis.*

Olea, José Luis Montiel, and Carolin Pflueger. 2013. "A Robust Test for Weak Instruments." *Journal of Business & Economic Statistics*, 31(3): 358–369.

Porter, Michael, and Claas Van der Linde. 1995. "Green and competitive: ending the stalemate." *The Dynamics of the eco-efficient economy: environmental regulation and competitive advantage*, 33: 120–134.

Rangel, Marcos A, and Tom S Vogl. 2019. "Agricultural Fires and Health at Birth." *Review of Economics and Statistics*, 101(4): 616–630.

Rosenstein-Rodan, Paul N. 1943. "Problems of industrialisation of eastern and south-eastern Europe." *The economic journal*, 53(210-211): 202–211.

Sant'Anna, Marcelo. 2024. "How Green Is Sugarcane Ethanol?" *Review of Economics and Statistics*, 106(1): 202–216.

SGPR. 2009. "Compromisso Nacional para Aperfeiçoar as Condições de Trabalho na Cana de Açucar." Secretaria Geral da Presidência da Republica.

Shapiro, Joseph S, and Reed Walker. 2018. "Why is pollution from US manufacturing declining? The roles of environmental regulation, productivity, and trade." *American economic review*, 108(12): 3814–3854.

Tanaka, Shinsuke, Wesley Yin, and Gary H Jefferson. 2014. "Environmental regulation and industrial performance: Evidence from China." Working paper.

Walker, W Reed. 2011. "Environmental regulation and labor reallocation: Evidence from the Clean Air Act." *The American Economic Review*, 101(3): 442–447.

Walker, W Reed. 2013. "The Transitional Costs of Sectoral Reallocation: Evidence From the Clean Air Act and the Workforce." *The Quarterly Journal of Economics*, 128(4): 1787–1835.

Walter, Arnaldo, Marcelo Valadares Galdos, Fabio Vale Scarpare, Manoel Regis Lima Verde Leal, Joaquim Eugênio Abel Seabra, Marcelo Pereira da Cunha, Michelle Cristina Araujo Picoli, and Camila Ortol. 2014. "Brazilian sugarcane ethanol: developments so far and challenges for the future." *Wiley Interdisciplinary Reviews: Energy and Environment*, 3(1): 70–92.

World Bank. 2008. "World Development Report 2008: Agriculture for Development."

Appendix

A Appendix Figures and Tables

Table A1: Summary Statistics of Control Variables

	(1)
Mechanization Index (M_j)	0.442
	(0.193)
Workforce in 2000	19041.452
	(45281.167)
Share of rural population in 2000	0.172
	(0.120)
Planted area in 2000	8318.284
	(10783.880)
Illiteracy rate in 2000	0.072
	(0.026)
Skilled rate in 2000	0.242
	(0.063)
Population density in 2000	0.037
	(0.027)
Distance to roads	0.786
	(0.900)
Delta soil suitability	7520.677
	(347.501)

Notes: This table displays the summary statistics – mean and standard deviations (in parenthesis) – for our explanatory and control variables. The unit of observation is the municipality (N = 393).

Table A2: Results – Unskilled employment share

	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Agricultural sector							
Mechanization Index (M_j)	0.012	-0.232***	-0.220***	-0.246***	-0.229***	-0.196***	-0.202***
	(0.021)	(0.072)	(0.068)	(0.077)	(0.070)	(0.065)	(0.067)
		[-0.450, -0.121]	[-0.423, -0.114]	[-0.495, -0.127]	[-0.437, -0.121]	[-0.383, -0.091]	[-0.407, -0.098]
Panel B: Manufacturing sector							
Mechanization Index (M_j)	-0.004	0.221***	0.210***	0.225***	0.218***	0.216***	0.208***
	(0.018)	(0.064)	(0.061)	(0.067)	(0.062)	(0.059)	(0.060)
		[0.128, 0.426]	[0.120, 0.402]	[0.126, 0.452]	[0.127, 0.413]	[0.124, 0.396]	[0.120, 0.400]
Panel C: Services sector							
Mechanization Index (M_j)	0.016	0.033	0.036	0.049	0.034	0.023	0.037
	(0.012)	(0.036)	(0.036)	(0.038)	(0.035)	(0.034)	(0.035)
		[-0.037, 0.119]	[-0.034, 0.122]	[-0.022, 0.150]	[-0.034, 0.119]	[-0.042, 0.102]	[-0.027, 0.126]
Standard	Y	Y	Y	Y	Y	Y	Y
Education			Y				Y
Population density				Y			Y
Distance to roads					Y		Y
Soil suitability						Y	Y
1st Stage (MP F-stat.)		37.37	37.60	33.91	39.57	46.16	41.95

Notes: This table reports estimates of mechanical harvesting adoption on unskilled employment share by sector (as indicated in the Panels), captured by β in equation (2). Column 1 presents OLS estimates, while columns 2–7 present 2SLS estimates, using sugarcane field slope as an instrument for mechanical harvesting. All regressions control for the rural population share in 2000, log labor force in 2000, and log sugarcane-planted area in 2003. Education controls include the shares of illiterate and skilled workers in 2000. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane comes from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. The Anderson-Rubin confidence interval is in brackets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3: Robustness College – Skilled-unskilled ratio

	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Agricultural sector							
Mechanization Index (M_j)	0.027	0.267**	0.271**	0.319***	0.264**	0.225**	0.274**
	(0.039)	(0.113)	(0.116)	(0.120)	(0.111)	(0.107)	(0.116)
		[0.057, 0.558]	[0.055, 0.571]	[0.115, 0.655]	[0.058, 0.550]	[0.026, 0.493]	[0.067, 0.591]
Panel B: Manufacturing sector							
Mechanization Index (M_j)	0.084	-0.304	-0.198	-0.264	-0.306	-0.370	-0.243
	(0.112)	(0.327)	(0.312)	(0.338)	(0.322)	(0.303)	(0.297)
		[-1.197, 0.253]	[-1.026, 0.358]	[-1.188, 0.338]	[-1.186, 0.242]	[-1.173, 0.145]	[-1.030, 0.285]
Panel C: Services sector							
Mechanization Index (M_j)	0.089	0.116	0.209	0.128	0.103	0.111	0.180
	(0.103)	(0.266)	(0.262)	(0.274)	(0.263)	(0.256)	(0.259)
		[-0.484, 0.674]	[-0.362, 0.780]	[-0.490, 0.702]	[-0.491, 0.634]	[-0.447, 0.649]	[-0.384, 0.744]
Standard	Y	Y	Y	Y	Y	Y	Y
Education			Y				Y
Population density				Y			Y
Distance to roads					Y		Y
Soil suitability						Y	Y
1st Stage (MP F-stat.)		37.37	37.88	33.91	39.57	46.16	42.74

Notes: This table reports estimates of mechanical harvesting adoption on skilled-unskilled workers ratio by sector (as indicated in the Panels), captured by β in equation (2). Differently from Table 7, we classified skilled workers as those with at least a *college degree*. Column 1 presents OLS estimates, while columns 2–7 present 2SLS estimates, using sugarcane field slope as an instrument for mechanical harvesting. All regressions control for the rural population share in 2000, log labor force in 2000, and log sugarcane-planted area in 2003. Education controls include the shares of illiterate and skilled workers in 2000. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane comes from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. The Anderson-Rubin confidence interval is in brackets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A4: Robustness Middle School – Skilled-unskilled ratio

	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Agricultural sector							
Mechanization Index (M_j)	0.027	0.267**	0.222*	0.319***	0.264**	0.225**	0.237**
	(0.039)	(0.113)	(0.113)	(0.120)	(0.111)	(0.107)	(0.114)
		[0.057, 0.558]	[0.011, 0.514]	[0.115, 0.655]	[0.058, 0.550]	[0.026, 0.493]	[0.034, 0.541]
Panel B: Manufacturing sector							
Mechanization Index (M_j)	0.084	-0.304	-0.327	-0.264	-0.306	-0.370	-0.333
	(0.112)	(0.327)	(0.321)	(0.338)	(0.322)	(0.303)	(0.312)
		[-1.197, 0.253]	[-1.180, 0.245]	[-1.188, 0.338]	[-1.186, 0.242]	[-1.173, 0.145]	[-1.160, 0.222]
Panel C: Services sector							
Mechanization Index (M_j)	0.089	0.116	0.118	0.128	0.103	0.111	0.118
	(0.103)	(0.266)	(0.274)	(0.274)	(0.263)	(0.256)	(0.269)
		[-0.484, 0.674]	[-0.478, 0.715]	[-0.490, 0.702]	[-0.491, 0.634]	[-0.447, 0.649]	[-0.468, 0.703]
Standard	Y	Y	Y	Y	Y	Y	Y
Education			Y				Y
Population density				Y			Y
Distance to roads					Y		Y
Soil suitability						Y	Y
1st Stage (MP F-stat.)		37.37	36.51	33.91	39.57	46.16	40.94

Notes: This table reports estimates of mechanical harvesting adoption on skilled-unskilled workers ratio by sector (as indicated in the Panels), captured by β in equation (2). Differently from Table 7, we classified skilled workers as those with at least a completed *middle school*. Column 1 presents OLS estimates, while columns 2–7 present 2SLS estimates, using sugarcane field slope as an instrument for mechanical harvesting. All regressions control for the rural population share in 2000, log labor force in 2000, and log sugarcane-planted area in 2003. Education controls include the shares of illiterate and skilled workers in 2000. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane comes from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. The Anderson-Rubin confidence interval is in brackets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A5: Robustness Linked Sectors – Employment share

	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
Panel A: Linked manufacturing sector							
Mechanization Index (M_j)	-0.021	0.187***	0.164***	0.184***	0.183***	0.176***	0.157***
	(0.015)	(0.059)	(0.055)	(0.060)	(0.057)	(0.054)	(0.052)
		[0.101, 0.376]	[0.084, 0.339]	[0.096, 0.386]	[0.100, 0.366]	[0.097, 0.344]	[0.081, 0.323]
Panel B: Non-linked manufacturing sector							
Mechanization Index (M_j)	0.009	-0.012	0.005	-0.003	-0.009	-0.005	0.012
	(0.008)	(0.022)	(0.021)	(0.022)	(0.021)	(0.021)	(0.020)
		[-0.066, 0.029]	[-0.046, 0.047]	[-0.056, 0.041]	[-0.060, 0.033]	[-0.054, 0.035]	[-0.035, 0.053]
Panel C: Linked services sector							
Mechanization Index (M_j)	0.011	0.017	0.018	0.020	0.016	0.012	0.015
	(0.008)	(0.022)	(0.022)	(0.023)	(0.021)	(0.020)	(0.021)
		[-0.024, 0.073]	[-0.023, 0.072]	[-0.020, 0.083]	[-0.023, 0.071]	[-0.026, 0.063]	[-0.024, 0.069]
Panel D: Non-linked services sector							
Mechanization Index (M_j)	0.006	0.016	0.023	0.025	0.017	0.010	0.022
	(0.008)	(0.027)	(0.026)	(0.027)	(0.026)	(0.025)	(0.025)
		[-0.040, 0.076]	[-0.032, 0.083]	[-0.031, 0.091]	[-0.037, 0.074]	[-0.042, 0.064]	[-0.029, 0.081]
Standard	Y	Y	Y	Y	Y	Y	Y
Education			Y				Y
Population density				Y			Y
Distance to roads					Y		Y
Soil suitability						Y	Y
1st Stage (MP F-stat.)		37.37	37.60	33.91	39.57	46.16	41.95

Notes: This table reports estimates of mechanical harvesting adoption on employment share by linked sector (as indicated in the Panels), captured by β in equation (2). Differently from Table 8, we use an alternative definition of linked sectors, applying a 1% threshold for linkages instead of 0.1%. Column 1 presents OLS estimates, while columns 2–7 present 2SLS estimates, using sugarcane field slope as an instrument for mechanical harvesting. All regressions control for the rural population share in 2000, log labor force in 2000, and log sugarcane-planted area in 2003. Education controls include the shares of illiterate and skilled workers in 2000. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane comes from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. The Anderson-Rubin confidence interval is in brackets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A6: Robustness Linked Sectors – Unskilled Employment Share

	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Linked manufacturing sector							
Mechanization Index (M_j)	-0.023	0.205***	0.176***	0.200***	0.200***	0.192***	0.167***
	(0.017)	(0.062)	(0.057)	(0.063)	(0.060)	(0.057)	(0.054)
		[0.114, 0.405]	[0.092, 0.354]	[0.108, 0.412]	[0.112, 0.388]	[0.109, 0.370]	[0.088, 0.340]
Panel B: Non-linked manufacturing sector							
Mechanization Index (M_j)	0.017**	0.010	0.025	0.016	0.012	0.017	0.031
	(0.008)	(0.021)	(0.022)	(0.022)	(0.021)	(0.020)	(0.021)
		[-0.039, 0.055]	[-0.022, 0.072]	[-0.031, 0.063]	[-0.035, 0.056]	[-0.027, 0.059]	[-0.012, 0.078]
Panel C: Linked services sector							
Mechanization Index (M_j)	0.013	0.020	0.022	0.027	0.021	0.016	0.022
	(0.008)	(0.023)	(0.024)	(0.025)	(0.023)	(0.022)	(0.023)
		[-0.023, 0.081]	[-0.022, 0.083]	[-0.018, 0.095]	[-0.022, 0.080]	[-0.025, 0.071]	[-0.019, 0.082]
Panel D: Non-linked services sector							
Mechanization Index (M_j)	0.003	0.012	0.014	0.022	0.014	0.007	0.015
	(0.008)	(0.027)	(0.026)	(0.027)	(0.026)	(0.025)	(0.025)
		[-0.043, 0.070]	[-0.042, 0.071]	[-0.033, 0.086]	[-0.041, 0.070]	[-0.047, 0.061]	[-0.038, 0.072]
Standard	Y	Y	Y	Y	Y	Y	Y
Education			Y				Y
Population density				Y			Y
Distance to roads					Y		Y
Soil suitability						Y	Y
1st Stage (MP F-stat.)		37.37	37.60	33.91	39.57	46.16	41.95

Notes: This table reports estimates of mechanical harvesting adoption on skilled-unskilled workers ratio by linked sector (as indicated in the Panels), captured by β in equation (2). Differently from Table 9, we use an alternative definition of linked sectors, applying a 1% threshold for linkages instead of 0.1%. Column 1 presents OLS estimates, while columns 2–7 present 2SLS estimates, using sugarcane field slope as an instrument for mechanical harvesting. All regressions control for the rural population share in 2000, log labor force in 2000, and log sugarcane-planted area in 2003. Education controls include the shares of illiterate and skilled workers in 2000. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane comes from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. The Anderson-Rubin confidence interval is in brackets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.