Structural Change Through Environmental Regulation: Evidence from São Paulo's Fire Ban*

Francisco Costa† Francisco Luis Lima‡ Letícia Nunes§

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Abstract

Does environmental regulation constrain or catalyze economic development? We study São Paulo's 2002 ban on pre-harvest burning in sugarcane, which forced rapid adoption of mechanical harvesting. Using land slope as an instrument for mechanization costs, we find that regulation-induced technology adoption triggered structural transformation in local labor markets. Mechanization reduced agricultural employment and increased manufacturing employment, accounting for over 75% of observed sectoral shifts between 2000 and 2010. Critically, labor reallocation was selective: employment gains occurred only in agro-linked manufacturing, such as biofuel production and sugar processing, rather than across all industries. This selectivity explains the smooth transition despite the displacement of workers in the agricultural sector. Mechanization also generated economy-wide gains: household incomes rose, unemployment declined, and poverty fell. Our findings demonstrate that environmental regulation can catalyze structural transformation and improve welfare when it forces technology upgrading in contexts with strong agro-industrial linkages.

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

‡Banco ABC Brasil.

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

1 Introduction

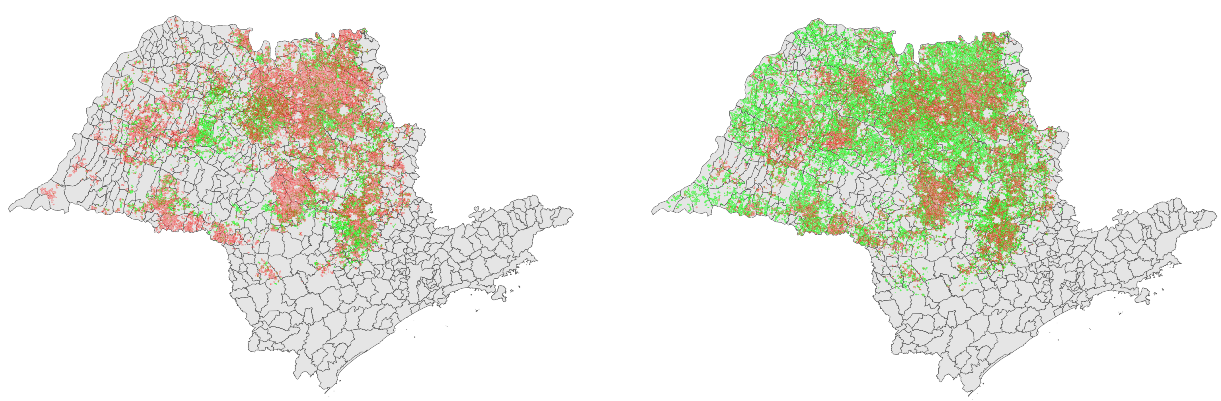
Does environmental regulation constrain or catalyze economic development? Most evidence from developed economies shows that emission regulations reduce firm competitiveness and impose costs on growth and employment (Berman et al., 1998; Greenstone, 2002; Greenstone et al., 2012; Walker, 2011, 2013). The Porter hypothesis argues that well-designed environmental policies can trigger innovation and productivity gains that offset compliance costs (Porter and Van der Linde, 1995), and recent evidence supports this view in manufacturing contexts (Shapiro and Walker, 2018; Metcalf and Stock, 2020; Dugoua, 2023; Lu and Pless, 2024). Yet virtually all this evidence comes from industrial sectors in rich countries. We know remarkably little about how environmental regulation affects economic development when it targets labor-intensive agriculture in low- and middle-income countries.

Agriculture presents a fundamentally different context. In developing economies, agriculture employs the largest share of the workforce (Gollin et al., 2014; McMillan et al., 2014) — often low-skilled workers with limited alternatives. Environmental regulations that force technological change in this sector could trigger structural transformation, reallocating labor from farming to manufacturing and services. But they could also simply destroy livelihoods if local economies lack the capacity to absorb displaced workers. Understanding these effects is critical because agricultural fires are widespread globally. Fires for crop harvesting and land clearing impose substantial health costs and contribute to emissions (Landrigan et al., 2018; Rangel and Vogl, 2019), prompting governments worldwide to design policies to reduce agricultural burning (Edwards et al., 2020; Cao and Ma, 2023; Balboni et al., 2021; Jack et al., 2025). Yet we lack evidence on whether such regulations harm or help local economic development in poor rural areas.

This paper demonstrates that environmental regulation can trigger structural transformation and generate substantial local economic benefits by promoting the adoption of productivity-enhancing technologies in agriculture. We study São Paulo state's 2002 ban on pre-harvest burning in sugarcane, implemented to reduce respiratory illness and emissions from agricultural fires. This case presents a rare opportunity to study emission regulation in a globally relevant context. Sugarcane is the world's largest crop by volume, cultivated on 27 million hectares across more than 90 countries, with global production reaching 2 billion tons in 2023. Brazil is the leading producer, and São Paulo alone accounts for over two-thirds of national output — roughly equivalent to India's entire production, making it the second-largest producer globally (Walter et al., 2014). The regulatory experience in São Paulo, therefore, carries lessons for agricultural policy in dozens of countries where sugarcane and similar fire-dependent crops are major employers.

The ban forced technology adoption. Until the early 2000s, sugarcane was harvested manually after fields were burned to remove straw and facilitate cutting by hand. São Paulo's 2002 legislation mandated a gradual phase-out of burning by 2021, accelerated to 2014 through a 2006 industry agreement. This made manual harvesting nonviable and effectively required producers to adopt mechanical harvesters, which eliminate the need for pre-harvest burning (Novaes et al., 2007). Mechanization proceeded rapidly: the share of area harvested mechanically rose to 30% by 2006 and 60% by 2012. Figure 2a shows a map of this expansion. Mechanical harvesting is sharply labor-saving. To identify causal effects, we exploit variation in mechanization costs driven by land slope. Mechanization is cheaper on flat terrain, so municipalities with steeper sugarcane fields adopted it more slowly. We combine high-resolution remote sensing data on mechanization from Brazil's National Institute for Space Research with census microdata on local labor markets, using land slope as an instrument for technology adoption.

Figure 1: Adoption of Mechanical Harvesting in Sugarcane



(a) 2006 (b) 2012

Notes: This figure presents the adoption of mechanical harvesting in sugarcane plantations in São Paulo state in 2006 — the first year we can measure mechanization with GIS data — and 2012. In both maps, manual harvesting is shown in red and mechanical harvesting in green. Dark lines mark the municipalities. Source: CANASAT/INPE.

We find that regulation-induced mechanization triggered substantial structural transformation in local labor markets. A one-standard-deviation increase in mechanization (0.193) reduced agriculture's employment share by 2.76 percentage points and raised manufacturing employment by 3.38 percentage points. These magnitudes are economically large: mechanization accounts for 77% of the decline in agricultural employment and 74% of the growth in manufacturing employment observed between 2000 and 2010. The reallocation was concentrated among male workers without a college education, who moved from agricultural to manufacturing jobs. This pattern aligns with standard models of structural transformation, where labor-saving technological change in agriculture drives workers into industry (Bustos et al., 2016; Gollin et al., 2021).

Critically, however, the labor reallocation was not broad-based but highly selective. Using input-output tables, we classify manufacturing and service industries as linked to agriculture if they supply to agriculture or source their inputs from agriculture. We find that mechanization raised employment in agro-linked manufacturing by 3.51 percentage points — accounting for 78% of observed growth in these industries — but did not affect non-linked manufacturing. The gains were concentrated in downstream industries -— biofuel production, sugar processing, and food manufacturing — that benefited from workers released from agriculture and expanded sugarcane output. We find that mechanization increased the share of agricultural land planted with sugarcane by 19.6 percentage points, accounting for 76% of sugarcane expansion during the period. This selectivity may explain why the transition proceeded smoothly despite displacing thousands of workers: local economies possessed strong agro-industrial linkages that channeled productivity gains into employment creation within an integrated supply chain. The pattern differs from canonical structural transformation, where labor reallocates broadly across sectors.

We also show that the local economic benefits from mechanization extended well beyond sectoral reallocation. Mechanization raised household income per capita by approximately 5.8% above baseline levels, lowered unemployment by 24%, and reduced poverty by 13%. These economy-wide gains demonstrate that environmental regulation catalyzed technological upgrading that simultaneously reduced pollution and improved local economic conditions.

Our findings contribute to three literatures. First, we provide evidence on the local economic effects of environmental regulation in developing country agriculture. A long-standing debate contrasts regulation as a constraint on growth (Berman et al., 1998; Greenstone, 2002; Greenstone et al., 2012; Walker, 2011, 2013) against the Porter hypothesis that regulation can spur productivity-enhancing innovation (Porter and Van der Linde, 1995). Recent evidence supports the Porter view in manufacturing contexts, showing that environmental policies can drive technological upgrading and accelerate adoption of cleaner production methods (Shapiro and Walker, 2018; Metcalf and Stock, 2020; Dugoua, 2023; Lu and Pless, 2024). We extend this literature by examining regulation in a labor-intensive agricultural sector in a middle-income country. We show that when environmental regulation forces the adoption of productivity-enhancing technology, it can trigger a structural transformation that benefits local workers and generates economy-wide welfare gains. This contrasts sharply with studies that find negative employment effects of regulation in manufacturing, highlighting that the sectoral context — particularly the presence of strong agro-industrial linkages — shapes whether regulation constrains or catalyzes development.

Second, we contribute to understanding the composition of structural transformation. Classical development models predict that rising agricultural productivity releases labor from farming, enabling industrialization (Lewis et al., 1954; Kuznets, 1957; Rosenstein-Rodan, 1943; Mellor, 1995). Yet this relationship is contested: productivity gains can reinforce agricultural comparative advantage rather than spurring broad-based industrialization (Matsuyama, 1992), and local spillovers from agricultural improvements often fail to materialize (Foster and Rosenzweig, 2004; Hornbeck and Keskin, 2015; Moscona, 2019). Recent work shows that structural transformation depends on the factor intensity of productivity gains (Bustos et al., 2016), skill composition of workers and firms (Bustos et al., 2019; Asher et al., 2022), and intersectoral linkages (Caselli and Coleman II, 2001; Acemoglu and Guerrieri, 2008; Caunedo and Kala, 2021; Amodio et al., 2025). We show that labor-saving agricultural technology drives industrialization through a specific channel: strengthening linkages to agro-industrial manufacturing rather than enabling broad sectoral diversification. This pattern of transformation -— concentrated in downstream industries — explains why agricultural productivity sometimes triggers local industrialization and sometimes does not. When strong linkages exist, productivity gains translate into employment creation within an integrated agro-industrial system. Without such linkages, the same technological change might simply displace workers without creating local alternatives.

Third, we contribute to understanding agricultural development pathways in an era of automation. As manufacturing employment stagnates in developing countries due to automation and offshoring, agriculture combined with agro-industry offers an alternative route to structural transformation and poverty reduction (Mellor, 1995; World Bank, 2008; De Janvry and Sadoulet, 2020). We demonstrate how this pathway operates: mechanization frees labor and expands agricultural output, and strong forward linkages to processing industries convert that expansion into manufacturing employment. The fact that less-educated workers transitioned smoothly from manual harvesting to agro-industrial jobs suggests that this development path does not require massive investments in education or skills training.

The rest of the paper proceeds as follows. Section 2 provides background on sugarcane production, harvesting technologies, and the fire ban. Section 3 describes the data. Section 4 presents the empirical strategy. Section 5 presents results on agriculture, structural transformation, linked industries, and economy-wide effects. Section 6 concludes.

2 Background

This section reviews the sugarcane industry in São Paulo with emphasis on harvesting technology and local labor markets.

Sugarcane in São Paulo. In 2023, sugarcane occupied about 27 million hectares across more than 90 countries, with a global harvest near 2 billion tons (FAO). Brazil is the largest producer, accounting for over one-third of world output (Walter et al., 2014). São Paulo produces more than two-thirds of Brazil's sugarcane. If São Paulo were an independent producer, it would rank second worldwide, alongside India (Brazilian Sugarcane Industry Union, UNICA). In 2003, 393 municipalities in São Paulo reported sugarcane production, concentrated in the central and northern regions. In producing municipalities, sugarcane covered over 46% of agricultural land, reaching 99% in some areas.

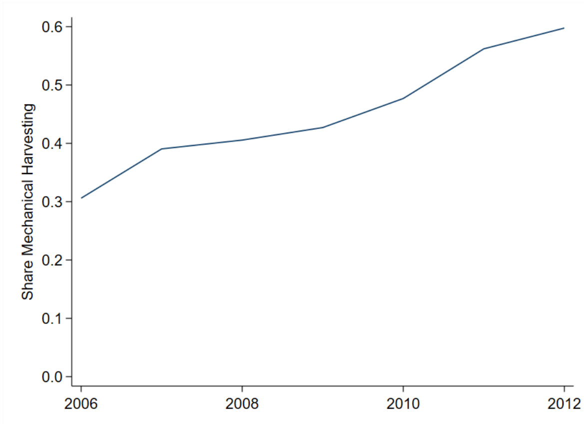
Sugarcane is a semi-perennial crop. In São Paulo, the harvest runs from April to December. After cutting, cane is hauled to a nearby mill. Because sugars deteriorate quickly, mills are typically within 40 km of fields (Sant'Anna, 2024). Mills process the sugarcane into sugar and/or ethanol, and most modern mills can produce both.

Harvesting technologies. Two methods dominate: manual and mechanical. Manual harvesting involves pre-harvest burning and hand cutting. Mechanical harvesting uses combine harvesters without burning.

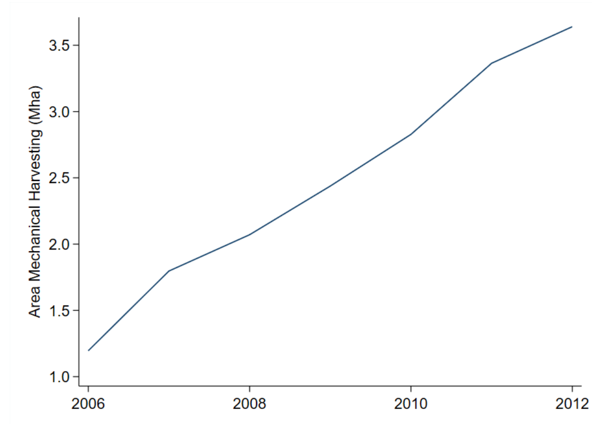
Pre-harvest burning removes straw and weeds but releases pollutants (Macedo et al., 2008), increases respiratory disease (Cançado et al., 2006; Dominici et al., 2014; Rangel and Vogl, 2019), and contaminates soil and groundwater (SGPR, 2009). Manual harvesting in Brazil is primarily organized through temporary employment.

Mechanical harvesting eliminates burning. Combine harvesters process straw during cutting, making this method less polluting. The technology is capital-intensive and exhibits economies of scale. Industry estimates suggest one harvester replaces about 80 workers (SGPR, 2009). Despite higher productivity, producers often relied on manual methods when low-wage seasonal labor was abundant. Mechanization also requires a different set of skills, e.g., operators and mechanics (Moraes et al., 2015). Our identification exploits that terrain slope increases mechanization costs: flat land is more suitable for combines. Mechanization is therefore cheaper on flatter land.

Policy to phase out pre-harvest burning. In 2002, São Paulo enacted State Law 11,241 to phase out pre-harvest burning by 2021 in most producing areas. The goals were to reduce respiratory illness and emissions. Because manual harvesting depends on burning, the law



(a) Share of Area



(b) Total Area

Figure 2: Adoption of Mechanical Harvesting in Sugarcane Over Time

Notes: The figures plot the share and total area harvested mechanically by year. Source: CANASAT.

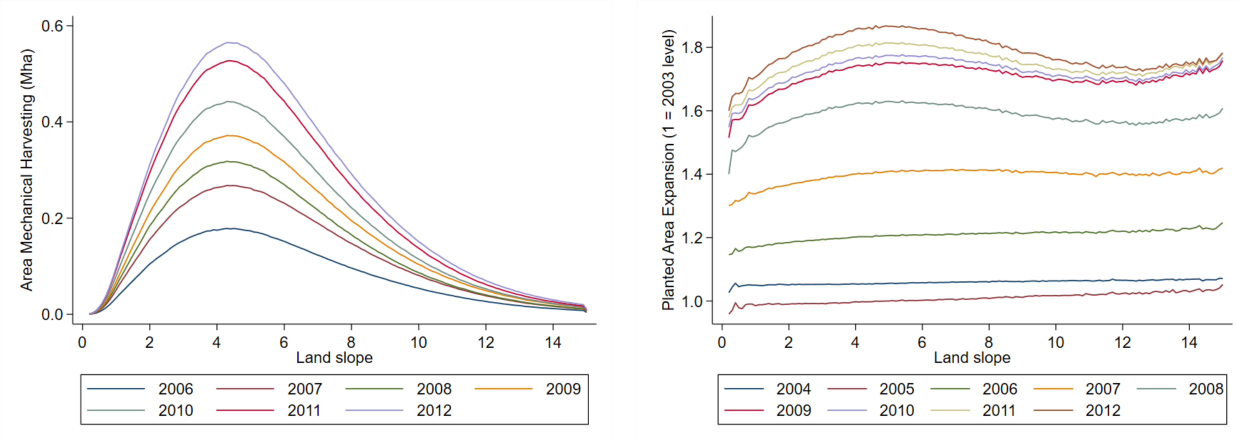
effectively made the manual methods nonviable and pushed producers toward mechanical methods (Novaes et al., 2007). In 2006, a Cooperation Protocol between the state and the Organization of Sugarcane Producers accelerated the phase-out timeline to 2014 and created clean sugarcane certification.

Before 2002, mechanized harvesting was limited. Adoption accelerated after the 2006 Protocol. As Figure 2a shows, by 2006, just over 30% of harvesting was mechanical (without fire), and by 2012, it exceeded 60%.[1] Figure 2b shows that the area harvested mechanically roughly tripled between 2006 and 2012. Adoption varied across municipalities with land suitability, firm investment, environmental enforcement, and labor markets (Davis, 2017).

Because adoption costs are lower on flat land, these areas mechanized earlier, while steeper terrain relied on manual harvesting for longer (SGPR, 2009). Figure 3a shows the rise of mechanization by terrain slope. In comparison to 2006, mechanization increased more rapidly on gentle and moderate slopes. For example, in plots with a slope of around 4, mechanical harvesting increased from under 200,000 hectares in 2006 to approximately 600,000 hectares in 2012, with smaller gains on steeper land. This adoption across slopes underpins our empirical strategy to study how the transition from manual to mechanical harvesting impacted local labor markets.

Local labor markets. In sugarcane-producing municipalities, about 16% of the workforce is in agriculture, 24% in services, and just over 10% in manufacturing (Table 1 Panel A). Most agricultural workers have not completed high school, with only 20% holding a high-

[1]As explained below, 2006 and 2012 are the first and last years with remote-sensing data on harvesting technology.



(a) Mechanical Harvesting vs. Slope

(b) Planted Area Expansion vs. Slope

Figure 3: Sugarcane Mechanical Harvesting by Land Slope Over Time

Notes: Panel (a) reports mechanical-harvested area by year and slope (million ha). Panel (b) reports planted-area expansion by year relative to 2003 (index=1 in 2003). Pixels with slope $>$ 15% are dropped due to a long right tail.

school degree or higher. Farms relying on manual harvesting typically hire seasonal workers, many of whom come from other states (Moraes et al., 2015). The sector has a record of child labor and poor conditions, with reports of criminal recruitment, exploitative work, inadequate housing, and high accident rates (SGPR, 2009).

Mechanization shifts labor demand through two channels. First, it reduces the number of workers needed to harvest a given area, displacing labor. Second, it raises the relative demand for skills in agriculture, with potential spillovers to the local economy. As a consequence, in 2009, UNICA, the federal government, and the National Confederation of Agricultural Workers (CONTAG) signed the Agreement to Improve Sugarcane Working Conditions to improve practices and support workers displaced by mechanization.

3 Data

We combine census microdata, remote sensing on sugarcane, land characteristics, and administrative records. Below we describe each dataset and its role in the analysis.

Labor market and demographics. We use Demographic Census data from the Brazilian Institute of Geography and Statistics (IBGE) for the years 1991, 2000, and 2010 as our primary source for the labor market. We restrict the sample to the working-age population, defined as ages 18–60. We aggregate to the municipality using IBGE sampling weights. For 1991 we rely on Administrative Minimum Comparable Areas (AMC).

Table 1: Summary Statistics of Labor Market 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)
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)

Notes: The table reports means and standard deviations (in parentheses) for labor market outcomes from the Census. The unit of observation is the municipality ($N = 393$).

We classify workers by employment sector in the previous week using CNAE 1.0 two-digit codes. We define three broad sectors: agriculture (codes 01–05), manufacturing (codes 15–37), and services (codes 40–74 and 80–94), which include public administration and education. For each municipality, we compute sectoral employment shares as the number of workers in each sector divided by the working-age population. We also calculate the share of unskilled employment within each sector measured as those without a high-school degree.

The census also provides demographic characteristics. We calculate the proportion of the working-age population residing in rural areas. We proxy population density by dividing the natural logarithm of population by municipal land area.

Industry linkages. We use the 2000 IBGE input–output table to measure linkages to agriculture. The table classifies 55 industries, which we merge to the census using CNAE 1.0. We classify an industry as upstream if at least 0.1% of its output is sold to agriculture, and as downstream if at least 0.1% of its inputs come from agriculture. Industries that meet neither criterion are non-linked. As a robustness check, we raise the threshold to 1%. Table 1 reports employment shares by linkage status. At baseline, approximately 80% of manufacturing workers are employed in industries upstream or downstream from agriculture. In services, employment is more balanced, with about two-thirds in linked industries.

Sugarcane production and mechanization. We measure sugarcane and harvesting methods using high-resolution remote sensing from CANASAT, developed by Brazil's National Institute for Space Research (INPE). CANASAT applies digital interpretation of Landsat 5 images at 30-meter resolution to produce annual pixel-level data on planted area and harvesting method (Aguiar et al., 2009, 2011). The coverage is São Paulo only, which limits external comparison across states.

The CANASAT–Planted Area dataset identifies pixels cultivated with sugarcane at the start of each harvest season from 2003 to 2012. The CANASAT–Harvest dataset, created to support enforcement of the 2006 Cooperation Protocol, classifies harvested pixels by use of pre-harvest burning (manual harvesting) versus mechanized harvesting (without burning). This classification is available for harvest seasons 2006–2012.

To quantify mechanization at the municipality level, we construct a *mechanization* index that captures the share of sugarcane-planted pixels harvested mechanically in 2010, the latest census year:

$$M_j \equiv \frac{m_{j,2010}}{a_{j,2010}}, \tag{1}$$

where $a_{j,2010}$ is the area cultivated with sugarcane in municipality j in 2010 and $m_{j,2010}$ is the area harvested mechanically in 2010. Because CANASAT does not provide data before 2006, we implicitly set $m_{j,2000} = 0$ and thus assume no mechanization in 2000. As a robustness check, we construct an alternative measure that assumes the 2000 mechanization share equals the 2006 share:

$$M_j^{\Delta} \equiv \frac{m_{j,2010}}{a_{j,2010}} - \frac{m_{j,2006}}{a_{j,2006}}. \tag{2}$$

Land characteristics. We measure land suitability for mechanization using TOPODATA, which is based on the Shuttle Radar Topography Mission (SRTM). The dataset provides elevation and slope at one-arcsecond resolution. We overlay TOPODATA with CANASAT fields to compute the average slope of sugarcane plots in each municipality.

We also use potential sugarcane yields from FAO–GAEZ to capture suitability for technological change. The database reports simulated yields under different input scenarios. For each municipality, we compute the difference between potential yields under high-input and low-input conditions as a measure of mechanization suitability. To proxy market access, we use road maps from Brazil's Ministry of Transportation and compute the average distance from sugarcane fields to the nearest road.

Socioeconomic and agricultural data. We add municipal controls from several sources. Using DATASUS/TabNet, we obtain household income per capita, unemployment rates, child labor rates, and poverty rates. For agriculture, we use the Municipal Agricultural Survey (PAM/IBGE). The survey provides annual data on total planted area, sugarcane area, yields, and other crops. IBGE agents collect the information and apply checks for inter-annual consistency. Table 2 reports summary statistics for these variables.

Table 2: Summary Statistics of Agriculture and Economy-wide Variables

	Land use			Economy-wide variables				
	Total Planted Area (1)	Sugarcane Planted Area (%) (2)	Sugarcane Productivity (3)	Household Income PC (4)	Wage (5)	Poverty (< 1.2 MW) (6)	Unemployment Rate (16+) (7)	Child Labor Rate (10-15) (8)
Panel A: 2000								
mean	13260.043	42.855	67820.893	547.386	536.320	0.384	0.116	0.137
s.d.	(15318.090)	(31.508)	(27404.623)	(156.812)	(134.614)	(0.113)	(0.038)	(0.048)
Panel B: Δ 2010-2000								
mean	4398.779	25.862	16161.982	171.016	570.367	-0.194	-0.057	-0.055
s.d.	(7826.134)	(26.727)	(31360.270)	(92.744)	(137.366)	(0.083)	(0.034)	(0.047)

Notes: The table reports means and standard deviations (in parentheses) for land-use variables from PAM and economy-wide characteristics from the Census. Income refers to the individual's primary source of employment. The unit of observation is the municipality ($N = 393$).

4 Empirical Strategy

We estimate the local economic effects of adopting the technology required to comply with the pre-harvest burning ban. We first present the baseline regression. We then discuss identification and implement an instrumental-variables approach.

We study municipality-level changes in outcomes between 2000 and 2010, $\Delta Y_j \equiv Y_{j,2010} - Y_{j,2000}$, using

$$\Delta Y_j = \alpha + \beta M_j + X_j' \gamma + \varepsilon_j, \tag{3}$$

where M_j is the mechanization index in equation (1). The coefficient β measures the effect of mechanization in the sugarcane sector on labor-market and economic outcomes. The error term ε_j captures unobserved municipality shocks. We report heteroskedasticity-robust standard errors (Bustos et al., 2016; Abadie et al., 2023).

We address identification concerns by adding controls X_j. To account for differential labor market trends, we control for the rural population share in 2000, population density in 2000, the log of the labor force in 2000, and the log of the sugarcane-planted area in 2003. Education can facilitate technology adoption and affect labor demand, so we include the 2000 shares of illiterate and high-school workers. To capture differential trends for infrastructure and urbanization, we control for log distance to roads and population density. We also control for potential sugarcane yield to absorb trends related to agronomic suitability. Table A1 reports descriptive statistics for the controls.

Even with these controls, equation (3) may suffer from endogeneity if local trends affect both mechanization and outcomes. For example, subsidies to the sugarcane industry or changes in labor regulation could shift adoption and employment. We address this concern with an instrumental-variables design.

4.1 Instrumental Variables

We instrument for mechanical harvesting with the average land slope of sugarcane-planted pixels in 2003. Mechanization is cheaper on flat land (Moraes et al., 2015), so producers on steeper terrain should adopt more slowly. The instrument identifies a local average treatment effect for municipalities whose mechanization responds to land slope in the 2000–2010 policy environment, provided that two conditions hold. First, land slope predicts mechanization. Second, land slope affects outcomes only through mechanization, so it is uncorrelated with ε_j in equation (3).

We assess the first condition in two ways. Figure 3a shows mechanization over time by slope. As discussed earlier, adoption is slower on steeper land, consistent with higher costs. We also estimate the first stage,

$$M_j = \alpha_0 + \lambda S_j + X_j' \gamma_0 + \varepsilon_j, \tag{4}$$

where S_j is the average slope in sugarcane-planted pixels in 2003. Table 3 reports the results. Slope is strongly and negatively related to mechanization across specifications. The Montiel Olea–Pflueger F-statistic (Olea and Pflueger, 2013) ranges from 37.37 to 46.16, which indicates instrument relevance.[2] To address potential weak-instrument concerns (Lee et al., 2022), we report confidence intervals that are robust to weak instruments (Anderson and Rubin, 1949).

We assess the exclusion restriction next. If sugarcane expansion before mechanization favored flat land, slope could correlate with other drivers of outcomes. Figure 3b plots the expansion in planted area by slope relative to 2003. Before 2006, expansion rates were similar across slope bins and moved in parallel. This pattern suggests no systematic preference for flatter land when manual harvesting dominated. The exclusion restriction is thus plausible. In the next section, we add placebo tests that relate 2000s technology adoption to pre-existing trends in agriculture and sugarcane area to provide further reassurance.

5 Results

5.1 Agriculture and Land Use

We begin by examining how mechanization affected the agricultural sector itself. This is a natural starting point for two reasons. First, the direct effects on land use reveal whether

[2] Table A2 reports first-stage estimates when the endogenous variable is the change in mechanization between 2006 and 2010 as in equation (2). The slope coefficient is negative, statistically significant, and close to the baseline first stage (e.g., −0.031 vs. −0.038).

Table 3: First Stage Results

	Dep. Var.: Mechanization (M_j)					
	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Slope (S_j)	-0.035***	-0.036***	-0.034***	-0.036***	-0.038***	-0.038***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Education		✓				✓
Population density			✓			✓
Distance to roads				✓		✓
Sugarcane suitability					✓	✓
1st Stage (MP F-stat.)	37.37	37.88	33.91	39.57	46.16	42.74

Notes: The table reports first-stage estimates of equation (4). All regressions include the rural population share in 2000, the log of the labor force in 2000, and the log of sugarcane-planted area in 2003. Education controls are the 2000 shares of illiterate and high-school workers. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

mechanization changed the agricultural landscape in these regions. Second, understanding the magnitudes of changes in agriculture helps us interpret downstream effects on local labor markets.

The technology shift could affect agriculture through several margins. Mechanization might lead producers to cultivate more land, as reduced labor costs make previously marginal plots profitable. Alternatively, producers might intensify production on existing fields, raising yields without expanding area. A third possibility is that mechanization facilitates substitution toward sugarcane at the expense of other crops. These scenarios have different implications for local economies. Pure intensification would concentrate gains within the sugarcane sector, while area expansion or crop substitution would reshape the broader agricultural landscape and potentially displace workers from other activities.

Table 4 reports the impact of mechanization on three outcomes: total agricultural area (Panel A), the share of agricultural land planted with sugarcane (Panel B), and sugarcane yield per hectare (Panel C). Column 1 presents OLS estimates as a benchmark. We find no statistically significant relationship between mechanization and total agricultural area or yield, but a positive correlation with sugarcane's share of agricultural land. This pattern suggests that mechanization primarily reallocates land toward sugarcane rather than expanding agriculture overall or raising productivity per hectare.

Table 4: Results – Agriculture and Land use

	$\Delta 2010-2000$							$\Delta 2000-1991$
	OLS	IV	IV	IV	IV	IV	IV	Pre-trend
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Total Agricultural Area								
Mechanization Index (M_j)	1502.08	10084.10	8754.45	4425.24	8603.57	9810.42	4411.40	4989.63
	(2496.09)	(6759.85)	(6575.79)	(6557.16)	(6411.50)	(6701.29)	(6322.45)	(5384.08)
		[-4101.77, 25340.60]	[-5045.15, 23595.50]	[-11412.30, 17666.50]	[-4851.28, 22566.10]	[-4252.54, 24934.70]	[-10358.60, 17178.70]	[-5882.75, 16714.70]
Panel B: Share of Sugarcane in Total Agricultural Area (%)								
Mechanization Index (M_j)	30.99***	127.11***	116.73***	112.80***	120.95***	117.45***	101.41***	24.71
	(7.81)	(23.58)	(21.67)	(23.00)	(22.15)	(21.47)	(19.50)	(17.76)
		[86.97, 191.52]	[78.13, 175.92]	[70.00, 172.00]	[81.47, 179.72]	[79.20, 172.71]	[65.12, 150.04]	[-8.34, 66.20]
Panel C: Sugarcane Yield								
Mechanization Index (M_j)	12980.23	79221.33**	69069.36**	67276.66*	78690.06**	65464.91**	53236.65*	50946.21
	(10674.35)	(33847.90)	(32793.95)	(35742.61)	(32920.18)	(30255.34)	(30874.34)	(31348.25)
		[148.62, 147572.00]	[-7541.19, 135292.00]	[-21883.30, 136623.00]	[4391.59, 145168.00]	[-5215.16, 124165.00]	[-23779.40, 110693.00]	[-14839.60, 116732.00]
Education			✓				✓	✓
Population density				✓			✓	✓
Distance to roads					✓		✓	✓
Soil suitability						✓	✓	✓
1st Stage (MP F-stat.)		37.56	38.70	36.34	39.79	46.37	45.07	43.76

Notes: The table reports estimates of the effect of mechanical harvesting adoption on agriculture and land use (coefficient β in equation (3)). Column 1 shows OLS. Columns 2–8 show 2SLS, instrumenting mechanization with sugarcane-field slope. Column 8 is a pre-trend test using 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 college 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 measured in 1991. Distance to roads is in logs. Sugarcane suitability is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$) in regressions 1–7 and the AMC ($N = 352$) in regression 8. Heteroskedasticity-robust standard errors are in parentheses. The Anderson–Rubin confidence interval is in brackets. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Columns 2–7 present instrumental variables estimates that address potential endogeneity concerns. The results confirm a substantial expansion in sugarcane cultivation. Panel B shows that the estimates are remarkably stable as we sequentially add controls for education (column 3), population density (column 4), distance to roads (column 5), and agronomic suitability (column 6). Our preferred specification in column 7 includes all controls. The point estimate implies that a one-standard-deviation increase in mechanization (0.193) raised the share of agricultural land planted with sugarcane by 19.6 percentage points between 2000 and 2010 [$= 0.193 \times 101.41$]. This magnitude is economically large. To put it in perspective, in municipalities at the 84th percentile of mechanization, sugarcane occupied over 88% of agricultural land, whereas a municipality at the 16th percentile occupied under 50% of it. This dramatic reallocation reshaped the agricultural landscape of São Paulo's sugarcane belt, concentrating production in a single crop.

This expansion came primarily because producers switched from other agricultural activities to sugarcane, rather than by bringing new land into cultivation. Panel A shows that total agricultural area did not expand significantly with mechanization. Point estimates are positive across all specifications, but imprecise and never statistically significant.[3] This substitution pattern is consistent with sugarcane's comparative advantage in the region and with the fixed supply of suitable agricultural land in the short run.

Panel C examines whether mechanization raised yields, measured as tons of sugarcane per hectare. The point estimates are positive and often large—a one-standard-deviation increase in mechanization is associated with an additional 10,274 tons per hectare [$= 0.193 \times 53{,}236.65$]. However, these estimates are sensitive to specification, and the weak-instrument-robust confidence intervals frequently include zero. We therefore cannot confidently attribute yield gains to mechanization. The evidence points toward land reallocation as the primary margin of adjustment, not intensification of production on existing plots.

Before moving to labor market outcomes, we assess whether our instrument satisfies the exclusion restriction. A potential threat is that municipalities with flatter terrain may have been on different growth trajectories even before mechanization accelerated. For example, if flat land attracted sugarcane expansion during the manual-harvesting era, then slope could proxy for pre-existing momentum rather than isolating the causal effect of mechanization.

Column 8 addresses this concern by relating mechanization in 2000–2010 to changes in outcomes over 1991–2000, the decade *before* mechanization took off. We find no systematic pre-trends. The coefficient on sugarcane planted area in Panel B is 24.71 and statistically insignificant, compared to 101.41 in our preferred specification. This tells us that munici-

[3]The magnitudes are economically relevant even if statistically uncertain. A one-standard-deviation increase in mechanization is associated with an 851-hectare rise in total planted area [$= 0.193 \times 4{,}411.4$].

palities that mechanized rapidly in the 2000s were not already expanding sugarcane faster in the 1990s. The parallel trends during the manual-harvesting period support the exclusion restriction: the relationship between slope and mechanization appears to be driven by the technology itself, not by other characteristics correlated with slope that would have generated differential growth regardless of mechanization.[4]

In sum, the evidence in Table 4 reveals a clear pattern. Mechanization enabled a substantial expansion in sugarcane cultivation, primarily by reallocating land from other crops. This expansion reshaped the agricultural landscape of São Paulo, concentrating production in sugarcane and reducing diversification. We find little evidence that mechanization raised yields or expanded total agricultural area. We also find no evidence of pre-trends that would violate the instrument's exclusion restriction.

5.2 Structural Transformation

Having established that mechanization reshaped agricultural production by concentrating land in sugarcane, we now examine its effects on local labor markets. The expansion in sugarcane area suggests rising labor demand in agriculture. However, mechanization fundamentally changed the labor requirements of production. Recall from Section 2 that one combine harvester replaces approximately 80 manual workers. Regulation, by mandating the phase-out of pre-harvest burning, effectively mandated this labor-saving technology. The question is not whether mechanization displaced agricultural workers – industry estimates make clear that it did – but rather where these workers went and how local economies adjusted to this shock.

Standard models of structural transformation predict that rising agricultural productivity pushes workers out of farming and into other sectors (e.g., Bustos et al., 2016; Gollin et al., 2021). In developing economies, this reallocation typically flows toward manufacturing and services as agriculture sheds labor. Our setting provides a sharp test of this mechanism. The policy-driven adoption of mechanization led to a sudden, large-scale displacement of agricultural workers over a relatively short period. If local labor markets absorbed this shock, we would expect to observe declining agricultural employment shares and corresponding increases in other sectors. If adjustment frictions were severe (as evidence from manufacturing emissions regulations in the US, e.g., Greenstone, 2002; Walker, 2011, 2013), we might instead see rising unemployment.

Table 5 reports the effects of mechanization on sectoral employment shares. The results reveal large and systematic labor reallocation, consistent with structural transformation. We

[4]Table A3 shows that results are robust when we measure mechanization as the change between 2006 and 2010, as in equation (2), rather than assuming zero mechanization in 2000.

measure employment shares as the fraction of the working-age population employed in each sector, so coefficients capture both workers moving between sectors and changes in overall employment rates.

Table 5: Results – Employment share

	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
Panel A: Agricultural sector							
Mechanization (M_j)	0.005	-0.173***	-0.156***	-0.185***	-0.172***	-0.146***	-0.143***
	(0.017)	(0.056)	(0.052)	(0.061)	(0.055)	(0.051)	(0.051)
		[-0.345, -0.086]	[-0.311, -0.072]	[-0.381, -0.091]	[-0.336, -0.087]	[-0.295, -0.063]	[-0.295, -0.063]
Panel B: Manufacturing sector							
Mechanization (M_j)	-0.009	0.183***	0.173***	0.190***	0.181***	0.178***	0.175***
	(0.017)	(0.058)	(0.055)	(0.062)	(0.057)	(0.054)	(0.055)
		[0.093, 0.364]	[0.089, 0.345]	[0.099, 0.395]	[0.094, 0.354]	[0.095, 0.342]	[0.095, 0.346]
Panel C: Services sector							
Mechanization (M_j)	0.018	0.033	0.034	0.045	0.034	0.022	0.032
	(0.011)	(0.035)	(0.034)	(0.036)	(0.034)	(0.032)	(0.033)
		[-0.034, 0.119]	[-0.032, 0.119]	[-0.022, 0.142]	[-0.032, 0.115]	[-0.041, 0.097]	[-0.029, 0.115]
Education			✓				✓
Population density				✓			✓
Distance to roads					✓		✓
Sugarcane suitability						✓	✓
1st Stage (MP F-stat.)		37.37	37.88	33.91	39.57	46.16	42.74

Notes: The table reports estimates of the effect of mechanical harvesting adoption on sectoral employment shares (coefficient β in equation (3)). Column 1 shows OLS. Columns 2–7 show 2SLS that instruments mechanization with average sugarcane–fields slope. All regressions include the rural population share in 2000, the log of the labor force in 2000, and the log of sugarcane–planted area in 2003. Education controls include the 2000 shares of illiterate and college-educated workers. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity–robust standard errors are in parentheses. Anderson–Rubin confidence intervals are in brackets. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A documents the decline in agricultural employment. Our preferred IV estimate in column 7 implies that a one-standard-deviation increase in mechanization lowered agriculture's employment share by 2.76 percentage points [$= 0.193 \times 0.143$], which accounts for 77% of the sector's decline between 2000 and 2010.

Panel B shows a corresponding shift toward manufacturing. A one standard deviation increase in mechanization raised manufacturing's employment share by 3.38 percentage points [$= 0.193 \times 0.175$]. This increase is nearly identical in magnitude to the agricultural decline, suggesting a direct reallocation of labor between sectors. Moreover, mechanization explains 74% of the average growth in manufacturing employment over the period.

Panel C examines services, which includes retail, education, public administration, and other tertiary activities. We find no significant overall effect of mechanization on the services employment share. Point estimates are small and statistically indistinguishable from zero across specifications.

The stability of estimates across specifications is reassuring. Columns 2 through 7 sequentially add controls, yet the coefficients remain remarkably consistent. This robustness suggests that our identification strategy successfully isolates the effect of mechanization from confounding factors. Results remain robust when we measure mechanization as the change between 2006 and 2010 (Table A4), providing additional confidence in our findings.

These aggregate patterns mask important heterogeneity. Not all workers are equally affected by technological change, and understanding who moves between sectors is crucial for interpreting the welfare implications of mechanization. We therefore examine how effects vary by education and gender—two dimensions that may shape workers' ability to transition between sectors.

Table 6 decomposes the employment effects by educational attainment. The results show that the structural transformation was concentrated among workers without college education. These workers experienced sharp declines in agricultural employment and corresponding increases in manufacturing. In contrast, we find little effect on college-educated workers. This pattern is consistent with the nature of the technology shock.

This skill composition has important implications. It suggests that local manufacturing sectors were able to absorb less-educated workers at scale, providing an employment pathway that did not require substantial retraining or educational upgrading. This stands in contrast to settings where agricultural productivity gains lead to chronic unemployment among displaced workers who lack the skills demanded by urban labor markets.

We also examine gender differences, a dimension that has received less attention in the structural transformation literature (e.g., Chiplunkar and Kleineberg, 2025). Table 7 reports effects separately for men (Panels A–C) and women (Panels D–F). The aggregate reallocation from agriculture to manufacturing is driven almost entirely by men. Male agricultural employment fell sharply with mechanization, while male manufacturing employment rose by nearly the same magnitude. For women, the pattern is more nuanced. We find some evidence of increases in the services employment share, although point estimates are less precise and vary across specifications.

These gendered patterns likely reflect both the structure of pre-mechanization employment and the opportunities available in local labor markets. Agricultural employment was overwhelmingly male-dominated (Table A5), so men bore the brunt of displacement. Manufacturing in these municipalities—often involving agro-industrial processing, machinery maintenance, and related activities—also tends to skew male. Women displaced from agriculture or seeking employment appear to have found opportunities in the service sector. This gender-specific reallocation highlights that structural transformation operates through

Table 6: Results – Employment Share by Educational Level

	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
Panel A: Non-College – Agricultural sector							
Mechanization (M_j)	0.007	-0.189***	-0.174***	-0.203***	-0.187***	-0.160***	-0.158***
	(0.018)	(0.059)	(0.055)	(0.064)	(0.058)	(0.054)	(0.055)
		[-0.370, -0.098]	[-0.339, -0.084]	[-0.408, -0.103]	[-0.359, -0.098]	[-0.315, -0.073]	[-0.320, -0.074]
Panel B: Non-College – Manufacturing sector							
Mechanization (M_j)	-0.007	0.194***	0.185***	0.201***	0.193***	0.190***	0.187***
	(0.017)	(0.060)	(0.057)	(0.064)	(0.058)	(0.055)	(0.057)
		[0.102, 0.381]	[0.097, 0.364]	[0.107, 0.410]	[0.103, 0.370]	[0.105, 0.359]	[0.104, 0.368]
Panel C: Non-College – Services sector							
Mechanization (M_j)	0.020*	0.037	0.040	0.051	0.037	0.025	0.038
	(0.011)	(0.036)	(0.035)	(0.037)	(0.035)	(0.033)	(0.034)
		[-0.032, 0.123]	[-0.028, 0.125]	[-0.019, 0.149]	[-0.031, 0.121]	[-0.039, 0.103]	[-0.025, 0.123]
Panel D: College – Agricultural sector							
Mechanization (M_j)	0.003	-0.001	-0.012	0.002	-0.005	-0.003	-0.011
	(0.017)	(0.030)	(0.032)	(0.031)	(0.030)	(0.030)	(0.031)
		[-0.069, 0.062]	[-0.086, 0.051]	[-0.068, 0.069]	[-0.074, 0.055]	[-0.070, 0.058]	[-0.084, 0.052]
Panel E: College – Manufacturing sector							
Mechanization (M_j)	-0.018	0.108*	0.105*	0.114*	0.106*	0.093*	0.096*
	(0.017)	(0.058)	(0.059)	(0.061)	(0.057)	(0.054)	(0.057)
		[0.004, 0.257]	[-0.004, 0.255]	[0.005, 0.281]	[0.000, 0.252]	[-0.007, 0.227]	[-0.010, 0.242]
Panel F: College – Services sector							
Mechanization (M_j)	0.002	-0.052	-0.037	-0.090	-0.054	-0.061	-0.067
	(0.046)	(0.100)	(0.102)	(0.101)	(0.099)	(0.096)	(0.098)
		[-0.254, 0.182]	[-0.243, 0.201]	[-0.310, 0.130]	[-0.254, 0.169]	[-0.255, 0.157]	[-0.272, 0.153]
Education			✓				✓
Population density				✓			✓
Distance to roads					✓		✓
Soil suitability						✓	✓
1st Stage (MP F-stat.)		37.81	38.63	34.13	40.03	46.74	43.50

Notes: The table reports estimates of the effect of mechanical-harvesting adoption on sectoral employment shares by educational level (coefficient β in equation (3)). Panels A–C show effects for non-college graduates, and Panels D–F for for college graduates. Column 1 shows OLS. Columns 2–7 show 2SLS that instruments mechanization with the average slope of sugarcane fields. All regressions include the rural–population share in 2000, log labor force in 2000, and log sugarcane–planted area in 2003. Education controls include the 2000 shares of illiterate and college-educated workers. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. Anderson–Rubin confidence intervals are in brackets. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Results – Employment Share by Gender

	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
Panel A: Men – Agricultural sector							
Mechanization (M_j)	0.001	-0.153***	-0.135***	-0.158***	-0.152***	-0.131***	-0.122***
	(0.013)	(0.047)	(0.042)	(0.050)	(0.046)	(0.042)	(0.041)
		[-0.300, -0.081]	[-0.264, -0.070]	[-0.322, -0.085]	[-0.292, -0.081]	[-0.258, -0.066]	[-0.248, -0.058]
Panel B: Men – Manufacturing sector							
Mechanization (M_j)	-0.010	0.180***	0.169***	0.183***	0.178***	0.174***	0.167***
	(0.014)	(0.055)	(0.052)	(0.058)	(0.053)	(0.051)	(0.051)
		[0.100, 0.356]	[0.093, 0.335]	[0.098, 0.377]	[0.099, 0.345]	[0.100, 0.332]	[0.093, 0.333]
Panel C: Men – Services sector							
Mechanization (M_j)	0.007	0.003	-0.001	0.009	0.004	-0.006	-0.004
	(0.008)	(0.023)	(0.023)	(0.024)	(0.022)	(0.022)	(0.022)
		[-0.043, 0.057]	[-0.049, 0.050]	[-0.039, 0.068]	[-0.041, 0.055]	[-0.051, 0.041]	[-0.050, 0.045]
Panel D: Women – Agricultural sector							
Mechanization (M_j)	0.004	-0.020	-0.021	-0.027*	-0.020	-0.015	-0.021
	(0.005)	(0.015)	(0.015)	(0.016)	(0.015)	(0.014)	(0.014)
		[-0.057, 0.009]	[-0.056, 0.008]	[-0.069, 0.002]	[-0.055, 0.008]	[-0.048, 0.012]	[-0.057, 0.006]
Panel E: Women – Manufacturing secto							
Mechanization (M_j)	0.001	0.003	0.005	0.007	0.004	0.004	0.009
	(0.005)	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)
		[-0.026, 0.030]	[-0.023, 0.030]	[-0.021, 0.037]	[-0.025, 0.030]	[-0.023, 0.030]	[-0.018, 0.035]
Panel F: Women – Services sector							
Mechanization (M_j)	0.011*	0.030	0.035*	0.036*	0.030*	0.028	0.036**
	(0.006)	(0.018)	(0.018)	(0.019)	(0.018)	(0.017)	(0.018)
		[-0.004, 0.077]	[0.003, 0.084]	[0.002, 0.088]	[-0.004, 0.074]	[-0.004, 0.071]	[0.005, 0.085]
Education			✓				✓
Population density				✓			✓
Distance to roads					✓		✓
Soil suitability						✓	✓
1st Stage (MP F-stat.)		37.37	37.88	33.91	39.57	46.16	42.74

Notes: The table reports estimates of the effect of mechanical-harvesting adoption on sectoral employment shares by gender (coefficient β in equation (3)). Panels A–C show effects for men, and Panels D–F for women. Column 1 shows OLS. Columns 2–7 show 2SLS that instruments mechanization with the average slope of sugarcane fields. All regressions include the rural–population share in 2000, log labor force in 2000, and log sugarcane–planted area in 2003. Education controls include the 2000 shares of illiterate and college-educated workers. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. Anderson–Rubin confidence intervals are in brackets. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

labor markets segmented by both skill and gender, with different workers following distinct pathways out of agriculture.

Taken together, the results imply a rapid structural transformation driven by agricultural mechanization. Mechanization displaced workers from agriculture, but local economies adjusted by expanding manufacturing employment. This reallocation was concentrated among less-educated men, who moved directly from agricultural to industrial jobs.

5.3 Linked Industries

The preceding results document a striking reallocation of labor from agriculture to manufacturing, with little movement into services. This pattern aligns with standard structural transformation models, where labor-saving technological change in agriculture releases workers who transition into industry (Bustos et al., 2016). Yet the specificity of the shift – manufacturing rising while services remain flat – suggests something more targeted than a broad sectoral reallocation.

This distinction matters for understanding how local economies respond to agricultural shocks. One possibility is that workers displaced from farming simply migrate to whatever industries happen to be present locally, with diffuse gains across all non-agricultural sectors. An alternative interpretation is that mechanization strengthened economic linkages between agriculture and manufacturing, creating new employment opportunities specifically in industries that process agricultural outputs or supply agricultural inputs. These linked industries would benefit directly from mechanization through two channels: increased availability of agricultural products to process (downstream linkages) and expanded demand for machinery, chemicals, and services used in modern agriculture (upstream linkages).

Table 8 investigates this mechanism by decomposing manufacturing and services employment into linked and non-linked industries. Panel A reveals that mechanization drove substantial employment growth in manufacturing industries linked to agriculture. Our preferred IV estimate in column 7 implies that a one-standard-deviation increase in mechanization raised the employment share of linked manufacturing by 3.51 percentage points [$= 0.193 \times 0.182$]. This increase accounts for 78% of the observed growth in these industries over the decade. That is, virtually all of the manufacturing employment gains occurred in industries tied to agriculture. Table A6 decomposes the linked manufacturing category into upstream and downstream industries. The results show that employment growth was particularly concentrated downstream—in industries that process agricultural outputs. This includes biofuel production (ethanol refineries) and food processing (sugar production and related activities). The pattern for upstream industries -— those supplying inputs to agricul-

Table 8: Results – Employment share in linked industries

	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
Panel A: Linked manufacturing sector							
Mechanization (M_j)	-0.009	0.190***	0.181***	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, 0.349]	[0.108, 0.399]	[0.102, 0.358]	[0.103, 0.341]	[0.104, 0.350]
Panel B: Non-linked manufacturing sector							
Mechanization (M_j)	-0.001	-0.010	-0.011	-0.010	-0.009	-0.008	-0.009
	(0.005)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)
		[-0.036, 0.017]	[-0.037, 0.016]	[-0.038, 0.018]	[-0.035, 0.016]	[-0.032, 0.017]	[-0.035, 0.017]
Panel C: Linked services sector							
Mechanization (M_j)	0.018**	0.039	0.038	0.046*	0.039	0.031	0.035
	(0.008)	(0.026)	(0.025)	(0.027)	(0.025)	(0.024)	(0.024)
		[-0.009, 0.106]	[-0.009, 0.103]	[-0.002, 0.121]	[-0.008, 0.104]	[-0.014, 0.090]	[-0.009, 0.097]
Panel D: Non-linked services sector							
Mechanization (M_j)	-0.001	-0.006	-0.004	-0.001	-0.005	-0.009	-0.003
	(0.007)	(0.024)	(0.024)	(0.025)	(0.023)	(0.022)	(0.023)
		[-0.057, 0.045]	[-0.056, 0.047]	[-0.055, 0.054]	[-0.055, 0.045]	[-0.057, 0.038]	[-0.051, 0.049]
Education			✓				✓
Population density				✓			✓
Distance to roads					✓		✓
Soil suitability						✓	✓
1st Stage (MP F-stat.)		37.37	37.88	33.91	39.57	46.16	42.74

Notes: The table reports estimates of the effect of mechanical-harvesting adoption on employment shares by linkage status (as indicated in the panels) (coefficient β in equation (3)). Column 1 shows OLS. Columns 2–7 show 2SLS that instruments mechanization with the average slope of sugarcane fields. All regressions include the rural–population share in 2000, log labor force in 2000, and log sugarcane–planted area in 2003. Education controls include the 2000 shares of illiterate and college-educated workers. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. Anderson–Rubin confidence intervals are in brackets. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

ture – is more muted. The dominance of downstream over upstream linkages suggests that the employment channel operated primarily through processing the increased agricultural output.

Table 8 Panel B examines non-linked manufacturing industries—those without direct connections to agriculture. The point estimates are negative across most specifications, and none approach statistical significance. This null result is as important as the positive finding for linked industries. It indicates that mechanization did not lead to a broad industrial expansion.

Panels C and D examine services. Panel C shows positive point estimates for employment in services linked to agriculture, though these estimates are imprecise and fail to reach conventional significance levels. Panel D finds no effect on non-linked service industries.

The contrast between linked and non-linked industries is stark.[5] Mechanization created employment opportunities specifically in the agricultural supply chain, not in the broader economy. This pattern differs from the canonical model of structural transformation, where agriculture releases labor that disperses across all urban sectors (e.g., Matsuyama, 1992). Instead, we observe a form of agricultural industrialization: the modernization of farming technology strengthened backward and forward linkages, transforming the local economy into an integrated agro-industrial system rather than simply shifting workers from farms to generic manufacturing.

Several factors likely explain why linkages mattered so much in this setting. First, sugarcane is a bulky, perishable crop that must be processed quickly after harvest. Mills must locate near fields, creating a natural spatial clustering of agricultural production and industrial processing. Second, the scale of expansion was enormous – sugarcane area increased by roughly 20 percentage points – generating substantial new throughput for processing facilities. Third, the policy environment encouraged investment in downstream activities. The 2006 Cooperation Protocol not only accelerated mechanization but also created certification for "clean" sugarcane, potentially opening new markets for ethanol and sugar produced without burning. These conditions created strong incentives for agro-industrial expansion in mechanized municipalities.

5.4 Economy-wide Effects

We now assess whether the reallocation of workers from agriculture to manufacturing, which we documented, translates into broader improvements in living standards in these regions. A purely compositional shift would generate little overall benefit. In contrast, if mechanization triggers productivity gains that raise incomes and improve labor market conditions, the welfare effects would be substantially larger.

Several economic channels could generate economy-wide gains. First, as manufacturing jobs pay higher wages than agricultural work, sectoral reallocation itself would raise average incomes. Second, the expansion of linked manufacturing may have created productivity spillovers, as larger-scale processing operations achieve economies of scale and technological upgrading. Third, increased local economic activity could generate multiplier effects through demand for local services and goods.

Table 9 examines these possibilities by testing whether mechanization affected key economy-wide outcomes: household income, wages, poverty, unemployment, and child labor. Panel A provides strong evidence that mechanization raised household incomes. Our preferred IV

[5] Table A7 shows that these results are robust to an alternative definition of linked sectors, applying a 1% threshold for linkages instead of 0.1%.

estimate in column 7 shows that a one-standard-deviation increase in mechanization raised household income per capita by 28.7 BRL [= 0.193 × 148.76], corresponding to about 17% of the total income growth observed over the decade. Panel B corroborates this finding by examining average wages. The pattern mirrors that of household income: mechanization is associated with significant wage increases.

Table 9: Results – Economy-wide outcomes

	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
Panel A: Household income per capita							
Mechanization (M_j)	1.488	151.342**	138.796*	184.838**	150.552**	148.767**	164.910**
	(31.786)	(73.681)	(74.959)	(78.939)	(72.980)	(68.749)	(74.796)
		[8.388, 329.305]	[-12.573, 319.847]	[37.935, 394.254]	[8.958, 326.821]	[15.384, 309.372]	[25.716, 357.412]
Panel B: Wage							
Mechanization (M_j)	39.126	221.486*	221.211*	291.953**	218.361*	219.722*	271.448**
	(45.249)	(125.620)	(131.181)	(127.059)	(123.312)	(114.465)	(119.482)
		[-52.081, 495.052]	[-54.078, 506.889]	[35.376, 598.839]	[-50.180, 486.902]	[-29.553, 468.996]	[39.634, 560.034]
Panel C: Poverty (< 1.2 MW)							
Mechanization (M_j)	-0.009	-0.327***	-0.278***	-0.323***	-0.316***	-0.304***	-0.258***
	(0.022)	(0.081)	(0.071)	(0.084)	(0.079)	(0.073)	(0.066)
		[-0.582, -0.202]	[-0.493, -0.169]	[-0.599, -0.201]	[-0.556, -0.195]	[-0.522, -0.191]	[-0.458, -0.157]
Panel D: Unemployment Rate (16+)							
Mechanization (M_j)	-0.034***	-0.140***	-0.145***	-0.149***	-0.136***	-0.141***	-0.145***
	(0.010)	(0.032)	(0.032)	(0.035)	(0.031)	(0.030)	(0.031)
		[-0.236, -0.091]	[-0.240, -0.095]	[-0.262, -0.095]	[-0.225, -0.086]	[-0.229, -0.091]	[-0.241, -0.097]
Panel E: Child Labor Rate (10-15)							
Mechanization (M_j)	0.005	-0.090*	-0.086	-0.090*	-0.085*	-0.088*	-0.083*
	(0.016)	(0.052)	(0.053)	(0.054)	(0.051)	(0.049)	(0.050)
		[-0.236, -0.005]	[-0.235, 0.004]	[-0.249, -0.002]	[-0.224, 0.002]	[-0.222, -0.004]	[-0.223, 0.002]
Education			✓				✓
Population density				✓			✓
Distance to roads					✓		✓
Soil suitability						✓	✓
1st Stage (MP F-stat.)		37.52	37.97	34.04	39.78	46.46	42.98

Notes: The table reports estimates of the effect of mechanical-harvesting adoption on economy-wide outcomes (as indicated in the panels) (coefficient β in equation (3)). Income refers to the individual's main job. Column 1 shows OLS. Columns 2–7 show 2SLS that instruments mechanization with the average slope of sugarcane fields. All regressions include the rural–population share in 2000, log labor force in 2000, and log sugarcane–planted area in 2003. Education controls include the 2000 shares of illiterate and college-educated workers. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. Anderson–Rubin confidence intervals are in brackets. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The income gains translated directly into poverty reduction. Panel C shows that mechanization significantly reduced poverty rates, measured as the share of individuals living below 1.25 times the minimum wage -— a standard poverty threshold in Brazil. A one-standard-deviation increase in mechanization reduced poverty by 4.9 percentage points [= 0.193 × 0.258]. Given a baseline poverty rate of 38.4%, this represents a 13% decline relative to the mean. The fact that poverty declined while incomes rose reinforces that the benefits of mechanization extended beyond high earners to reach lower-income households.

Mechanization also improved labor market conditions more broadly. Panel D documents a sharp decline in unemployment. A one-standard-deviation increase in mechanization lowered the unemployment rate by 2.8 percentage points [$= 0.193 \times 0.145$], which represents a 24% reduction relative to the baseline unemployment rate of 11.6%. This suggests that not only did manufacturing expand enough to absorb displaced agricultural workers, but overall unemployment actually fell, indicating that mechanization created net employment opportunities rather than destroying them.

Finally, Panel E examines child labor, an important outcome given the sector's history of exploitative practices. We might expect mechanization to reduce child labor through two channels: by eliminating the manual harvesting jobs where children were employed, and by raising household incomes enough that families no longer needed child earnings to survive. The point estimates support this expectation. A one-standard-deviation increase in mechanization is associated with a 1.6 percentage point reduction in the share of children aged 10–15 engaged in labor [$= 0.193 \times 0.083$]. Given a baseline child labor rate of 16.9%, this implies an approximately 9.5% decline. However, the estimates are noisier than those for other outcomes, and confidence intervals often include zero.

Tables A10 and A11 examine whether these economy-wide gains differed by gender. The results show broadly similar effects for men and women across most outcomes. This similarity is somewhat surprising given the gendered patterns in sectoral reallocation documented earlier. The convergence in welfare outcomes suggests that, although men and women followed different pathways through the labor market, the ultimate economic consequences were comparable.

6 Conclusion

This paper examines the local economic effects of technology adoption required by a ban on agricultural fire. In 2002, São Paulo enacted legislation to phase out pre-harvest burning in sugarcane, effectively mandating the use of mechanical harvesting. We show that this regulation-induced technological change triggered structural transformation in local labor markets, yielding predominantly positive economic outcomes.

Mechanization reduced agricultural employment but generated offsetting gains in manufacturing, specifically in industries linked to agriculture through input-output relationships. This selective reallocation pattern explains why the transition proceeded smoothly despite displacing thousands of workers: the local economy possessed strong linkages that channeled productivity gains into employment creation within an integrated agro-industrial system.

The economic benefits extended beyond sectoral reallocation. Mechanization increased household income per capita, reduced the poverty rate, and lowered unemployment. These welfare improvements suggest that environmental regulation can catalyze technological upgrading that simultaneously reduces pollution and improves local economic conditions.

Our findings contribute to debates about the economic costs of environmental policy. A common concern is that emissions regulations impose substantial burdens on regulated industries and their surrounding communities, potentially leading to job losses and reduced incomes (e.g., Berman et al., 1998; Greenstone, 2002; Greenstone et al., 2012; Walker, 2011, 2013). Our results show that when regulation drives adoption of productivity-enhancing technology, the opposite can occur: workers transition to higher-productivity sectors, and incomes rise. The key mechanism is that mechanization not only eliminated harmful burning practices but also expanded agricultural output and strengthened linkages to downstream manufacturing. Environmental protection and economic development proved to be complementary rather than conflicting.

These results carry important implications for the design of environmental policies in agricultural contexts in low- and middle-income countries. Regulations that mandate cleaner technologies can succeed economically when they trigger productivity gains large enough to generate output expansion and when local economies possess sufficient linkages to absorb displaced workers. Policymakers considering similar regulations in other contexts should assess whether these enabling conditions exist or can be created through complementary investments in downstream processing capacity.

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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
	(10771.522)
Illiteracy rate in 2000	0.072
	(0.026)
College rate in 2000	0.051
	(0.024)
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: First Stage – Robustness – Mechanization 2010-2006

	Dep. Var.: Mechanization 2010-2006 (M_j)					
	(1)	(2)	(3)	(4)	(5)	(6)
Slope (S_j)	-0.031***	-0.029***	-0.031***	-0.032***	-0.032***	-0.031***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Education		✓				✓
Population density			✓			✓
Distance to roads				✓		✓
Sugarcane suitability					✓	✓
1st Stage (MP F-stat.)	18.11	14.92	17.11	18.58	19.34	16.44

Notes: The table reports first-stage estimates of equation (4) considering variation in mechanization between 2010 and 2006 as in equation (2). All regressions include the rural population share in 2000, the log of the labor force in 2000, and the log of sugarcane-planted area in 2003. Education controls are the 2000 shares of illiterate and high-school workers. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Results – Robustness – Mechanization 2010-2006 – Agriculture and Land use

	$\Delta 2010 - 2006$							$\Delta 2000 - 1991$
	OLS	IV	IV	IV	IV	IV	IV	Pre-trend
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Total Planted Area								
Mechanization (M_j)	-1661.56	5563.07	5746.33	1394.89	4809.20	5514.53	2227.51	4978.94
	(1243.23)	(5433.82)	(5844.81)	(5200.35)	(5132.49)	(5454.47)	(5394.64)	(5381.98)
		[-5409.76, 18687.40]	[-6056.44, 20789.10]	[-10341.90, 12719.90]	[-5961.58, 16799.30]	[-5499.99, 18688.80]	[-9520.60, 14402.80]	[-5889.21, 16699.50]
Panel B: Share of Sugarcane in Total Planted Area (%)								
Mechanization (M_j)	9.09**	78.64***	78.99***	66.19***	76.73***	77.41***	68.51***	24.59
	(3.57)	(24.57)	(26.73)	(24.42)	(23.54)	(23.69)	(24.76)	(17.76)
		[38.75, 153.56]	[35.59, 166.84]	[24.61, 136.78]	[38.52, 146.63]	[38.95, 147.78]	[28.31, 144.00]	[-8.46, 66.09]
Panel C: Sugarcane Productivity								
Mechanization (M_j)	-297.43	26016.36	30787.30	17079.60	28272.24	22290.67	22155.68	50861.32
	(5914.19)	(22601.05)	(26073.35)	(22956.67)	(21657.01)	(21392.59)	(23483.36)	(31376.85)
		[-19623.20, 80604.90]	[-19799.30, 99956.80]	[-32914.00, 70709.10]	[-13746.00, 82295.60]	[-20908.60, 73960.40]	[-23405.90, 82594.60]	[-14984.50, 116707.00]
Education			✓				✓	✓
Population density				✓			✓	✓
Distance to roads					✓		✓	✓
Sugarcane suitability						✓	✓	✓
1st Stage (MP F-stat.)		17.86	14.59	16.89	18.34	19.09	15.96	43.73

Notes: The table reports estimates of the effect of mechanical harvesting adoption on agriculture and land use (coefficient β in equation (3)) considering variation in mechanization between 2010 and 2006 as in equation (2). Column 1 shows OLS. Columns 2–8 show 2SLS, instrumenting mechanization with sugarcane-field slope. Column 8 is a pre-trend test using 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 college 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 measured in 1991. Distance to roads is in logs. Sugarcane suitability is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$) in regressions 1–7 and the AMC ($N = 352$) in regression 8. Heteroskedasticity-robust standard errors are in parentheses. The Anderson–Rubin confidence interval is in brackets. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Results – Robustness – Mechanization 2010-2006 – Employment share

	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
Panel A: Agricultural sector							
Mechanization (M_j)	-0.000	-0.194***	-0.193**	-0.204***	-0.192***	-0.170***	-0.175**
	(0.012)	(0.068)	(0.075)	(0.072)	(0.067)	(0.063)	(0.069)
		[-0.413, -0.088]	[-0.457, -0.083]	[-0.440, -0.099]	[-0.401, -0.089]	[-0.362, -0.073]	[-0.401, -0.069]
Panel B: Manufacturing sector							
Mechanization (M_j)	-0.005	0.205***	0.214***	0.210***	0.203***	0.205***	0.212***
	(0.012)	(0.065)	(0.073)	(0.068)	(0.063)	(0.063)	(0.069)
		[0.105, 0.412]	[0.108, 0.470]	[0.110, 0.433]	[0.106, 0.398]	[0.108, 0.407]	[0.111, 0.444]
Panel C: Services sector							
Mechanization (M_j)	0.018**	0.047	0.053	0.062	0.047	0.035	0.052
	(0.008)	(0.039)	(0.042)	(0.039)	(0.038)	(0.037)	(0.039)
		[-0.028, 0.143]	[-0.031, 0.160]	[-0.012, 0.166]	[-0.027, 0.141]	[-0.040, 0.124]	[-0.027, 0.148]
Education			✓				✓
Population density				✓			✓
Distance to roads					✓		✓
Sugarcane suitability						✓	✓
1st Stage (MP F-stat.)		18.11	14.92	17.11	18.58	19.34	16.44

Notes: The table reports estimates of the effect of mechanical harvesting adoption on sectoral employment shares (coefficient β in equation (3)) considering variation in mechanization between 2010 and 2006 as in equation (2).. Column 1 shows OLS. Columns 2–7 show 2SLS that instruments mechanization with average sugarcane–fields slope. All regressions include the rural population share in 2000, the log of the labor force in 2000, and the log of sugarcane–planted area in 2003. Education controls include the 2000 shares of illiterate and college-educated workers. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity–robust standard errors are in parentheses. Anderson–Rubin confidence intervals are in brackets. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Summary Statistics of Structural Transformation Variables

	Agricultural sector	Manufacturing sector			Services sector		
		All	Linked	Non-linked	All	Linked	Non-linked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Men – 2000							
Employment share	0.138	0.077	0.066	0.011	0.162	0.103	0.059
	(0.074)	(0.046)	(0.042)	(0.012)	(0.048)	(0.033)	(0.022)
Panel B: Women – 2000							
Employment share	0.026	0.030	0.017	0.014	0.079	0.046	0.033
	(0.021)	(0.023)	(0.017)	(0.014)	(0.029)	(0.019)	(0.013)
Panel C: Men – Δ 2010-2000							
Employment share	-0.039	0.033	0.033	-0.000	-0.004	-0.007	0.004
	(0.043)	(0.046)	(0.045)	(0.008)	(0.025)	(0.021)	(0.016)
Panel D: Women – Δ 2010-2000							
Employment share	0.003	0.013	0.012	0.001	0.035	0.024	0.011
	(0.016)	(0.017)	(0.015)	(0.009)	(0.019)	(0.013)	(0.012)

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).

Table A6: Results – Employment Share in Upstream/Downstream Industries

	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
Panel A: Linked manufacturing sector							
Upstream							
Mechanization (M_j)	0.005	0.011	0.013	0.014	0.013	0.014	0.018
	(0.007)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)
		[-0.031, 0.046]	[-0.027, 0.047]	[-0.028, 0.050]	[-0.027, 0.047]	[-0.025, 0.048]	[-0.019, 0.051]
Downstream							
Mechanization (M_j)	-0.014	0.174***	0.163***	0.177***	0.171***	0.165***	0.158***
	(0.015)	(0.055)	(0.052)	(0.059)	(0.054)	(0.051)	(0.051)
		[0.093, 0.347]	[0.086, 0.326]	[0.091, 0.374]	[0.092, 0.339]	[0.086, 0.320]	[0.083, 0.321]
Panel B: Linked services sector							
Upstream							
Mechanization (M_j)	0.006*	-0.006	-0.004	-0.006	-0.005	-0.004	-0.002
	(0.003)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
		[-0.027, 0.014]	[-0.024, 0.016]	[-0.027, 0.015]	[-0.025, 0.014]	[-0.022, 0.015]	[-0.022, 0.017]
Downstream							
Mechanization (M_j)	0.012	0.045*	0.043*	0.053*	0.045*	0.035	0.039
	(0.008)	(0.026)	(0.026)	(0.028)	(0.026)	(0.024)	(0.024)
		[-0.001, 0.115]	[-0.005, 0.109]	[0.004, 0.130]	[-0.001, 0.111]	[-0.009, 0.094]	[-0.004, 0.100]
Education			✓				✓
Population density				✓			✓
Distance to roads					✓		✓
Soil suitability						✓	✓
1st Stage (MP F-stat.)		37.37	37.88	33.91	39.57	46.16	42.74

Notes: The table reports estimates of the effect of mechanical-harvesting adoption on employment shares in upstream and downstream industries (as indicated in the panels) (coefficient β in equation (3)). Column 1 shows OLS. Columns 2–7 show 2SLS that instruments mechanization with the average slope of sugarcane fields. All regressions include the rural–population share in 2000, log labor force in 2000, and log sugarcane–planted area in 2003. Education controls include the 2000 shares of illiterate and college-educated workers. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. Anderson–Rubin confidence intervals are in brackets. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: 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 (M_j)	-0.021	0.187***	0.170***	0.184***	0.183***	0.176***	0.161***
	(0.015)	(0.059)	(0.055)	(0.060)	(0.057)	(0.054)	(0.052)
		[0.101, 0.376]	[0.089, 0.347]	[0.096, 0.386]	[0.100, 0.366]	[0.097, 0.344]	[0.085, 0.327]
Panel B: Non-linked manufacturing sector							
Mechanization (M_j)	0.009	-0.012	-0.004	-0.003	-0.009	-0.005	0.006
	(0.008)	(0.022)	(0.021)	(0.022)	(0.021)	(0.021)	(0.020)
		[-0.066, 0.029]	[-0.057, 0.037]	[-0.056, 0.041]	[-0.060, 0.033]	[-0.054, 0.035]	[-0.041, 0.046]
Panel C: Linked services sector							
Mechanization (M_j)	0.011	0.017	0.015	0.020	0.016	0.012	0.013
	(0.008)	(0.022)	(0.021)	(0.023)	(0.021)	(0.020)	(0.021)
		[-0.024, 0.073]	[-0.025, 0.069]	[-0.020, 0.083]	[-0.023, 0.071]	[-0.026, 0.063]	[-0.026, 0.066]
Panel D: Non-linked services sector							
Mechanization (M_j)	0.006	0.016	0.019	0.025	0.017	0.010	0.020
	(0.008)	(0.027)	(0.026)	(0.027)	(0.026)	(0.025)	(0.025)
		[-0.040, 0.076]	[-0.036, 0.079]	[-0.031, 0.091]	[-0.037, 0.074]	[-0.042, 0.064]	[-0.031, 0.079]
Education			✓				✓
Population density				✓			✓
Distance to roads					✓		✓
Soil suitability						✓	✓
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 employment share by linked sector (as indicated in the Panels), captured by β in equation (3). 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 college 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 A8: Results – Netmigration

	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
Panel A: Total							
Mechanization Index (M_j)	-25.382	76.196	46.768	53.807	79.408	46.082	20.586
	(24.952)	(79.300)	(77.343)	(77.966)	(78.251)	(74.686)	(72.950)
		[-65.100, 286.570]	[-91.041, 245.826]	[-85.113, 260.642]	[-60.019, 286.999]	[-86.992, 238.301]	[-115.171, 208.336]
Panel B: College							
Mechanization Index (M_j)	-26.168	9.256	-77.146	-51.704	25.653	-35.488	-116.206
	(76.584)	(238.338)	(258.595)	(253.699)	(232.069)	(252.281)	(266.218)
		[-472.033, 547.167]	[-619.819, 486.006]	[-604.194, 520.878]	[-442.977, 567.793]	[-564.911, 513.913]	[-695.959, 463.547]
Panel C: Non-College							
Mechanization Index (M_j)	-26.372	79.929	46.100	58.569	82.360	49.296	21.389
	(26.142)	(83.652)	(80.929)	(82.630)	(82.419)	(78.433)	(76.570)
		[-69.121, 308.473]	[-98.098, 260.795]	[-88.659, 284.320]	[-64.493, 301.008]	[-90.454, 251.157]	[-115.043, 224.520]
Education			✓				✓
Population density				✓			✓
Distance to roads					✓		✓
Soil suitability						✓	✓
1st Stage (MP F-stat.)		37.37	37.88	33.91	39.57	46.16	42.74

Notes: The table reports estimates of the effect of mechanical harvesting adoption on sectoral employment shares (coefficient β in equation (3)). Column 1 shows OLS. Columns 2–7 show 2SLS that instruments mechanization with average sugarcane–fields slope. All regressions include the rural population share in 2000, the log of the labor force in 2000, and the log of sugarcane–planted area in 2003. Education controls include the 2000 shares of illiterate and college-educated workers. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity–robust standard errors are in parentheses. Anderson–Rubin confidence intervals are in brackets. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A9: Results – Netmigration Metropolitan region

	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
Panel A: Total							
Mechanization Index (M_j)	-5.690	137.167***	115.352**	125.828**	136.226***	113.942**	95.146**
	(12.828)	(52.581)	(50.003)	(51.152)	(51.687)	(47.081)	(45.333)
		[55.971, 297.478]	[34.177, 263.843]	[46.839, 285.831]	[56.410, 289.717]	[37.511, 250.026]	[21.551, 229.770]
Panel B: College							
Mechanization Index (M_j)	16.922	256.204**	192.547*	237.797**	257.093**	243.926**	189.754*
	(48.344)	(116.256)	(103.150)	(117.723)	(115.176)	(110.674)	(102.486)
		[58.268, 583.028]	[16.924, 474.360]	[37.362, 568.748]	[60.995, 580.884]	[55.494, 537.530]	[7.145, 469.754]
Panel C: Non-College							
Mechanization Index (M_j)	-7.232	135.859**	113.802**	125.010**	134.174**	110.429**	91.775**
	(12.760)	(53.491)	(50.809)	(52.035)	(52.423)	(47.438)	(45.729)
		[53.258, 298.943]	[31.318, 264.686]	[44.656, 287.778]	[53.221, 289.852]	[33.419, 247.546]	[17.538, 227.574]
Education			✓				✓
Population density				✓			✓
Distance to roads					✓		✓
Soil suitability						✓	✓
1st Stage (MP F-stat.)		37.37	37.88	33.91	39.57	46.16	42.74

Notes: The table reports estimates of the effect of mechanical harvesting adoption on sectoral employment shares (coefficient β in equation (3)). Column 1 shows OLS. Columns 2–7 show 2SLS that instruments mechanization with average sugarcane–fields slope. All regressions include the rural population share in 2000, the log of the labor force in 2000, and the log of sugarcane–planted area in 2003. Education controls include the 2000 shares of illiterate and college-educated workers. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity–robust standard errors are in parentheses. Anderson–Rubin confidence intervals are in brackets. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table A10: Summary Statistics of Economy-wide Variables

	Economy-wide Effects									
	Household Income PC		Wage		Poverty (< 1.2 MW)		Unemployment Rate (16+)		Child Labor Rate (10-15)	
	Men (1)	Women (2)	Men (3)	Women (4)	Men (5)	Women (6)	Men (7)	Women (8)	Men (9)	Women (10)
Panel A: 2000										
mean	297.422	124.638	618.325	375.421	0.298	0.360	0.051	0.066	0.087	0.050
s.d.	(94.458)	(44.910)	(174.419)	(89.989)	(0.034)	(0.014)	(0.021)	(0.021)	(0.033)	(0.025)
Panel B: Δ 2010-2000										
mean	87.335	88.978	663.143	454.590	-0.051	-0.040	-0.029	-0.025	-0.040	-0.018
s.d.	(83.377)	(32.307)	(194.651)	(111.677)	(0.038)	(0.023)	(0.019)	(0.021)	(0.033)	(0.028)

Notes: This table displays the deconomy-wide effects summary statistics – mean and standard deviations (in parenthesis). The income considered was from the individual's principal occupation. The unit of observation is the municipality (N = 393).

Table A11: Results – Economy-wide Outcomes by Gender

	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)
I.Men							
Panel A: Household income per capita							
Mechanization (M_j)	3.426	127.120**	112.616*	144.278**	124.946**	129.280**	133.174**
	(35.701)	(63.315)	(62.216)	(65.984)	(62.356)	(58.414)	(60.594)
		[-0.735, 275.032]	[-13.020, 257.959]	[16.259, 308.875]	[-0.974, 270.617]	[11.322, 265.741]	[15.612, 284.325]
Panel B: Wage							
Mechanization (M_j)	68.055	277.648	278.812	372.030*	272.091	282.485	351.572*
	(63.623)	(194.894)	(204.077)	(195.394)	(190.757)	(177.086)	(183.513)
		[-146.779, 702.075]	[-165.615, 723.239]	[-38.014, 828.493]	[-143.327, 672.404]	[-103.161, 654.108]	[-19.007, 780.280]
Panel C: Poverty (< 1.2 MW)							
Mechanization (M_j)	-0.027*	-0.144***	-0.139***	-0.149***	-0.141***	-0.144***	-0.143***
	(0.015)	(0.040)	(0.040)	(0.043)	(0.039)	(0.038)	(0.039)
		[-0.270, -0.082]	[-0.263, -0.078]	[-0.289, -0.087]	[-0.260, -0.081]	[-0.256, -0.086]	[-0.266, -0.086]
Panel D: Unemployment Rate (16+)							
Mechanization (M_j)	-0.011*	-0.063***	-0.065***	-0.068***	-0.062***	-0.065***	-0.066***
	(0.006)	(0.018)	(0.018)	(0.019)	(0.018)	(0.017)	(0.018)
		[-0.115, -0.034]	[-0.117, -0.036]	[-0.126, -0.036]	[-0.111, -0.032]	[-0.114, -0.036]	[-0.117, -0.038]
Panel E: Child Labor Rate (10-15)							
Mechanization (M_j)	0.012	-0.058*	-0.049	-0.054	-0.055*	-0.050	-0.041
	(0.010)	(0.033)	(0.032)	(0.034)	(0.032)	(0.031)	(0.030)
		[-0.152, -0.004]	[-0.141, 0.006]	[-0.151, 0.004]	[-0.143, 0.000]	[-0.133, 0.003]	[-0.122, 0.010]
II.Women							
Panel A: Household income per capita							
Mechanization (M_j)	1.987	44.738	40.325	49.129	43.501	42.311	44.961
	(9.481)	(30.582)	(31.996)	(32.484)	(30.554)	(28.076)	(31.586)
		[-12.173, 123.446]	[-19.218, 122.672]	[-11.322, 135.304]	[-13.359, 119.718]	[-9.938, 112.347]	[-11.318, 128.755]
Panel B: Wage							
Mechanization (M_j)	25.149	128.779*	139.725*	168.554**	129.740*	118.661*	159.636**
	(33.165)	(77.039)	(80.785)	(80.011)	(76.608)	(70.519)	(75.303)
		[-38.993, 296.550]	[-29.807, 322.051]	[6.984, 361.805]	[-31.026, 296.573]	[-34.910, 266.647]	[13.535, 341.518]
Panel C: Poverty (< 1.2 MW)							
Mechanization (M_j)	0.006	-0.044**	-0.043**	-0.043**	-0.042**	-0.040**	-0.040*
	(0.009)	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)	(0.021)
		[-0.099, -0.007]	[-0.099, -0.005]	[-0.099, -0.006]	[-0.095, -0.006]	[-0.090, -0.005]	[-0.097, -0.003]
Panel D: Unemployment Rate (16+)							
Mechanization (M_j)	-0.022***	-0.071***	-0.074***	-0.075***	-0.069***	-0.071***	-0.075***
	(0.007)	(0.019)	(0.019)	(0.020)	(0.018)	(0.018)	(0.018)
		[-0.123, -0.039]	[-0.127, -0.042]	[-0.135, -0.043]	[-0.117, -0.038]	[-0.119, -0.041]	[-0.126, -0.044]
Panel E: Child Labor Rate (10-15)							
Mechanization (M_j)	-0.003	-0.034	-0.039	-0.037	-0.032	-0.038	-0.041
	(0.011)	(0.029)	(0.029)	(0.030)	(0.028)	(0.028)	(0.028)
		[-0.110, 0.017]	[-0.115, 0.012]	[-0.118, 0.017]	[-0.105, 0.018]	[-0.109, 0.012]	[-0.116, 0.009]
Education			✓				✓
Population density				✓			✓
Distance to roads					✓		✓
Sugarcane suitability						✓	✓
1st Stage (MP F-stat.)		37.37	37.88	33.91	39.57	46.16	42.74

Notes: The table reports estimates of the effect of mechanical-harvesting adoption on economy-wide outcomes (as indicated in the panels) (coefficient β in equation (3)) by gender. Income refers to the individual's main job. Column 1 shows OLS. Columns 2–7 show 2SLS that instruments mechanization with the average slope of sugarcane fields. All regressions include the rural–population share in 2000, log labor force in 2000, and log sugarcane–planted area in 2003. Education controls include the 2000 shares of illiterate and college-educated workers. Population density is measured in 2000. Distance to roads is in logs. Soil suitability for sugarcane is from GAEZ/FAO. The unit of observation is the municipality ($N = 393$). Heteroskedasticity-robust standard errors are in parentheses. Anderson–Rubin confidence intervals are in brackets. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.