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Environmental Regulation, Technology Adoption and Structural Transformation: Evidence from Brazilian Sugarcane Industry

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ENVIRONMENTAL REGULATION, TECHNOLOGY ADOPTION AND STRUCTURAL TRANSFORMATION: EVIDENCE FROM BRAZILIAN SUGARCANE INDUSTRY.

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Abstract

We estimate the effects of the adoption of mechanized agriculture led by a new environmental regulation on structural change of local labor markets within a large emerging country, Brazil. In 2002, the state of São Paulo passed a law outlying the timeline to end sugarcane pre-harvest burning in the state. The environmental law led to the fast adoption of mechanized harvest. We investigate if the labor intensity of sugarcane production decreases; and, if so, if it leads to structural changes in the labor market. We use satellite data containing the type of sugarcane harvesting – manual or mechanic harvest – paired with official labor market data.We find suggestive evidence that mechanization of the field led to an increase in utilization of formal workers and a reduction in formal labor intensity in the sugarcane sector. This is partially compensated by an increase in the share of workers in other agricultural crops and in the construction and services sector. Although we find a reduction in employment in the manufacturing sector, the demand generated by the new agro-industries affected positively the all sectors via an increase in workers' wage.

KEYWORDS: *Environmental Regulation; Technology Adoption; Structural Transformation; Sugarcane; Brazil.*

Contents

List of Figures

List of Tables

1 Introduction

The main focus of environmental regulation is to correct for externalities and other market failures. Very often, in order to comply with new environmental goals, the productive sector needs to adopt new and cleaner technologies. In particular in agriculture, technological changes may trigger structural transformation as it changes the factor-content of production in the field and/or generates demand for services and manufacturing goods. Matsuyama (1992) and Bustos et al. (2013) argue that the positive impacts of agricultural productivity on industrialization occur only in closed economies (e.g., productivity growth in agriculture can release labor or generate demand for manufacturing goods), while in open economies the impacts are indeterminate because comparative advantage in agriculture can reduce industrial growth. What happens is that the agricultural sector will employ more workers because of the increase in productivity, what reduces manufacturing sector and its benefits from external scale economies.

This paper estimates the causal effects of the adoption of mechanized agriculture led by a new environmental regulation on structural change of local labor markets within a large emerging country, Brazil. Our object is an environmental law aimed at ending sugarcane pre-harvest burning, which promoted the adoption of mechanical sugarcane harvesting. We investigate two underlying questions: is harvest mechanization a labor saving technical change – i.e., does the labor intensity of sugarcane production decrease?; and, if so, does harvest mechanization lead to structural changes in the local 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 that sugarcane was cultivated on about 26.0 million hectares, in more than 90 countries, with a worldwide harvest of 1.83 billion tons. Sugarcane can be harvested using two different technologies: the traditional one, by hand with necessary pre-harvest field burning; or mechanically, mainly without pre-harvest burning.[1] 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). Many other countries already implemented environmental regulation to correct this externality that arises from the productivity side of the economy (e.g., Greenstone

[1] Although mechanical harvest can be made with or without pre-harvest burning, Nyko et al. (2013) shows that around 80% of the mechanical harvesting is unburnt.

(2002); Greenstone and Hanna (2014); Barreca et al. (2014).

In Brazil, the state of So Paulo the richest and largest producer state passed a law in 2002 outlying a timeline to end sugarcane pre-harvest burning on large properties by 2021. In 2007, the Cooperation Protocol was sealed between So 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. The environmental law and the new protocol led to the fast adoption of mechanized harvest. In 2008 49.1% of the harvest area in So Paulo was without pre-harvest burning, while in 2012 this number increased to 72.6%, we also see a increase in total harvest area in this period.

The expansion of mechanical harvest can affect labor demand in the sugarcane sector through two channels. First, less workers are needed to harvest the same planted area. Second, this changes the work relations with more formal workers being employed and less temporary workers. Given the size of this sector in many localities, a technological change in this sector could have impacts on the remaining sectors of the economy.

We use two main datasets to investigate this relation: remote sensing data with sugarcane production by harvest type (CANASAT/INPE), and matched employer-employee dataset with the universe of formal workers in Brazil (RAIS/MTE). We use the satellite data to create our measure for the evolution of adoption of mechanization in sugarcane production in different microregions. We construct a clean adoption index that defines the intensity of mechanization in sugarcane as the fraction of land (pixels) without pre-harvesting burning out of the total number of land (pixels) with sugarcane harvest, relative to the baseline mechanization intensity in 2006, which is a way to observe mechanization in sugarcane production. We create a balanced panel of microregions, from 2006 to 2012.

In order to unveil the causal relation between the adoption of mechanized harvest technology and labor market outcomes, we use an instrumental variable strategy. We use the first two moments of land slope as an instrument for harvest mechanization, this is georeferenced topographical data (TOPODATA). The intuition for this instrument is that it is more costly to adopt mechanized harvest in steeper plots of land. We find a negative relation between the land slope and, both, the expansion of mechanization and our clean adoption index. Our identifying assumption is that declivity does not affect

the evolution of labor market outcome directly, but only indirectly via the adoption of technologies in the field.

Using the registers of all formally employed workers aggregated at the sector-local labor market level, we find that the adoption of clean harvesting reduces, not statistically, the formal labor intensity per plot of land. We find weak evidence that the new technology increases the number of formal permanent jobs in the sugarcane sector, however, we see a reduction in the employment share of this sector at the microregion-year level. We find that this reduction may have been compensated by an increase in the number of workers in the "construction and services" and agriculture sectors and a decrease in the manufacturing sector, all not statistically significant. Interestingly, we find economically meaningful but not statistically significant increase in the total wages at all sectors and in the average worker wage. We interpret these results as suggestive evidence that mechanization of the field leads to an increase in utilization of formal workers as well as with an increase in their productivity in a manner that it reduces formal labor intensity and increases wages in the sugarcane sector. Although this may represent less labor supply for industries, the demand generated by the new agro-industries affects positively workers via wages in all other sectors.

Several previous studies try to understand what the determinants of technology adoption in non-developed economies (Esther Duflo and Robinson, 2006; Conley and Udry, 2010; Bandiera and Rasul, 2002). Esther Duflo and Robinson (2006) tries to measure the returns to fertilizer use through a field experiment with farmers in Kenya. Miguel and Kremer (2004) study of the adoption of wormicide pills among school-age children in Kenya, for example, found that deworming improved health and school participation in both treatment schools and neighboring schools. Foster and Rosenzweig (2010) argues that the net gains, inclusive the new costs, are important determinants of a new technology adoption. When considering profit-maximizing entities, Foster and Rosenzweig (2010) says that is clear that technology profitability is the key for technology adoption, agents decide to use a technology based on the gain in welfare, which cannot be directly measured, in the case of medical technologies (e.g., bed nets, water purifiers, curative pills) adoption will depend on how health is valued. In our case, environmental regulation wants reduces pollutant gases, what may reduce respiratory diseases caused by sugarcane straw burning, and the channel is trough mechanization, but it also impacts

labor markets.

This paper contributes to the literature on the consequences of technology adoption on local development by showing how sugarcane harvest mechanization affects workers' labor market outcomes (Berman et al., 1998; Beaudry et al., 2006). Also, to the literature of environmental regulation consequences on local labor markets (Kahn and Mansur, 2013; Deschenes, 2010). We see evidence that sugarcane mechanization increases wages at manufacturing, construction and services, and also agricultural sectors.

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. (2013), however, differ from 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. (2013) provides direct empirical evidence on the effects of technical change in agriculture on the industrial sector by studying the effects of 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. Our paper provides suggestive evidence that the adoption of a labor saving technology, which weakly reduce the labor-land ratio, reduced the size of the manufacturing sector.

The remaining of this work is organized as follows: section 2 gives background information on sugarcane harvesting and labor market in Brazil; section 3 describes the data and our empirical strategy; section 4 presents our empirical results; section 5 shows a robustness check; and, section 6 concludes this work pointing the direction of this research.

2 Background

In this section we briefly discuss the sugarcane industry background in Brazil and in So 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), So Paulo state contributes with more then a half of Brazilian production as in Table 1. Sugarcane is a semi-perennial crop that, in So Paulo State, reaches its maximum vegetative development in April. Its planting can be done at two moments: at SeptemberOctober, when twelve-month sugarcane is planted; or at FebruaryMarch, when eighteen-month sugarcane is planted. And the sugarcane harvesting happens between April and December.

There are two harvesting technologies: the traditional one, by hand with pre-harvest field burning; and mechanically, without burning. In hand harvesting, field burning is necessary because of ergonomic restrictions, to clean the area from other weeds and to chase away any dangerous animals. However, mechanical harvesting can be made without burning, keeping leaves and straws intact, what is called called green or clean harvesting. Leaves and straws can be used for energy production or as vegetable coverage for conventional or organic agriculture. The sugarcane straw burning produces a negative externality 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 So Paulo passed a law outlying the timeline to end sugarcane pre-harvest burning. There was two calendars with the targets to adopt mechanical harvest according to the slope of the land: mechanizable areas, properties bigger than 150 hectares and with slope greater or equal to 12%; and non-mechanizable areas, properties smaller than 150 hectares or with slope greater than 12% or with soil structures impossible to mechanize. The different calendars are presented in Table 2.

In 2007, the Cooperation Protocol was sealed between So Paulo state and the Organization of Sugarcane Producers (ORPLANA). The phase out process was accelerated with the deadline being shortened to 2014 for properties with slope less or equal 12%, or to 2021 for properties with slope greater than 12%, and with the creation of an agro-environmental certificate for unburnt sugarcane. The Protocol also anticipated the reduction of burning practices from 50% to 70% in 2010 for properties with slope less or equal 12%, and from 10% to 30% in 2010 for properties with slope greater than 12%. For this protocol, there is no differentiation between mechanizable or non-mechanizable areas, only in slope level. [2]

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.

Table 3 shows the evolution on mechanical harvest in the Center-South region, where So Paulo state is located. Since mechanical harvest can be made with or without pre-harvest burning we make this distinction in the table. We can see that around 80% of the mechanical harvesting is unburnt. With this table we see a reversal in the type of sugarcane harvesting, in 2006 hand harvesting comprehended 63.3% while in 2012 this number reduced to 14.9%. Also we see that in 2006, around 30% of mechanical harvesting used pre-harvesting burning while in 2012 this number reduced to 15%.

The sugarcane ethanol sector has a bad record in labor relations and environmental rules.[3]. In 2007, there were around 498 thousand formal employees in the sugarcane crop activity, 54% in the state of So Paulo. In the sugarcane crop, especially in hand harvesting, the most part are of unskilled and temporary jobs, with different levels according to seasons. Table 4 shows that aggregating the whole sugarcane industry in 2007, we had

[2]Braunbeck and Magalhães (2010) discuss some issues that might be considered before mechanizing harvest. One of them is the maximal slope that is able to mechanizing. Theoretically it should be 46% but because of ground irregularities and other driving problems the critical slope is 12%. It should lead to the end of sugarcane production in steep areas. However, with advances in the off-road vehicle engineering such as four wheel drive, harvesters can be used in terrains with slopes greater than 12% around 15%-18%.

[3]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)

a total of 1.26 million formal workers, 520 thousand in So Paulo, with 270 thousands working directly in sugarcane crop. 91% of the formal workers were under 50 years old, 52% had 4 years of study or less and 7% were illiterate. However, 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 eighty hand workers.

In 2009, was signed the National Agreement to Improve Sugarcane Working Conditions between UNICA, by the Federal Government and the National Confederation of Agricultural Workers (CONTAG). This Agreement was about improving better labor practices and to promoting the reintegration of workers unemployed by the advance in mechanized harvesting.

3 Empirical Strategy and Data

This section is divided in two subsections, first we describe the three main data sources used in this paper and briefly present how we treated the data. Then, we describe our empirical strategy, where we first discuss some problems that could appear from a Ordinary Least Squares (OLS) approach and then present our Two Stages Least Squares (2SLS).

3.1 Data

We use three main data sources: formal register of employees (the Annual Report of Social Information - RAIS); spatial data of sugarcane harvesting type (CANASAT-INPE); and geomorphometric data in Brazil (TOPODATA).

RAIS consists in a national database that processes formal labor market statistics, containing all information across years from all formal workers in Brazil. Every commercial establishment must report to the ministry of Employment and Labor (MTE), through RAIS, information about all employees. The main variables we use from RAIS are: number of workers (permanent and temporary), total wage (the sum of all monthly wages at microregion and also at municipality) and average worker wage (the reason of total wage by the number of workers at microregion and also at municipality). Using

RAIS, we also generate some variables: employment share (the fraction of one sector in the total amount of formal workers), and formal labor intensity (number of workers per harvested area). Although we have the individual level data, at this preliminary stage we aggregate all variables at the microregion level to investigate the impact of the mechanized harvest adoption in the local labor market. We use CNAE 2.0 to separate the market in four sectors: sugarcane (code 113), agriculture (codes from 1 to 999 and different from 113), industry (codes from 1000 to 3390), and construction and services (codes from 4100 to 9799).

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 So Paulo state from 2006/07 to 2012/13, distinguishing two types of harvesting: with or without pre-harvest burning (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).

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 raw data is one arcsecond, but this has only been released over United States territory, for Brazil the resolution is 3 arcseconds. The resolution used in this work is thirty arcsecond the same as half arcminute.

We aggregate the remote sensing data at half arcminute level, also. From CANASAT, we have the distribution of harvesting and planted area across So Paulo state. Using this information we add up at municipality level and then at microregion level, our variable is the number of pixels of each harvesting type or the number of pixels with planted area. Planted area is used to check exogeneity of our instrument variable. From TOPODATA,

we have the distribution of slope across So Paulo state. Using this distribution we aggregate at municipality level and calculate some moments and after at microregion level, for this work we use the first and the second.

We create a balanced panel of microregions from 2006 to 2012, with 44 microregions, where we observe at least one type of sugarcane harvesting all years. Finally, in order to perform some robustness checks we disaggregate our variables at the municipality level. We then have 408 municipalities with some sugarcane harvesting from 2006 to 2012.

3.2 Empirical Strategy

We need to measure how much of the sugarcane harvesting is clean, in order to capture mechanization, and we observe this in data. Thus, our empirical strategy begins with a construction of a clean technology index. This index consists in the proportion of land plots with clean harvesting in the microregion. Such as the formula below:

$$CleanIndex_{jt} \equiv \left(\frac{Clean_{jt}}{HarvestedArea_{jt}} \right) \tag{1}$$

Where $Clean_{jt}$ represents the number of pixels with green harvesting, and $HarvestedArea_{jt}$ the total number of pixels with harvesting, at microregion j and year t. Notice that this clean technology index is bounded between 0 and 1, so microregions that do all the harvest using green technology has 1 and microregions using only pre-harvest burning technology get 0. The interpretation of these numbers are: microregions with 1 use only mechanized harvest, but this does not mean that microregions with a 0 use only hand harvest because we can do pre-harvest burning and still use mechanical harvesting, as discussed in background section.

We define our clean technology adoption index:

$$CleanAdoptionIndex_{jt} \equiv \Delta CleanIndex_{jt} = CleanIndex_{jt} - CleanIndex_{j,2006} \tag{2}$$

Where $CleanIndex_{j,2006}$ is the share of the total number of pixels with harvesting with green harvesting in microregion j and year 2006.

3.3 Main Regression

Our variables of interest are labor market outcomes like labor intensity in the sugarcane industry, employment share, number of total employees logarithm, number of permanent employees logarithm, total wage logarithm, average worker wage logarithm. We evaluate the evolution of these variables relative to 2006 ($\Delta Y_{ijt} \equiv Y_{ijt} \quad Y_{ij2006}$), in order to make them consistent with our clean adoption index. Variables are indexed by productivity (cnae) sector (i), microregion (j), and year (t).

Our main regression equation is:

$$\Delta Y_{ijt} = \beta CleanAdoptionIndex_{jt} + \gamma X_{jt} + \nu_{ijt} \tag{3}$$

Where X_{jt} are time and microregions controls, like year dummy variables, and total harvesting and clean harvesting in 2006.

This OLS specification that may present some identification problems. There may have some endogenous relation between labor market development and adoption of new mechanized technology in the field, so causal relations are not clear. For example, consider a shock in labor market increasing wages at a level that producers prefer paying fixed costs of mechanical harvest and employing few workers than making only hand harvest employing more workers. Now consider the case of a positive shock to investments in the local economy, for example government subsidies. In this scenario technology adoption may be cheaper by itself and labor market outcomes would improve anyway.

This analysis can be extended to the whole microregion economy, using a general equilibrium scope. Consider a shock in machinery prices, like a reduction of import tariffs. This would impact positively in clean harvesting and in industrialization – and in others sectors too. What would be the final effect in labor market? One hypothetic scenario could be a labor saving investment in manufacturing sector increasing labor offer in that microregion, that could make more profitable invest in hand harvesting rather than in clean harvesting. Now think the other direction, increase of clean harvesting making attractive for the manufacturing firms to employ more workers rather than buying more productive machines.

We do our analysis at microregion level because municipalities are commonly integrated with their neighbours, economically integrated and also labor market integrated.

In order to see the difference of labor market changes between microregion and municipality level we redo all estimations at municipality level as a robustness check.

Tables 5 and 6 report summary statistics. Table 5 presents summary statistics of our independent variables, controls, clean adoption index and instruments. In table 6 we present summary statistics of our dependent variables in level and in difference from 2006, mean, standard deviation, and median.

3.4 Instrumental Variable

In order to avoid endogeneity and to find some causality we look for instrumental variables. Our candidate is the first and second moments of land slope at the microregion level. The first moment is a strong candidate because the law is different according to the slope of the terrain and also because of the discussion about technical problems and solutions to mechanical harvesting in steep terrain. What we have in mind is that it is more difficult and expensive to mechanize steep areas, so we expect more resistance of the producers in mechanizing areas with greater slope. Second moment comes as candidate because if we have a lot of variance in terrain it makes harder for mechanization. Also we see some quadratic relation between clean harvesting and slope as in Figure 1. The relation of Clean Adoption Index and slope's first and second moments can be seen in Figure 2 and 3.

However, to use slope as an instrument we should satisfy two assumptions: (i) slope must be related to Clean Adoption Index; and (ii) slope must be uncorrelated to the error term. In other words, slope must be correlated with technology adoption and must be not directly affect the development of local labor markets, except via the mechanized harvesting. To characterize assumption (i) we show in Figure 2 that Clean Adoption Index is negatively related to slope first moment, after slope 5, and in Figure 3 that shows a negative relation between our index and slope second moment.

To shed light on the exogeneity assumption (ii), we analyze a panel data of sugarcane planted area for the whole So Paulo state from 2003 to 2013. Figures 4 and 5 show the distribution of planted area across different slope levels, wee can see that it does not change between years. The growth of planted areas, which is defined as planted area at year t divided by planted area in 2003, is relatively homogeneous across slope levels at least until 2008. We notice a change in the quantity, but no change in the relation what

is a uniform across slope first moment. Our intuition for this evidence is that if producers used to choose more flat terrains to begin with, then slope would be endogenous, but it seems not to be the case.

Our first stage regression[4] equation is:

$$CleanAdoptionIndex_{jt} = \Pi_1 Slope_j + \Pi_2 Slope_j^2 + \lambda X_{jt} + \varepsilon_{jt} \tag{4}$$

where X was already mentioned, and $Slope$ and $Slope^2$ are the first and second moments of land slope at microregion j, respectively. Notice that slope does not change between years, so were assuming that producers dont make structural changes in terrain, like terrace for example. In order to avoid for heteroskedasticity and arbitrary intra-group correlation, serial correlation, we do clustered standard errors at microregion level.

One potential problem that may arise in our regression is the weak instrument problem. This is the case where slope's first and second moments are poor predictors of the Clean Adoption Index. If this is the case, Clean Adoption Index will have little variation and then will be a bad predictor of our labor market outcomes. We test for weak instruments analyzing Kleibergen-Paap F statistic and the Montiel-Pflueger clustered weak instrument test.

Kleibergen-Paap statistic generalizes the Cragg-Donald statistic to the case of non-i.i.d. case, in our case we cluster in microregions. It tests whether the instruments jointly explain enough variation in the multiple endogenous regressors to conduct meaningful hypothesis tests of causal effects. In our case, a single endogenous regressor, the Kleibergen-Paap Wald F (K-P F) statistic is simply the clustered, first-stage F statistic (Kleibergen and Paap, 2006).

Weak instruments can bias point estimates and lead to substantial test size distortions. The null hypothesis for Montiel-Pflueger clustered weak instrument test is that the estimator presents weak instrument bias. The test rejects the null hypothesis when the test statistic, the effective F statistic, exceeds a critical value. This critical value depends on the significance level α, and the desired threshold τ. Where τ is defined as a fraction of a worst-case benchmark, this benchmark is related with the OLS bias when errors are conditionally homoskedastic and serially uncorrelated. Montiel-Pflueger clustered weak

[4] In order to justify the necessity of both first and second moments of slope distribution, in appendix A we do the first stage regression considering only first moment.

instrument test can be implemented for multiple instruments but for only one endogenous variable, which is our case, and also supports clustered variance-covariance matrix estimates (Olea and Pflueger, 2013; Pflueger and Wang, 2014).

Table 7 presents the first stage results. The sign of our instrumental variables are different, first moment of land slope is negatively related with our Index, and the second moment is positively related. Figure 2 and 3 show how Clean Adoption Index is negatively related with slope first moment, for values greater than 5, and with slope second moment, respectively. In aggregate we have a negative relation of Slope and Clean Adoption Index. As can be seen in the table, our K-P F statistic is 8.79 The Montiel-Pflueger clustered weak instrument test present different values and significance levels for each outcome variable, but we reject the weak IV bias hypothesis at 20% level for all different outcomes. After these tests we believe we are not in a weak IV case, so we can go on to interpret our 2SLS estimates in next section.

4 Empirical Results

We study the effects of environmental regulation and technology adoption on structural transformation in local labor markets. For this purpose, we analyze the sugarcane industry in Brazil, more specifically in So Paulo state. In this section, we present the results of clean harvesting adoption in Brazilian sugarcane industry on local labor market outcomes, discussing potential OLS biases caused by endogeneity, and analyzing the causal estimates from our 2SLS approach.

Table 8 presents the main OLS and 2SLS results of equation 3, dividing by sectors with a total of four panels. We report the coefficient of Clean Adoption Index, clustered standard errors and the mean of each dependent variable in 2006, the first of our data basis. The unit of observation is a microregion-year, and all regressions are controled with year effects and total harvest in 2006 and clean harvesting in 2006.

In terms of comparison we will discuss columns 1 and 2. For Panel A, which presents the results for sugarcane industry, OLS and 2SLS coefficients present different signs. In OLS, when we have more clean harvesting we have an increase in Employment Share, however in 2SLS the effect is the opposite. The 2SLS estimates show suggest that the adoption of clean harvesting reduces sugarcane Employment Share.

Labor intensity is studied only for sugarcane, we do not analyze planted or harvest area for other cultures. The coefficient of our 2SLS estimate, presented in column 12, is not statistically significant but suggests that clean adopting leads to a reduction in labor intensity, we have less workers per harvested area. One harvest machine may substitute around eighty hand workers, so even employing more workers the harvested area has grown more. This can be seen as an increase in worker productivity, because now we need less workers to harvest bigger areas.

Our first question is if this is a labor saving technical change. We can't answer this for sure, however the evidence of a reduction in labor intensity and a reduction in employment share suggests that sugarcane is employing less workers than other sectors. Therefore, we find weak evidence that this is a labor saving technical change, we now turn to look if it led to structural changes in the labor market. We try to see if sugarcane mechanization changed relations in other sectors, for this we also analyze wages and number of workers in different sectors, looking for sugarcane mechanization impacts in these outcomes.

Still in Employment Share, columns 1 and 2, in Panel B we also see different signs for the coefficients of Clean Adoption Index, OLS points to a reduction in employment share and 2SLS estimation is an increase, concluding that in the Agriculture sector OLS is negatively biased. For the manufacturing sector we see a negative impact of clean adoption in employment share and we can see in Panel C see that OLS is positively biased, computing a smaller effect of clean adoption in OLS than in 2SLS. And, in Panel D we see another change in the sign of the effect, the OLS estimator is negatively biased, and the correction with instrumental variable reports a positive estimation.

The way were going to interpret our coefficients is that if we have one unit in clean adoption index – that is if an unity area with initial production is fully based on pre-harvest burning technique fully converts to mechanical harvesting – we expect an impact of $100\beta\%$ in our dependent variable in relation of its value in 2006. Thus, if our clean index is zero in 2006 and becomes 1, we expect that our dependent variable changes from Y_{2006} to $(1+\beta)Y_{2006}$. The median microregion had a clean adoption index of 0.137, and the mean microregion had the index of 0.163.

Back to employment share, column 2, in the sugarcane sector we see an impact of -8,6% in employment share for one unit of our clean adoption index, so if one microregion presented no clean harvesting in 2006 and totally adopts at year t we expect an employ-

ment share of 0.038 at this microregion-year. The impact is in other direction in the agriculture sector, as presented in Panel B, we estimate an increase in 6.5% of this sector employment share for one unit of clean adoption index, so we expect an employment share around 0.029 for a microregion-year that had no clean harvesting and only present this type of harvesting.

Analyzing Change in Total Wage, column 4, for all sectors we see a positive impact of clean adoption. The coefficient means that one unit of clean adoption index impacts in Total Wage by 241.8% in sugarcane, 76.5% in agriculture, 37.6% in manufacturing, and by 23.8% in construction & services from 2006 value at microregion-year. Thus, if clean index of one microregion was zero in 2006 and becomes one at some year we expect Total Wage of the sugarcane sector to more than triple, for example, the increase is around 11 million reais, in 2006 values, in the total amount of wages at microregion-year level.

Column 6 reports the coefficients for Change in Average Worker Wage. For all sectors the coefficient is positive, so an increase in clean harvesting leads to greater worker wage when compared to 2006. Coefficients are significant for sugarcane sector, at 1% level, and for agricultural sector at 10% level. For sugarcane sector, a change in one unit in clean adoption index leads to an increase, of 48.8% for sugarcane sector, 15.4% for agriculture. In terms of 2006, the impact of one unit of clean adoption index is an increase of around R$360 in sugarcane sector, R$92 in agriculture sector.

Analyzing the impact of clean harvesting adoption in number of formal employees we estimate a reduction in manufacturing sectors, and in other sectors we estimate that more clean harvesting leads to a greater number of workers. For sugarcane it might be counterintuitive, but as discussed in background section the sugarcane sector was characterized by informality in labor market, but with mechanization the number of formal workers has grown, so its reasonable. We distinguish number of formal employees between total and permanent. The results are quite the same; we do this as way to observe if there is a structural change in number of temporary workers, however we have very few observations of temporary employment making impossible for us to conclude anything for now. We have no significant coefficients. The coefficient for sugarcane, panel A, means that a municipality with one in clean adoption index will show an increase of 147.7% in Total Employment and an increase of 147.4% in Permanent Employment. In terms of 2006, its expected that in a microregion-year that presented no clean harvesting in

2006 and totally adopts clean harvesting will employ 8291 new workers with 8265 being permanent workers.

With these results together we can answer our two main questions. First, we find suggestive evidence that sugarcane mechanization is a labor saving technical change. Second, we find some evidence of a structural change in local labor markets. Sugarcane mechanization leads to an increase in utilization of formal workers as well with an increase in their wages. This may represent less labor supply for other sectors, the demand generated by the new agro-industries affects positively workers via wages in all other sectors.

5 Robustness Check

In this section we do one robustness check. We redo all our results but disaggregating at municipality level instead of microregion level.

In order to gain more cross section observations we redo all estimations at municipality-year level. We maintain in our sample only municipalities where we observe any type of sugarcane harvest for all years. Three municipalities were dropped out because we observed harvesting just some years, what could be a error because of aggregation level we worked in our spatial data. We have a balanced panel of 408 municipalities and 7 years of observation, from 2006 to 2012.

The sign of instrumental variables are according to microregion level estimation, but the effect is not the same. Here, the first moment of slope distribution has less impact in clean adoption index. Also we have a smaller K-P F statistic but the Montiel-Pflueger clustered weak instrument test present different results, in most cases we reject the null hypothesis at 5% level, but for some we reject only at 20% level.

The 2SLS estimation now is quite different from our main estimates. Analyzing Panel A, wich resumes sugarcane sector coefficients the direction of our causality is different. For example, at municipality level the clean adoption index coefficient for change in employment share, column 2, suggests that sugarcane sector is employing more than other sector, but our main result is the opposite. The same happens with labor intensity estimative.

By using municipality level data, we lose a lot of local labor market observations,

because now we only use municipalities where we observe at least one type of sugarcane harvesting all years, since microregion level data we have more workers in local labor markets. Also when we make the analysis at the municipality level, we lose a lot of information because we don't observe local work migration and or workers commuting.

We can conclude that labor market dynamics at microregion and municipality level are different, such that what we observe are almost incomparable. One possible cause might be that for this robustness check we maintain only municipalities that we observe at least one type of sugarcane harvest, and in our main regression we observe the whole microregion so we can see migration between municipalities. We understand that a microregion is a better representation of a local labor market as it considers local economic complementarity.

6 Conclusion

This paper estimates the causal effects of the adoption of mechanized agriculture led by a new environmental regulation on local labor markets within a large emerging country, Brazil.We find that the adoption of clean harvesting leads to a non-significant reduction in employment share and a non-significant reduction in labor intensity in the sugarcane sector, that of a labor saving technical change. We find as well that mechanization increases the number of formal permanent workers and the wage bill in the sugarcane sector.

We see evidence of structural transformation on labor market by finding that clean harvesting adoption increases average worker wages in agricultural and manufacturing sectors. Also, we have suggestive evidence that mechanization in sugarcane harvest reduces the number of worker in manufacturing but increases in construction & services and in agricultural sectors.

Thus we interpret our results as preliminary evidence that mechanization leads to more formal workers in sugarcane and releases manpower to other cultures, also to construction and services, although this may represent less labor supply to manufacturing. The demand generated by the new agro-industries affects positively labor market of these microregions.

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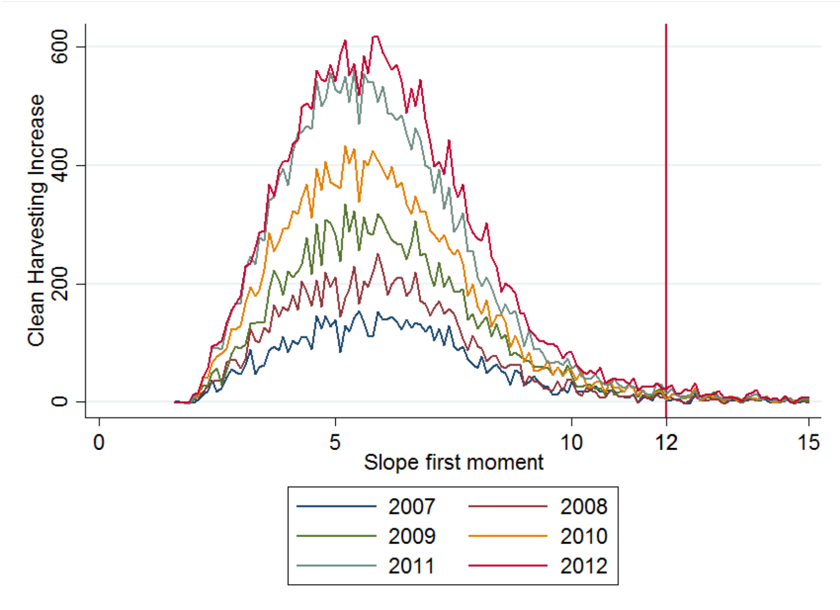
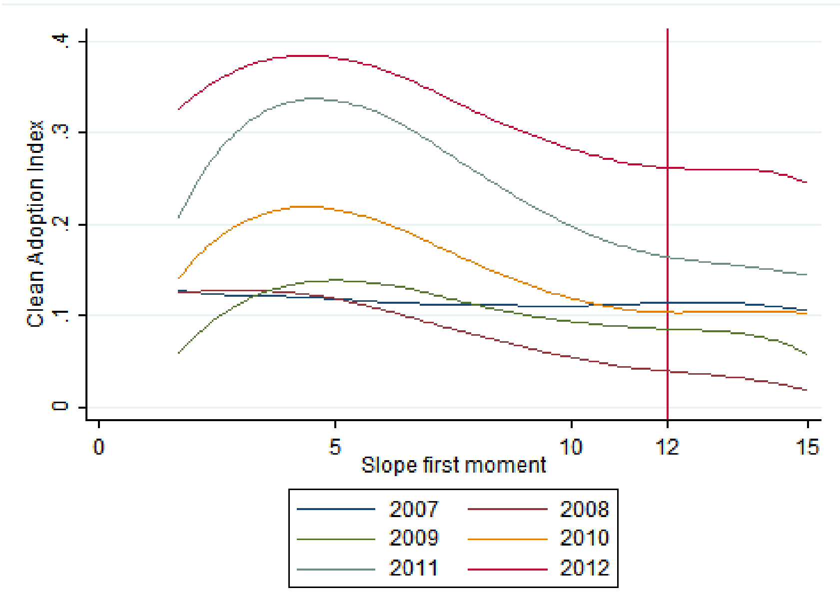


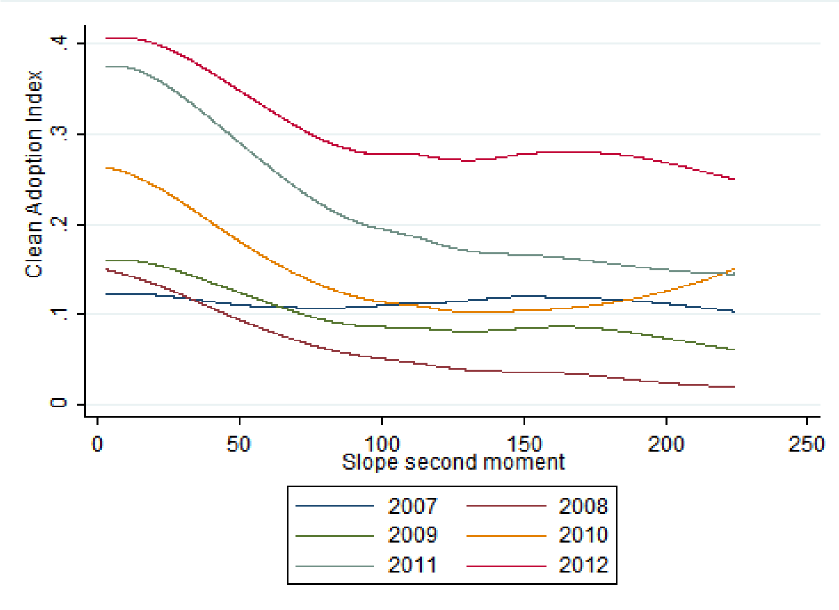
Notes: The figure presents clean harvesting in year t divided by clean harvesting in 2006 per value of slope first moment. To do this we round slope first moment to the first decimal place, so we have more observations at one slope first moment point. We drop slope first moment values greater than 15%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

Figure 1: Clean Harvesting vs Slope first moment



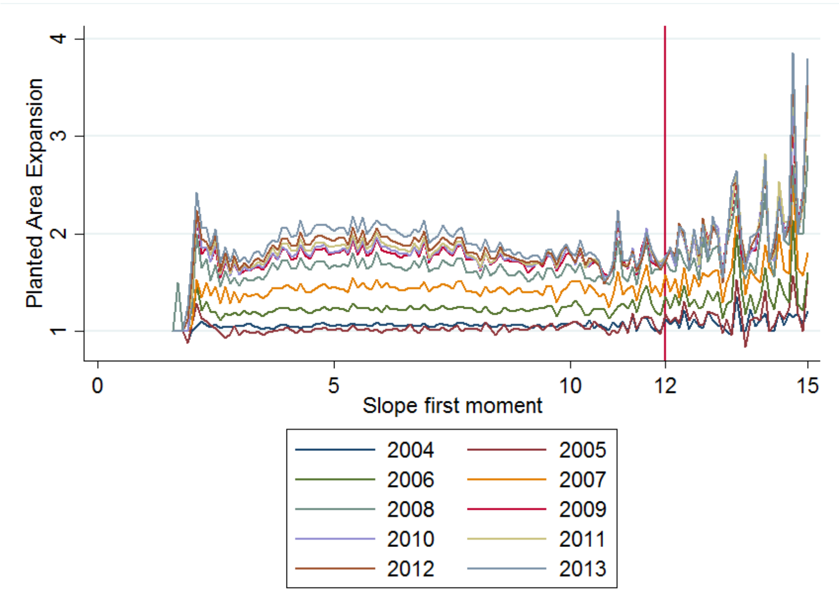
Notes: The figure presents clean adoption index in year t per value of slope first moment, locally weighted scatterplot smoothing (lowess). To do this we round slope first moment to the first decimal place and then calculate clean adoption index at each rounded value and each year t. We drop slope first moment values greater than 15% because of very few observations.

Figure 2: Clean Adoption Index vs Slope first moment



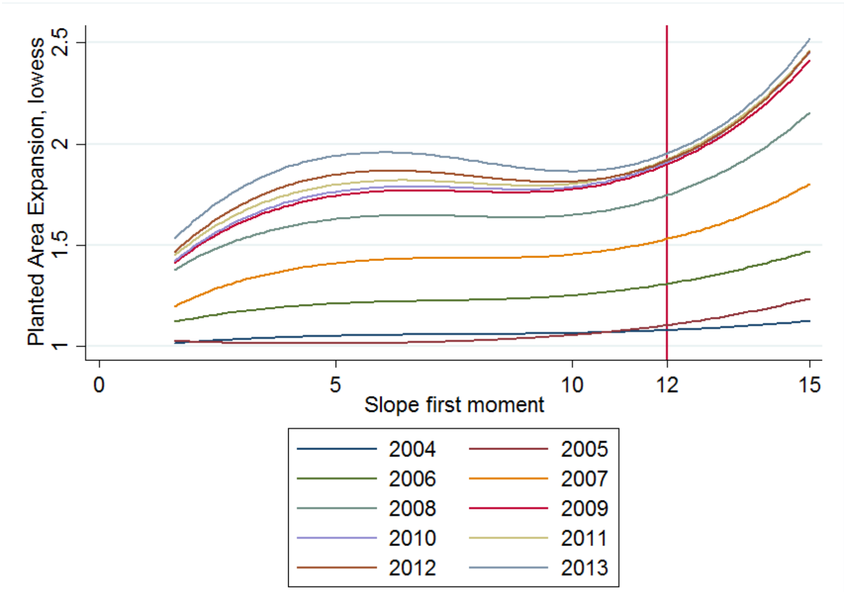
Notes: The figure presents clean adoption index in year t per value of slope second moment, locally weighted scatterplot smoothing (lowess). To do this we round slope first moment to the first decimal place and then calculate rounded slope second moment, so we calculate clean adoption index at each rounded value and each year t. We drop slope first moment values greater than 15% because of very few observations.

Figure 3: Clean Adoption Index vs Slope second moment



Notes: The 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.

Figure 4: Planted Area Expansion vs Slope first moment



Notes: The figure presents presents planted area in year t divided by clean harvesting in 2003 per value of slope first moment, locally weighted scatterplot smoothing (lowess). 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.

Figure 5: Lowess Planted Area Expansion vs Slope first moment

Table 1: Sugarcane Production (thousands ton)

Year	Brazil	So Paulo	%
2006	427,723	264,339	62
2007	495,723	296,243	60
2008	569,216	346,293	61
2009	602,193	361,261	60
2010	620,409	359,503	58
2011	559,215	304,230	54
2012	588,478	329,923	56

Notes: The table presents sugarcane production in thousands of ton from Brazil and So Paulo state.
Source: UNICADATA

Table 2: Timeline

Year	Mechanizable Areas	Non-mechanizable Areas
2002	20% reduction	
2006	30% reduction	
2011	50% reduction	10% reduction
2016	80% reduction	20% reduction
2021	100% reduction	30% reduction
2026		50% reduction
2031		100% reduction

Notes: The table resumes the reduction timeline to end sugarcane pre-harvest burning.

Table 3: Mechanical Harvesting Evolution (%)

Center-South	2006	2007	2008	2009	2010	2011	2012
Mechanical Harvesting	36,7	42,8	53,4	60,1	72,8	79,2	85,1
Green	25,1	29,9	38,2	42,9	52,5	66,3	73,8
Burning	11,6	12,9	15,2	17,1	20,3	13,0	10,8
Hand Harvesting	63,3	57,2	46,6	39,9	27,2	20,8	14,9

Notes: The table presents mechanical harvesting evolution in percentages for the Brazilian Center-South region.
Source: Nyko et al. (2013)

Table 4: Employees in the Sugarcane Industry (2007)

Region	Sugarcane crop		Sugar Production		Ethanol Production		Total
North/ Northeast	83,843	16.85%	252,250	44.09%	40,348	21.14%	376,441
Center-South	413,827	83.15%	319,897	55.91%	150,546	78.86%	884,270
So Paulo	268,282	53.91%	199,512	34.87%	51,824	27.15%	519,618
BRAZIL	497,670	100.0%	512,147	100.0%	190,894	100.0%	1,260,711

Notes: This table presents formal workers in sugarcane industry in Brazil at 2007, differentiating between workers of sugarcane crop, sugar production, and ethanol production.
Source: SGPR (2009)

Table 5: Descriptive Statistics: Independent Variables

	Mean	Median
Slope	7.255	6.984
	(1.657)	
Slope^2	61.895	55.164
	(32.740)	
Harvest Area 2006	951.932	685
	(896.834)	
Clean 2006	314.136	210
	(314.615)	
Clean Adoption Index	0.189	0.167
	(0.177)	

Note: The table reports descriptive statistics of the independent variables used in regressions. Standard deviation reported in brackets.

Table 6: Descriptive Statistics: Dependent Variables

	Employment Share		Total Wage		Average Worker Wage		Total Employment		Permanent Employment		Labor Intensity	
	Level	Dif	Level	Dif	Level	Dif	Level	Dif	Level	Dif	Level	Dif
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Sugarcane												
Mean	0.055	-0.015	5407.420	867.703	1.045	0.306	4933.127	-680.305	4930.422	-676.714	4.172	-1.883
Std. Deviation	(0.063)	(0.033)	(6023.102)	(2321.949)	(0.298)	(0.264)	(5300.260)	(2260.568)	(5298.576)	(2260.522)	(3.645)	(2.731)
Median	0.035	-0.003	3353.150	285.604	1.015	0.260	2911	0	2911	0	3.022	-0.991
Panel B: Agriculture												
Mean	0.104	-0.011	8418.621	2421.698	0.826	0.228	10365.270	247.4026	10358.160	260.6169		
Std. Deviation	(0.065)	(0.023)	(7164.818)	(3387.854)	(0.206)	(0.186)	(8637.834)	(2040.833)	(8634.894)	(2039.943)		
Median	0.085	-0.006	6321.076	1325.303	0.786	0.202	8350	150	8350	148		
Panel C: Manufacturing												
Mean	0.271	0.005	60286.140	19806.400	1.243	0.266	40323.310	6430.782	40301.620	6419.260		
Std. Deviation	(0.080)	(0.029)	(109006.300)	(42633.630)	(0.343)	(0.218)	(52479.550)	(10555.390)	(52455.590)	(10541.360)		
Median	0.260	0	29096.670	7918.585	1.207	0.243	24014	2815.5	24014	2815.5		
Panel D: Construction & Services												
Mean	0.571	0.021	115452	43020.880	1.121	0.234	91861.850	19011.940	89157.260	19018.710		
Std. Deviation	(0.093)	(0.039)	(229421.900)	(109766.600)	(0.227)	(0.199)	(149161.800)	(43690.580)	(140976.900)	(43372.740)		
Median	0.569	0.013	52982.990	14980.480	1.089	0.209	47487.5	7412	45885	7522		

Notes: The table reports descriptive statistics of dependent variables used in regressions. Variables in level are considered all observations at microregion level between 2006 and 2012. Variables in difference are calculated at microregion level taking the difference between year t and 2006, where t is from 2007 to 2012.

Table 7: First Stage

	CleanAdoptionIndex
Slope	-0.152***
	(0.036)
$Slope^2$	0.007***
	(0.002)
Kleibergen-Paap Wald rk F statistic	8.79

Note: The table reports first-stage estimated coefficients of equation 4 in the text. The unit of observation are microregions. Clustered standard errors at microregion level are reported in brackets. We have 44 microregions. Significance level: ***p¡0.01, **p¡0.05, *p¡0.10.

Table 8: OLS and 2SLS

	Change in Employment Share		Change in Total Wage		Change in Average Worker Wage		Change in Total Employment		Change in Permanent Employment		Change in Labor Intensity	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Sugarcane												
Clean Adoption Index	0.032*	-0.086	1.553	2.418	0.197**	0.488***	1.159	1.477	1.159	1.474	0.234	-6.263
	(0.031)	(0.087)	(1.227)	(1.858)	(0.096)	(0.164)	(1.068)	(1.741)	(1.068)	(1.741)	(2.939)	(7.259)
Average Dependent Variable 2006	0.070		4539.717		0.739		5613.432		5607.136		6.055	
Panel B: Agriculture												
Clean Adoption Index	-0.010	0.065	-0.034	0.765	0.030	0.154*	-0.102	0.419	-0.104	0.420		
	(0.020)	(0.058)	(0.226)	(0.559)	(0.032)	(0.091)	(0.189)	(0.536)	(0.189)	(0.537)		
Average Dependent Variable 2006	0.115		5996.923		0.598		10117.860		10097.550			
Panel C: Manufacturing												
Clean Adoption Index	-0.015	-0.026	-0.068	0.376	0.001	0.131	-0.088	-0.015	-0.086	-0.011		
	(0.024)	(0.054)	(0.161)	(0.312)	(0.044)	(0.086)	(0.125)	(0.273)	(0.125)	(0.273)		
Average Dependent Variable 2006	0.266		40479.740		0.977		33892.520		33882.360			
Panel D: Construction & Services												
Clean Adoption Index	-0.006	0.047	-0.124	0.238	-0.059	0.031	-0.018	0.145	-0.019	0.130		
	(0.036)	(0.063)	(0.098)	(0.208)	(0.044)	(0.055)	(0.079)	(0.192)	(0.079)	(0.192)		
Average Dependent Variable 2006	0.549		72431.100		0.887		72849.910		70138.550			

Notes: The table reports OLS and 2SLS results of equation 3 in the text. The unit of observation is microregion-year. Clustered standard errors at microregion level are reported in brackets. We have 44 microregions and 6 years. All outcomes are in difference with 2006 value. Employment Share and Labor Intensity are fraction, and all other variables are in log. All regressions have year effects and are controled for total harvest in 2006 and clean harvesting in 2006. Significance level: ***p¡0.01, **p¡0.05, *p¡0.10.

Table 9: Municipality Robustness Check: First Stage

	CleanAdoptionIndex
Slope	-0.092***
	(0.026)
$Slope^2$	0.004***
	(0.001)
Kleibergen-Paap Wald rk F statistic	8,34

Note: The table reports first-stage estimated coefficients of equation 4 in the text. The unit of observation are municipalities. Clustered standard errors at microregion level are reported in brackets. We have 2448 municipalities and 44 microregions. Significance level: ***p¡0.01, **p¡0.05, *p¡0.10.

Table 10: Municipality Robustness Check: OLS and 2SLS

	Change in Employment Share		Change in Total Wage		Change in Average Worker Wage		Change in Total Employment		Change in Permanent Employment		Change in Labor Intensity	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Sugarcane												
Clean Adoption Index	-0.009	0.063	-0.115	0.705	0.042	0.369***	-0.098	0.122	-0.099	0.136	0.870	5.297
	(0.021)	(0.174)	(0.290)	(1.590)	(0.061)	(0.157)	(0.290)	(1.641)	(0.290)	(1.639)	(2.002)	(16.649)
Average Dependent Variable 2006	0.093		487.845		0.594		603.718		603.039		4.986	
Panel B: Agriculture												
Clean Adoption Index	-0.020	-0.078	-0.106	0.231	0.010	0.032	-0.123	0.240	-0.125	0.244		
	(0.015)	(0.080)	(0.084)	(0.613)	(0.010)	(0.056)	(0.080)	(0.652)	(0.080)	(0.653)		
Average Dependent Variable 2006	0.189		585.890		0.607		980.297		978.105			
Panel C: Manufacturing												
Clean Adoption Index	0.019	0.157	0.123	2.017*	-0.007	0.254*	0.114	1.865*	0.114	1.869*		
	(0.015)	(0.107)	(0.178)	(1.051)	(0.025)	(0.150)	(0.178)	(1.029)	(0.178)	(1.029)		
Average Dependent Variable 2006	0.229		3953.393		0.817		3353.549		3352.561			
Panel D: Construction & Services												
Clean Adoption Index	0.010	-0.142	0.012	-0.001	-0.008	0.038	0.028	-0.049	0.029	-0.003		
	(0.024)	(0.150)	(0.046)	(0.232)	(0.009)	(0.050)	(0.041)	(0.217)	(0.041)	(0.207)		
Average Dependent Variable 2006	0.489		7181.421		0.848		7201.387		6929.809			

Notes: The table reports OLS and 2SLS results of equation 3 in the text. The unit of observation is municipality-year. Clustered standard errors at microregion level are reported in brackets. We have 2448 municipalities, 6 years and 44 microregions. All outcomes are in difference with 2006 value. Employment Share and Labor Intensity are fraction, and all other variables are in log. All regressions have year effects and are controled for total harvest in 2006 and clean harvesting in 2006. Significance level: ***p¡0.01, **p¡0.05, *p¡0.10.

A Appendix

This appendix contains first stage results considering only slope first moment as instrument. Table 11 reports coefficient and K-P F statistic. The coefficient sign is still negative, but we lose in statistical significance and in relevance, the estimated parameter is very different, suggesting that we have a missing instrument bias. Also, K-P F statistic now is only 3.38, smaller than before, and Montiel-Pflueger clustered weak instrument test do not reject weak instrument bias hypothesis.

Table 11: Only Slope First Moment: First Stage

	CleanAdoptionIndex
Slope	-0.020*
	(0.011)
Kleibergen-Paap Wald rk F statistic	3.38

Note: The table reports first-stage estimated coefficients of equation 4 in the text, considering only first moment. The unit of observation are microregions. Clustered standard errors at microregion level are reported in brackets. We have 44 microregions. Significance level: ***p¡0.01, **p¡0.05, *p¡0.10.