Environmental Regulation, Structural Transformation and Skilled Migration: Evidence from the Brazilian Sugarcane Industry

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[PRELIMINARY AND INCOMPLETE.]

Abstract

This paper shows how environmental regulation can lead to technology adoption and structural transformation in rural economies. We document that one factor of production scarce to rural areas is key to this process: skilled workers. We study a clean air regulation that timed the end of sugarcane pre-harvest burning in the state of São Paulo, Brazil. We use remote-sensing data on sugarcane production to show that the environmental law led to the fast adoption of mechanical clean harvesting. We present a partial equilibrium two-sector model where rural technology adoption leads to an increase in the skilled-unskilled workers ratio via migration of skilled workers. Using demographic censuses data and land characteristics that affect the cost of mechanization as an instrument to technology adoption, we estimate the effect of clean harvesting on local labor markets. Our findings broadly corroborate the predictions of the model. We find that technology adoption led to structural transformation in rural economies. In particular, we find that the adoption of clean harvesting led to an increase of around half standard deviation on the skilled-unskilled workers ratio, on average, and a three-fold increase in the number of recent skilled migrants.

Keywords: Environmental Regulation; Technology Adoption; Structural Transformation; Sugarcane; Brazil.
JEL Codes: O14, Q16, Q52.

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1 Introduction

The main focus of environmental regulation is to cope with externalities. Compliance with environmental regulation may trigger the adoption of cleaner technologies. For example, it has been documented that the Clear Air Act in the USA impacted firms and workers in industries affected by the new environmental regulation (Greenstone, 2002; Walker, 2011, 2013; Kahn and Mansur, 2013). At the same time, in rural developing areas, it has been argued that technological shocks in the agriculture sector may lead to structural transformation of the local economies (Matsuyama, 1992; Bustos et al., 2016) as it changes the factor-content of production in the field or generates demand for services and manufactured goods.

This paper shows how environmental regulation can lead to technology adoption and subsequent structural transformation in rural economies. Our object is a clean air regulation that timed the end of sugarcane pre-harvest burning in the state of São Paulo, Brazil.

Sugarcane is one of the main crops in Brazil and world's largest crop by production quantity (Walter et al., 2014). FAO estimated that sugarcane was cultivated on about 26 million hectares, in more than 90 countries, with a worldwide harvest of 1.83 billion tons in 2012. Sugarcane can be harvested using two different technologies: the traditional harvesting, by hand with pre-harvest field burning; and the mechanical harvesting, without burning, that we call the clean harvesting. Sugarcane straw burning is responsible for a great amount of pollutant gases in atmosphere (Macedo et al., 2008) which cause respiratory diseases in the local population (Cançado et al., 2006; Dominici et al., 2014; Rangel and Vogl, 2015). Health concerns led São Paulo – the richest and largest producer state in Brazil – to pass a state law in 2002 outlying a timeline to end sugarcane pre-harvest burning on large properties by 2021. In 2007, a cooperation protocol between São Paulo state and the Organization of Sugarcane Producers (ORPLANA) revised the law and set tho halt sugarcane pre-harverst burning by 2014. Figure 6.1 shows a map from São Paulo with the sugarcane planted area colored by harvesting type in 2006 and in 2010. We see that, the area in the state with clean sugarcane harvest grew from 26,5% in 2006 to 47% four years later.

We exploit this fast adoption of clean technology as a productivity shock in the field, and ask whether it affected the composition of the local economies. To guide our work, we present a theoretical framework based on Young (2013) describing a small open economy with two perfectly competitive industries – rural and urban – using two freely mobile production factors – skilled and unskilled workers. The rural economy can choose between using a pollutant and a clean technology, which is more skill intensive. Following the introduction of a Pigouvian tax on pollution, the rural economy will adopt the clean technology when its costs are sufficiently small relative the tax. In these cases, the model predicts that the adoption of the clean technology will change the local demand for skilled/unskilled workers. When skilled workers are scarce in the rural economy, the increase the ratio of skilled-unskilled workers happens through an influx of skilled migrants.

We estimate the short-run impact of the adoption of clean harvesting on local labor market structure and test predictions from the theoretical framework. To this goal, we use two main datasets: satellite data with sugarcane production by harvest type (CANASAT/INPE), and Brazilian Demographic Census (*Censo Demográfico*) for 2000 and 2010. We use the remote sensing data to create an index for the adoption of mechanization in sugarcane production in different municipalities. In order to characterize the evolution of mechanization in sugarcane harvesting, we define a *clean adoption index* as the fraction of the area (number of pixels) with clean harvesting out of the total area (number of pixels) with sugarcane planted area relative to the baseline fraction of clean harvest in 2000. We pair this index with labor market data for all municipalities in the state of São Paulo, for 2000 and 2010.

In order to unveil the causal relation between the adoption of clean technology and the evolution of labor market outcomes between 2000 and 2010, we use land slope from georeferenced topographical data (TOPODATA) as an instrument for the adoption of harvest mechanization. The intuition for this instrument comes from engineering constraints: it is more costly to introduce clean mechanical harvest in steeper plots of land. Our identifying assumption is that land slope does not affect the evolution of labor market outcome directly, but only indirectly via the adoption of technologies in the field.

We find that the adoption of clean harvesting led to an increase of around half standard deviation on the skilled-unskilled workers ratio in rural economies, and this effect is concentrated in the agricultural sector. Since skilled workers are scarce in rural economies, we find a three-fold increase in the number of recent skilled migrants in the short-run. We also find an overall increase in average hourly wages in rural economies that adopted this clean technology, which may reflect an increase in the marginal workers productivity in these areas. Last, we find evidence of structural transformation. The size of manufacturing sector falls, compensated by an increase in the size of Construction & Services sector.

A lot of attention has been drawn to understanding the determinants of technology adoption in non-developed countries (Esther Duflo and Robinson, 2006; Conley and Udry, 2010; Bandiera and Rasul, 2002). Foster and Rosenzweig (2010) argues that technology profitability is key for technology adoption, and that agents decide to use a technology based on the gain in welfare, not necessarily the pecuniary profits. Since welfare cannot be measured directly, technologies which address health externalities – e.g. bed nets, water purifiers, or vaccines – adoption will depend on how health is valued by the individuals. In our case, environmental regulation aimed at reducing the level of pollutant gases, may trigger the adoption of improved technology which may impact labor markets. In this way, this paper contributes to the literature of environmental regulation consequences on local labor markets (Kahn and Mansur, 2013; Deschenes, 2011), and more broadly to the literature on the consequences of technology adoption on local development (Berman et al., 1998; Beaudry et al., 2006), by investigating how sugarcane harvest mechanization affected workers' labor market outcomes.

At last, we also contribute to the literature on structural transformation. Matsuyama (1992) shows that for small open economies facing perfectly elastic demand for agricultural and manufacturing goods the demand and supply channels on labor markets are no longer operative. His model – which has only one type of production factor, labor – predicts that a Hicks-neutral increase in agricultural productivity reduces the industrial sector by reallocating labor towards agriculture. Bustos et al. (2016), however, extend Matsuyama (1992) by using two production factors: land and labor. In this case, technical change can be factor-biased. When technical change in agriculture is strongly labor saving, an increase in agricultural productivity leads to manufacturing growth as it increases residual labor supply even in open economies. Bustos et al. (2016) provides direct empirical evidence on the impacts of technical change in agriculture on the industrial sector by studying the adoption of genetically engineered soybean seeds (a labor saving technology change), and the adoption of second-harvest maize (a labor demanding technology change) in Brazil. Their findings corroborate the model predictions.

The remaining of the paper is organized as follows. Section 2 presents our theoretical framework. Section 3 provides background information about the sugarcane sector in Brazil, and describes the data. Section 4 discuss our empirical strategy. Section 5 presents the results, and Section 6 concludes.

2 Theoretical Framework

In this section we follow Young (2013) to develop our model. Consider a small economy with two perfectly competitive industries, urban (u) and rural (r). There are only two production factors, skilled workers (S) and unskilled workers (US), with free mobility between industries, and the total quantity of these factors is fixed (L_S,L_{US}). Urban industry profit maximization problem is:

$$\Pi_u = \max_{S_u, US_u} p_u A_u S_u^{\alpha_u} US_u^{\alpha_u} - w_S S_u - w_{US} S_u \tag{2.1}$$

where p_u is the price of the urban product, A_u is productivity in urban industry.

Rural industry chooses between two technologies, pollutant (p) and clean(c). Pollutant technology is cheaper to adopt, however each unit produced using the pollutant technology generates externality e. And, rural firms have to pay a fixed cost (K) to adopt the clean technology. Thus, rural firms profit maximization problem is:

$$\max\{\Pi_p, \Pi_c - K\} \tag{2.2}$$

where,

$$\Pi_p = \max_{S_r, US_r} p_r A_p S_r^{\alpha_p} US_r^{\alpha_p} - w_S S_r - w_{US} US_r \tag{2.3}$$

$$\Pi_c = \max_{S_r, US_r} p_r A_c S_r^{\alpha_c} US_r^{\alpha_c} - w_S S_r - w_{US} US_r \tag{2.4}$$

where, p_r is the price of the good from the rural industry, and A_p,A_c are the productivity of the pollutant and clean technologies, respectively. We assume: $0 < \alpha_p < \alpha_c < \alpha_u < 1$. Thus, urban industry is more intensive in skilled workers then rural industry, and clean technology is more intensive in skilled workers then pollutant technology. In equilibrium, if the fixed cost is sufficiently high ($\Pi_c - \Pi_p < K$), the rural industry uses the pollutant technology: $\theta^{\star p} \equiv \{w_S^{\star p}, w_{US}^{\star p}, S_r^{\star p}, US_r^{\star p}, S_u^{\star p}, US_u^{\star p}\}$. Otherwise, the rural industry uses the clean technology: $\theta^{\star c} \equiv \{w_S^{\star c}, w_{US}^{\star c}, S_r^{\star c}, US_r^{\star c}, S_u^{\star c}, US_u^{\star c}\}$.

Suppose the economy is initially in the $\theta^{\star p}$ equilibrium, but the government introduces a tax τ in the pollutant technology to avoid externality e. Thus, the rural industry problem becomes:

$$\max\left\{(1-\tau)\,\Pi_p, \Pi_c - K\right\} \tag{2.5}$$

If τ is large enough $\left(\frac{\Pi_p-\Pi_c+K}{\Pi_p} < \tau\right)$, the rural industry adopts the clean technology and the economy shifts to equilibrium $\theta^{\star c}$. We explore the clean technology adoption by the rural industry in the following propositions.

Proposition 1. *Clean technology adoption increases the skilled-unskilled workers ratio in rural sector if and only if the difference between the wage gap in the two equilibria is bounded from above:*

$$\frac{S_r^{\star c}}{US_r^{\star c}} - \frac{S_r^{\star p}}{US_r^{\star p}} > 0 \Longleftrightarrow \frac{(w_S/w_{US})_c}{(w_S/w_{US})_p} < \psi_1, \, where \, \psi_1 \equiv \frac{\alpha_c}{1-\alpha_c}\frac{1-\alpha_p}{\alpha_p} > 1.$$

Proof: see appendix.

The economic intuition is that if the wage of the skilled workers does not increase too much relative to the unskilled workers wage, the rural sector will increase the ratio of skilled-unskilled workers. Thus, the rural sector adopting the clean technology will employ more skilled workers relative to unskilled workers.

Proposition 2. *Clean technology adoption*

(i) increases the number of skilled workers in rural sector;

(ii) and, the increase of skilled workers is greater than the increase of unskilled workers in rural sector

if the amount of skilled workers relative to unskilled workers in the whole economy is sufficiently small and if the difference between the wage gap in the two equilibria is bounded from above:

$$\frac{S_r^{\star c}}{S_r^{\star p}} > 1, \, and \, \frac{S_r^{\star c}}{S_r^{\star p}} > \frac{US_r^{\star c}}{US_r^{\star p}} \; if \; \frac{L_S}{L_{US}} < \psi_2, \, and \, \frac{(w_S/w_{US})_c}{(w_S/w_{US})_p} < \psi_3.$$

Proof: see appendix.

The economic intuition for these two results is that if the rural sector adopts clean technology, and if the skilled workers wage does not increase too much relative to the unskilled workers wage we will see the rural sector employing more skilled workers in absolute, and at a rate greater than of the unskilled workers. Since we are in equilibrium with full employment, all the new skilled workers employed in rural sector will come from the urban industry. Thus, we will have an increase in the migration of skilled worker to rural areas.

3 Background and Data

3.1 Background

In this section we briefly discuss the sugarcane industry background in Brazil and in São Paulo state, the largest producer in the country. Two main aspects are discussed: harvesting and labor market.

Sugarcane is one of the main crops in Brazil and world's largest crop by production quantity (Walter et al., 2014). In 2012, FAO estimates about 26.0 million hectares of cultivated area, in more than 90 countries, with a worldwide harvest about 1.83 billion tons. Brazil being the top producer responsible for more then a quarter of worldwide production. According to UNICA (Sugarcane Industry Union), São Paulo state contributes with more then half of Brazilian production. Sugarcane is a semi-perennial crop that, in São Paulo State, reaches its maximum vegetative development in April. Its planting can be done at two moments: at September–October, when twelve-month sugarcane is planted; or at February–March, when eighteen-month sugarcane is planted. And the sugarcane harvesting happens between April and December.

There are two harvesting technologies: the traditional, by hand with pre-harvest field burning, that we call pollutant technology; and mechanical harvesting, without burning, that we call clean harvesting. Field burning is necessary because of ergonomic restrictions, to clean the area from other weeds and to chase away any dangerous animals, making the field ready for hand harvesting. However, mechanical harvesting can be made without burning, keeping leaves and straws intact, what is called clean harvesting. The sugarcane straw burning produces negative externalities and is responsible for a great amount of pollutant gases in atmosphere (Macedo et al., 2008) which cause respiratory diseases in the local population (Cançado et al., 2006; Dominici et al., 2014; Rangel and Vogl, 2015). Other environmental problems related to sugarcane straw burning were soil and groundwater contamination (Brasil, 2009).

With the goal of mitigating climate change problems and respiratory diseases, in 2002, the state of São Paulo passed a law outlying the timeline to end sugarcane pre-harvest burning by 2021. In 2007, the Cooperation Protocol was sealed between São Paulo state and the Organization of Sugarcane Producers (ORPLANA). The phase out process was accelerated with the deadline being shortened to 2014, and with the creation of an agro-environmental certificate for unburnt sugarcane.

Novaes et al. (2007) point out three elements about the adoption of mechanized technology. First, the prohibition of the pre-harvest burning would reduce directly the hand harvesting productivity. Second, there are natural conditions for machinery introduction, it is easier to do mechanic harvesting in more flat terrain. Third, the increase in labor productivity and the low wages in hand harvesting are an obstacle to mechanical harvesting.

The sugarcane ethanol sector has a bad record in labor relations and environmental rules.[1]. In the sugarcane crop, especially in hand harvesting, the most part are of unskilled and temporary jobs, with different levels according to seasons. In the past few years, with the expansion of mechanical harvesting, the sugarcane industry started recruiting more skilled workers, substituting the hand worker for machine operators and other occupations (e.g., engineers and mechanics). According to some estimates from the industry (SGPR, 2009), one harvest machine can substitute around eighty hand workers.

[1]Reports about criminal recruitment and overexploitation of labor were common, as well as reports showing precarious accommodation, high level of work place accident, death by exhausting, and child labor (SGPR, 2009)

3.2 Data

In this section we describe the three main data sources used in this paper and how we treated the data. We use three main data sources: Brazilian Demographic Census (*Censo Demográfico*) for 2000 and 2010; spatial data of sugarcane harvesting type (CANASAT-INPE); and geomorphometric data in Brazil (TOPODATA).

Brazilian Census is sourced from the Brazilian Institute of Geography and Statistics (IBGE). We restrict our analysis to working-age population, defining labor force as all individuals between 18 and 60 years old. We aggregate all individual level information to municipality level. We calculate average hourly wages by deflating the reported monthly wage by the number of hours worked per week multiplied by 4.33 weeks, and we use a consumer price index (IPCA) from IBGE to deflate wages so that they are measured in 2010 Brazilian reals. We define log skill wage premium as the difference between log hourly wage of workers with college and log hourly wage of workers without college degree. Skilled-unskilled workers ratio is defined as the number of workers of college divided by the number of workers without college. We use information in the census on whether an individual moved to their current location within the previous five years, and from which location they moved to construct our migration variable. We define migration as an individual that moved in from a metropolitan region (urban areas), and then we divide in skilled (college) migration and unskilled (non-college) migration.

To construct our variables for the structural transformation exercise, we use CNAE 2.0 to separate the market in three sectors: agricultural sector (codes from 1 to 999), manufacturing sector (codes from 1000 to 3390), and construction & services sector (codes from 4100 to 9799). We compute skilled-unskilled workers ratio and log average hourly wage for each sector. And, employment share is defined as the number of workers in one sector divided by the number of workers in all the three sectors.

CANASAT-INPE has two different data base: CANASAT-Planted Area; and CANASAT-Harvest. CANASAT-Planted Area annually monitors sugarcane planted area in different classes and regions between 2003/04 and 2013/14. CANASAT-Harvest monitors sugarcane harvest of São Paulo state from 2006/07 to 2012/13, distinguishing two types of harvesting: clean or pollutant harvesting (Rudorff et al., 2010; Adami et al., 2012). CANASAT-Harvest uses visual interpretation technique of remote sensing images, obtained between April and December in each crop year, to identify and map the two types of sugarcane harvest practices. Most of the sugarcane harvesting is performed during the dry season, when it is relatively favorable to acquire cloud free images. Identification of harvest type is based on the reflectance difference between green harvested and pre-harvest burned fields (Aguiar et al., 2011). Figure 6.1 presents sugarcane harvest differentiating between clean harvesting and pre-harvesting burning.

TOPODATA project offers the Digital Elevation Model (MDE) and its derivations at national level. MDE is a computational mathematic representation of a spatial phenomenon. The original data is from the Shuttle Radar Topography Mission (SRTM), which is an international research effort that obtained digital elevation models on a near-global scale to generate the most complete high-resolution digital topographic database of Earth. The resolution of the TOPODATA data is one arcsecond, approximately 9,49 hectares.

We use the remote sensing data at one second resolution (9,49 ha), also. From CANASAT, we have the distribution of harvesting and planted area across São Paulo state. Using this information we add up at municipality level and then at municipality level, our variable is the number of pixels of each harvesting type or the number of pixels with planted area. From TOPODATA, we have the distribution of slope across São Paulo state. Using this distribution we aggregate at municipality level and calculate the share of sugarcane planted area in each slope interval as in 4.5 at municipality level.

São Paulo state has 645 municipalities and we observe sugarcane cropping in 393 of them.

4 Empirical Strategy

In this section we describe our empirical strategy. We first define a measure used to capture the evolution of clean harvest. We then present our main regression specification and discuss potential identification issues. At last, we propose an instrumental variable strategy to overcome these issues.

We start by creating a *clean index* to capture the degree of adoption of clean harvesting within a municipality in one point in time. This index consists in the share of planted area (number of pixels) with clean harvesting in a municipality j in year t:

$$CleanIndex_{jt} \equiv \frac{Clean_{jt}}{PlantedArea_{jt}} \tag{4.1}$$

where $Clean_{jt}$ is the area (number of pixels) with clean harvesting, and $PlantedArea_{jt}$ is the total area (number of pixels) with sugarcane in municipality j and year t. Note that this index is bounded between 0 and 1, so municipalities in which all production use clean harvesting have an index equal to 1, whether municipalities using only pollutant harvesting have an index equal to 0.

Our main measure of interest is the $CleanAdoptionIndex$ which is the evolution of clean adoption between 2000 and 2010:

$$CleanAdoptionIndex_j \equiv CleanIndex_{j,2010} - CleanIndex_{j,2000} \tag{4.2}$$

where $CleanIndex_{j,2000}$ and $CleanIndex_{j,2010}$ were defined in 4.1.

We do not observe sugarcane planted area for 2000, then we consider 2003 planted area as the right measure for 2000. We also do not observe clean harvest data for 2000, thus in our main results we assume no clean harvesting in 2000[2].

4.1 Main Regression

Our variables of interest are labor market outcomes, e.g. skill wage premium, average wage, skilled workers ratio, and migration. We evaluate the evolution of these variables relative to 2000 ($\Delta Y_j \equiv Y_{j,2010} - Y_{j,2000}$), in order to make them consistent with our clean adoption index.

[2]In appendix we construct our $CleanAdoptionIndex$ assuming a clean harvest pattern in 2000 as the observed in data for 2006.

Variables are indexed by municipality (j). Our main regression equation is:

$$\Delta Y_j = \beta CleanAdoptionIndex_j + \gamma X_j + \nu_j \tag{4.3}$$

where X_j is a vector of controls that we divide in standard controls (the log of total planted area in 2000, the share of rural population in 2000, and the log of labor force in 2000), and education controls (illiteracy rate in 2000, and the share of skilled in 2000). The coefficient of interest is β which capture the effect of the adoption of mechanical harvesting on the evolution of labor market outcome ΔY_j. We use heteroskedasticity-consistent standard error estimators. Tables 1 and 2 report summary statistics of our explanatory and dependent variables, respectively.

4.2 Structural Transformation

Now, we investigate if clean technology adoption leads to structural transformation in local labor markets. Thus, our structural transformation outcomes of interest are: skilled workers ratio, employment share, and log average hourly wages. We, also, evaluate the evolution of these variables relative to 2000 ($\Delta Y_{ij} \equiv Y_{ij,2010} - Y_{ij,2000}$), but now our variables are indexed by municipality (j) and by industrial sector (i). Our structural transformation regression is:

$$\Delta Y_{ij} = \beta^{st} CleanAdoptionIndex_j + \gamma^{st} X_j + \nu_{ij} \tag{4.4}$$

where X_j is a vector of standard controls (the log of total planted area in 2000, the share of rural population in 2000, and the log of labor force in 2000), and education controls (illiteracy rate in 2000, and the share of skilled in 2000). β^{st} is the coefficient of interest, the structural transformation coefficient. We, also, use heteroskedasticity-consistent standard error estimators. Table 3 reports summary statistics of our dependent variables by sector.

Reduced form estimates of the equation above may have identification issues if there is any endogeneity between labor market development and the adoption of new technology in the field. For example, consider a shock in labor market which increases wages at a level that producers opt to pay the fixed costs of acquiring a new technology. Alternatively, consider, for example, the case of a positive shock to investments in the local economy, such as government subsidies, which affects directly both technology adoption and labor market outcomes. In these cases, ordinary least square estimates would be biased and one would not unveil the causal relation we are interested at first. Next, we propose a strategy to overcome this issue.

4.3 Instrumental Variable

We use instrumental variable strategy to overcome potential endogeneity between labor market development and adoption of clean technology. We use the land slope as an instrument for the adoption of clean harvesting in the sugarcane industry. The intuition for using this instrument is that it is more costly to mechanize steep areas, so producers with land in steep terrains would resist more to mechanize their harvest. This is a natural candidate, because even the original law passed in 2002 acknowledged that the slope of the terrain could impose technical problems to mechanization. Figure ?? plots the total adoption (number of pixels) of mechanical harvesting relative to 2006 against the slope of the terrain, as presented in the georeferenced data.

Our estimates using land slope as an instrument for the adoption of clean technology will capture the causal relation between technology adoption and labor market outcomes if: (i) slope is correlated to the $CleanAdoptionIndex$; and (ii) slope is uncorrelated to the error term ν_j in equation 4.3. In words, slope must be correlated with the adoption of mechanical harvesting in the sugarcane industry, and slope must have no direct influence on the evolution of labor market outcomes, except via the clean harvesting adopted in the sugarcane sector.

To shed light on the exogeneity assumption (ii), we analyze a panel data of sugarcane planted area for the whole São Paulo state from 2003 to 2013. Figure ?? plots expansion of planted areas since 2003 across different slope levels. We can see that the growth of planted areas, which is the planted area in year t divided by planted area in 2003, is relatively homogeneous across slope levels at least until 2008. We can observe an increase in total planted area which is not concentrated in terrains with certain slopes. After 2008, however, we see a greater growth in planted areas in land with moderate slopes, between 3 and 8 degrees. Our intuition for this evidence is that if producers used to choose more flat terrains to begin with, we would observe a negative relation between expansion of sugarcane production and land slope since before the Cooperation Protocol was signed, but it seems not to be the case.

Our first stage regression equation is:

$$\begin{aligned} CleanAdoptionIndex_j = \Pi_1 ShareSlope_j^{4-8} + \Pi_2 ShareSlope_j^{8-12} + \\ \Pi_3 ShareSlope_j^{12-16} + \Pi_4 ShareSlope_j^{16} + \lambda X_j + \varepsilon_j \end{aligned} \tag{4.5}$$

where X is a vector of controls, and $ShareSlope^{i-i'}$ is the share of sugarcane planted area in municipality j with slope in the interval $[i,i')$ and $ShareSlope^{16}$ is the share of planted area with slope greater than 16. Note that the omitted category is the share of land with sugarcane planted in slopes between 0 and 4 degrees.[3]

One potential problem that may arise in our regression is the weak instrument problem. This would be the case if land slope is a poor predictor of the Clean Adoption Index. If this is the case, our fitted Clean Adoption Index will have little variation. We test for weak instruments analyzing Kleibergen-Paap F statistic. Kleibergen-Paap statistic tests whether the instruments jointly explain enough variation in the multiple endogenous regressors to conduct meaningful hypothesis tests of causal effects (Kleibergen and Paap, 2006). Weak instruments can bias point estimates and lead to substantial test size distortions.

Table 4 presents the first stage results. The signs of the coefficients are consistent with the relation between Clean Adoption Index and land slope observed in Figure ??. As we can see in the table 4, our KP F statistic is 19.06 with standard controls only and 18.87 adding education controls, above standard levels.

[3] Notice that slope does not change between years, so we assume that producers don't directly change terrain, like terrace for example. Even if this is the case, this would represent part of the differential cost of adopting mechanical harvesting.

5 Results

In this section, we present the results of the impacts of the adoption of clean harvesting in Brazilian sugarcane industry on local labor market outcomes. Since standard OLS estimates are potentially biased due to endogeneity and omitted variables, we focus our discussion on the estimates from our IV regressions.

5.1 Main Results

Tables 5 and 6 present the main results of equation 4.3. We report the coefficient of *Clean Adoption Index* and robust standard errors. The unit of observation is a municipality, all regressions are controlled for standard controls (the log of total planted area in 2000, the share of rural population in 2000, and the log of labor force in 2000), and regressions in column 3 are controlled for education controls (illiteracy rate in 2000, and the share of skilled in 2000). Coefficients should be interpret as follows. If a municipality which initial production is fully based on pollutant technology fully converts to clean technology, technology adoption will change the outcome in question by $100\beta\%$. To put in perspective, the mean (median) municipality had clean adoption index equal to 0.470 (0.472).

Table 5 presents the results to wages. In column 1 we present the results for OLS estimation with standard controls. Columns 2 and 3 present the results for our IV estimation, the difference between these columns is that we add education controls in the estimates in column 3. OLS results have different sign than IV results. First, we want to investigate if the difference between the wage gap from 2010 to 2000 is bounded from above. In columns 2 and 3 from panel A we see that the skill wage premium significantly reduced with the adoption of clean technology. However, this does not mean a reduction in wages. In panel B, we observe an increase in average hourly wages in municipalities that adopted the clean technology, the increase is around 30% if the technology has fully adopted clean technology.

In table 6 we investigate if clean technology adoption changed the workforce composition increasing the skilled-unskilled workers ratio, and also if this increase is due to and increase in skilled migration. In panel A, columns 2 and 3, we see a significant increase in the skilled unskilled workers ratio around 5% for municipalities that fully adopted the clean technology. And, as we can see in panel B, columns 2 and 3, we find significant results for the increase in skilled migration around 200%. In panel C, columns 2 and 3, we find no significant results for unskilled migration, with a negative sign although. Thus, we find evidence that this clean technology adoption led to an increase on the skilled-unskilled ratio, and this change in composition is via migration of skilled individuals.

5.2 Structural Transformation

Now, we take a look at structural transformation in local labor markets. Table 7 presents the results from equation 4.4. We report the coefficient of *Clean Adoption Index* and robust standard errors. The unit of observation is a sector in a municipality, thus we present a table with three panels, one for each sector. All regressions are controlled for standard controls (the log of total planted area in 2000, the share of rural population in 2000, and the log of labor force in 2000), and education controls (illiteracy rate in 2000, and the share of skilled in 2000) at municipality level.

In panel A we present the results for the agricultural sector, in column 1 we see a significant increase in the skilled-unskilled workers ratio in this sector. Also in panel A, we find no significant results for employment share or average hourly wages. In panel B for manufacturing sector, we find a significant result for a reduction in employment share for around 12% for a municipality that fully adopted the clean technology. And, in panel C for construction & services sector, we see a significant increase in the employment share, and a significant increase in average hourly wages.

These results together suggest that this clean technology adoption increased the skilled-unskilled ratio in rural economies, as this effect is concentrated in the agricultural sector. And, since skilled workers are scarce in rural economies, in the short-run, the change in the workforce composition might be due to skilled individuals migration. Also, we find an overall increase in average hourly wages in rural economies that adopted this clean technology, and we find this increase is more concentrated in the construction & services sectors. And, we find a reduction in the size of manufacturing sector compensated by an increase in the size of construction & services sector via employment share, we interpret this as construction & services sector being complementary to the clean agricultural technology.

6 Conclusion

This paper estimates the causal effects of the adoption of clean technology led by a new environmental regulation on rural economies within a large emerging country, Brazil, seeking if this leads to structural change of local labor markets. We go through an IV approach using land slope as instrumental variable.

We find evidence that a clean air environmental regulation trigger clean technology adoption and trigger structural transformation in rural economies. This clean technology is more intensive in skilled workers than the previous pollutant technology. Our findings suggest that the technology adoption lead to an increase of around half standard deviation on the skilled-unskilled workers ratio, and this change is concentrated in the agricultural sector. Since skilled workers are scarce in rural economies, in the short-run, the change in the composition is via migration of skilled individuals.

We see structural transformation on labor market by finding that the employment share in the manufacturing sector decreased being compensated by an increase in the construction & services sector. And, also we find an increase in wages concentrated in construction & services sector. Thus, we observe a complementarity between technology adoption and services sector.

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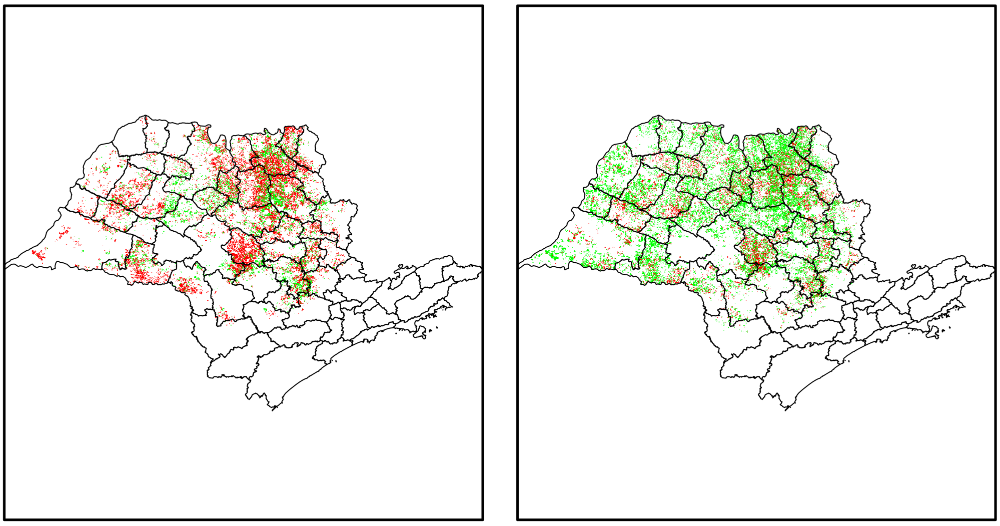

(a) Harvest in 2006 (b) Harvest in 2010

Figure 6.1: Sugarcane Harvest

These figures presents sugarcane harvest. Figure 6.1a presents sugarcane harvest in 2006 and figure 6.1b presents sugarcane harvest in 2010. In both figures green means clean harvesting and red means pre-harvest burning. We see São Paulo state divided by municipalities.

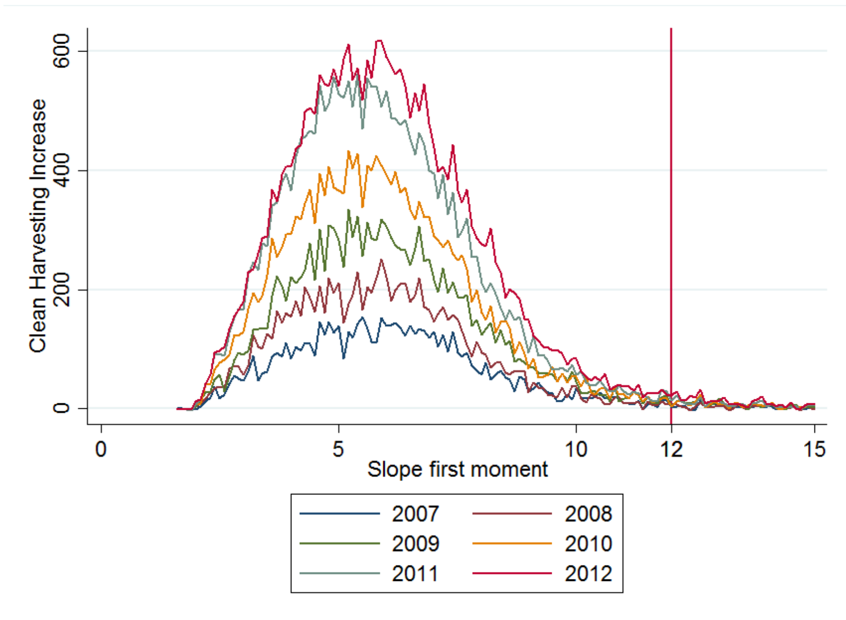

Figure 6.2: Clean Harvesting vs Slope

R

This figure presents clean harvesting in year t divided by clean harvesting in 2006 per value of slope first moment. To do this we round slope first moment to the first decimal place, so we have more observations at one slope first moment point. We drop slope first moment values greater than 15% because of very few observations.

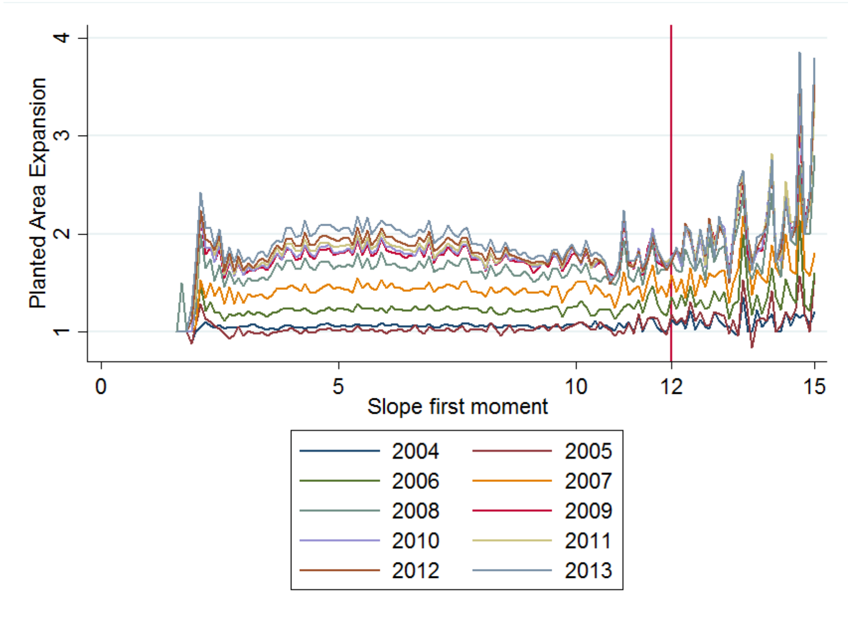

Figure 6.3: Planted Area Expansion vs Slope

This figure presents presents planted area in year t divided by clean harvesting in 2003 per value of slope first moment. To do this we round slope first moment to the first decimal place, so we have more observations at one slope first moment value. We drop slope first moment values greater than 15% because of very few observations.

Table 1: Descriptive Statistics: explanatory variables

Clean adoption index	0.470
	(0.155)
Labor force	19041.450
	(45333.120)
Share of rural population	0.172
	(0.609)
Illiteracy rate	0.072
	(0.026)
Skilled rate	0.086
	(0.037)
Planted area	835889
	(1086869)

Notes: This table reports descriptive statistics of explanatory variables used in regressions 4.3 and 4.4. We report variables in level at 2000 values.

Table 2: Descriptive Statistics: dependent variables

Skill wage premium	2.657
	(1.222)
Average hourly wages	4.346
	(1.159)
Skilled-unskilled workers ratio	0.087
	(0.045)
Skilled migration	142.291
	(535.388)
Unskilled migration	748.624
	(1958.685)

Notes: This table reports descriptive statistics of dependent variables used in regression 4.3. We report variables in level at 2000 values.

Table 3: Descriptive Statistics: structural transformation dependent variables

	Skilled-unskilled workers ratio	Employment share	Average hourly wages
	(1)	(2)	(3)
Panel A. Agricultural Sectors			
	0.088	0.402	4.497
	(0.072)	(0.136)	(1.611)
Panel B. Manufacturing Sectors			
	0.150	0.152	6.177
	(0.163)	(0.060)	(2.484)
Panel C. Construction & Services Sectors			
	0.082	0.446	4.351
	(0.040)	(0.100)	(1.219)

Notes: This table reports descriptive statistics of dependent variables used in regression 4.4. We report variables in level at 2000 values.

Table 4: Results – First Stage

	Clean Adoption Index	
	(1)	(2)
4 – 8	0.044	0.045
	(0.169)	(0.170)
8 – 12	-0.373**	-0.375**
	(0.164)	(0.165)
12 – 16	-0.008	-0.024
	(0.391)	(0.395)
> 16	-0.865***	-0.864***
	(0.199)	(0.197)
1st Stage (KP F-stat.)	19.06	18.87
Education Controls		Y

Notes: this table reports the estimates of the first-stage regression from equation 4.5. The dependent variable is the difference between *CleanAdoptionIndex* in 2010 and in 2000. All regressions include standard controls (the log of total planted area in 2000, the share of rural population in 2000, and the log of labor force in 2000), and when indicated the regression also include education controls (illiteracy rate in 2000, and the share of skilled in 2000). The unit of observation is a municipality, we have 393 observations. Robust standard errors are reported in parentheses. Significance level: ***p<0.01, **p<0.05, *p<0.10.

Table 5: Results – Wages

	OLS	IV	IV
	(1)	(2)	(3)
Panel A. Log skill wage premium			
Clean Adoption Index	.1351***	-.557*	-.6187*
	(.1242)	(.3156)	(.3195)
1st Stage (KP F-stat.)		18.47	18.22
N = 392			
Panel B. Log average hourly wages			
Clean Adoption Index	-.053***	.2998**	.2816**
	(.0623)	(.1319)	(.1335)
1st Stage (KP F-stat.)		19.06	18.87
N = 393			
Education Controls			Y

Notes: this table reports the estimates of the impact of *CleanAdoptionIndex* on labor market outcomes, β, from equation 4.3. Columns indicated with IV were estimated using land slope as instrument for *CleanAdoptionIndex* as in equation 4.5. The dependent variables are the difference between the variable indicated in the columns between 2010 and in 2000. Skilled-unskilled workers ratio is in fraction, and skilled migration and unskilled migration are in log. All regressions include standard controls (the log of total planted area in 2000, the share of rural population in 2000, and the log of labor force in 2000), and when indicated the regression also include education controls (illiteracy rate in 2000, and the share of skilled in 2000). The unit of observation is a municipality. Robust standard errors are reported in parentheses. Significance level: ***p<0.01, **p<0.05, *p<0.10.*** p< .01, ** p< .05, * p< .1.

Table 6: Results – Workforce Composition and Migration

	OLS	IV	IV
	(1)	(2)	(3)
Panel A. Skilled-unskilled workers ratio			
Clean Adoption Index	.019***	.0534**	.0497**
	(.0116)	(.0265)	(.025)
1st Stage (KP F-stat.)		19.06	18.87
N = 393			
Panel B. Log skilled migration			
Clean Adoption Index	.0721***	1.884*	1.938*
	(.4155)	(1.044)	(1.026)
1st Stage (KP F-stat.)		19.06	18.87
N = 393			
Panel C. Log unskilled migration			
Clean Adoption Index	-.1394***	-.1774	-.1576
	(.1932)	(.4647)	(.4687)
1st Stage (KP F-stat.)		19.06	18.87
N = 393			
Education Controls			Y

Notes: this table reports the estimates of the impact of $CleanAdoptionIndex$ on labor market outcomes, β, from equation 4.3. Columns indicated with IV were estimated using land slope as instrument for $CleanAdoptionIndex$ as in equation 4.5. The dependent variables are the difference between the variable indicated in the columns between 2010 and in 2000. Skilled-unskilled workers ratio is in fraction, and skilled migration and unskilled migration are in log. All regressions include standard controls (the log of total planted area in 2000, the share of rural population in 2000, and the log of labor force in 2000), and when indicated the regression also include education controls (illiteracy rate in 2000, and the share of skilled in 2000). The unit of observation is a municipality. Robust standard errors are reported in parentheses. Significance level: ***p<0.01, **p<0.05, *p<0.10.*** p< .01, ** p< .05, * p< .1.

Table 7: Results – Structural Transformation

	Skilled-unskilled workers ratio	Employment share	Log average hourly wages
	(1)	(2)	(3)
Panel A. Agricultural Sectors			
Clean Adoption Index	.0747**	-.0143	.3957
	(.0338)	(.0734)	(.2479)
1st Stage (KP F-stat.)	18.05	18.05	18.05
N	393	393	393
Panel B. Manufacturing Sectors			
Clean Adoption Index	-.0836	-.1166*	.3983
	(.1542)	(.0612)	(.2806)
1st Stage (KP F-stat.)	18.05	18.05	18.05
N	393	393	393
Panel C. Construction & Services Sectors			
Clean Adoption Index	.0608	.1309**	.4541***
	(.0428)	(.0657)	(.1479)
1st Stage (KP F-stat.)	18.05	18.05	18.05
N	393	393	393

Notes: this table reports the estimates of the impact of $CleanAdoptionIndex$ on labor market outcomes, β^{st}, from equation 4.4. Columns indicated with IV were estimated using land slope as instrument for $CleanAdoptionIndex$ as in equation 4.5. The dependent variables are the difference between the variable indicated in the columns between 2010 and in 2000. Skilled-unskilled workers ratio and Employment share are fraction, and average hourly wages is in log. All regressions include standard controls (the log of total planted area in 2000, the share of rural population in 2000, and the log of labor force in 2000), and when indicated the regression also include education controls (illiteracy rate in 2000, and the share of skilled in 2000). The unit of observation is a municipality. Robust standard errors are reported in parentheses. Significance level: ***p<0.01, **p<0.05, *p<0.10.*** p< .01, ** p< .05, * p< .1.