The Cost of Compliance: Informality, Technical Change, and Structural Transformation in Brazil

Xiaojun Guan*

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Abstract

This paper investigates the effects of labor-saving technological advancements in agriculture on sectoral labor reallocation in the context of informality and examines how labor regulation enforcement influences this process. Exploiting the 2003 legalization of genetically modified (GM) soy in Brazil and leveraging variation in potential soy yields across municipalities, I find that between 2000 and 2010, municipalities with more significant potential gains from adopting GM soy experienced larger reallocation of labor from agriculture to the formal manufacturing sector, along with a decline in informal manufacturing employment. This resulted in a decrease in the overall informality rate within manufacturing in these areas. Furthermore, stricter enforcement of labor regulations—measured as one standard deviation higher in inspection intensity—reduced the overall labor shift to manufacturing by 29%, an effect driven entirely by changes in formal employment. To rationalize the empirical findings and conduct counterfactual policy experiments, I develop and calibrate a two-sector general equilibrium model. Counterfactual analyses indicate that intensifying enforcement to reduce manufacturing informality by 50% decreases labor reallocation to manufacturing by 4.5%. Additional simulations suggest that lowering entry and fixed costs for firms facilitates labor movement into manufacturing and reduces informality.

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1 Introduction

Economic development has typically been accompanied by structural transformation - a process where workers reallocate from agriculture to manufacturing and services as economies develop (Lewis 1954; Kuznets 1973). This transition can be facilitated by technological advancements that reduce the relative demand for labor in the agricultural sector. However, labor market regulations such as worker's formal registration and firing restrictions, although designed to protect workers' welfare, can inadvertently hinder the reallocation of labor by discouraging job creation and limiting labor mobility (Aghion et al. 2008; Kambourov 2009). Moreover, since firms are primarily responsible for complying with these regulations, the costs associated with compliance and the intensity of enforcement directly influence not only the number of firms established and the jobs they create but also the nature of these jobs—formal versus informal—in the expanding sectors. High compliance costs and stringent enforcement may push firms to evade regulations by operating informally or hiring informally despite registering, thereby increasing the prevalence of informal employment in the economy.

In this paper, I investigate how technological advancement in agriculture affects labor reallocation in the presence of informality and how labor regulation enforcement influences this process. Previous work by Bustos et al. (2016) demonstrated that the introduction of genetically modified (GM) soy seeds in Brazil in 2003, which they showed to be a labor-saving technical change, has led to labor reallocation from agriculture to manufacturing within local labor markets. Building on that work, the first part of this paper investigates how such labor-saving technological changes affect the reallocation of labor to formal and informal manufacturing sectors. Furthermore, because of the importance of regulation enforcement in affecting the extent of informality and job creation, I then examine how the intensity of labor regulation enforcement influences this process. Lastly, I construct a structural model to rationalize the empirical findings and to explore potential policy counterfactuals.

Incorporating informality is essential given the widespread prevalence of informality in developing countries (Ohnsorge and Yu 2022), and the literature highlighting that informal jobs typically offer lower wages on average (Botelho and Ponczek 2011)[1], experience higher wage volatility (Engbom et al. 2022) and job instability (Donovan et al. 2022). In the context of Brazil, the intensity of labor market regulation enforcement significantly influences the size of the informal sector, as more intensive enforcement leads to a greater crackdown on some informal economic activities.

[1] However, Ulyssea (2018) using matched employer-employee data from both formal and informal Brazilian firms find that the wage gap between formal and informal workers disappears after controlling for firm fixed effects. This suggests that self-selection significantly drives the wage disparity among observably similar workers and that formal and informal workers perform similar tasks within firms, conditional on skill.

Additionally, the perceived probability of detection and subsequent penalty will also affect a firm's incentive to comply with regulations.

Informality can be modeled from two perspectives: firm informality, where firms choose to operate without registration (extensive margin) or hire workers informally despite being registered (intensive margin) (Ulyssea 2018), and worker informality, where workers choose between formal and informal employment comparing costs and benefits. The literature on the latter has largely focused on the effect of welfare policies on labor supply (Levy 2008; Bosch and Esteban-Pretel 2012). Since this paper focuses on labor demand and regulatory enforcement measures targeted at firms, I adopt the firm informality framework. Unfortunately, since informal firms and informal workers within formal firms are not directly observable in the data, the empirical analysis in this paper relies on the Brazilian Population Census to measure informal employment by municipality and sector.

In this paper, I first investigate whether labor-saving technological changes (i.e., the introduction of GM soy) in agriculture have differential impacts on the reallocation of labor to formal and informal manufacturing jobs in Brazil from 2000 to 2010. Following Bustos et al. (2016), the GM soy shock is constructed using data from the FAO Global Agro-Ecological Zones database, which provides estimates of potential soy yields under various input and management scenarios. These estimates incorporate local soil, terrain, and climate characteristics to predict maximum attainable yields. Moreover, the difference between potential soy yields under low and high input levels captures the potential gains from adopting GM soybeans in different geographic locations, which I use as the main independent variable.

To estimate the impact of GM soy on formal/informal employment shares of manufacturing, I employ a first-difference approach, which effectively controls for unobserved time-invariant characteristics of municipalities. To account for differential trends across municipalities with varying initial characteristics, I include a set of baseline municipality-level controls. Additionally, state dummies are included to capture any state-level trends. Finally, to address potential "catch-up effects," I include lagged sectoral employment shares from 1991. This controls for the possibility that municipalities with initially lower manufacturing employment might experience faster growth independent of technological changes.

I find that municipalities where the potential soy yields increased by one standard deviation would experience a 1.02 percentage point (17.9%) higher increase in the formal manufacturing employment share and a 0.15 percentage points (3 %) larger decrease in informal manufacturing employment share between 2000 and 2010. As a result, the informality rate in manufacturing decreases in municipalities benefiting more from agricultural technological advancements. These results suggest that technological advancements in agriculture not only drive a shift of workers into the manufacturing sector but also facilitate a reallocation from informal to formal employment within the industry. The intuition is that the labor-saving technical change reduces the demand for labor in the agricultural sector, which could lead to a decrease in wages (i.e., labor cost). The lower wages make formal operations more profitable for firms across all productivity levels, encouraging a shift toward formality.

Next, I examine the effects of the intensity of labor regulation enforcement on moderating the previous results. To do this, I interact the GM soy shocks with the measure of enforcement intensity. Enforcement intensity is measured using the number of firm inspections conducted by the Ministry of Labor per hundred firms in each municipality, following Almeida and Carneiro (2009). By doing so, I test whether municipalities with more intensive enforcement experience differential employment outcomes than those with weaker enforcement. However, enforcement intensity may be correlated with factors such as local economic development and political conditions in different cities. To address these potential endogeneity concerns, I adopt an instrumental variable approach following Ponczek and Ulyssea (2022). Specifically, I use the distance to the nearest labor office (LO) and an interaction term between the number of inspectors per state and the distance to the LO to instrument for the endogenous variable—the number of firm inspections per hundred firms. The IV estimates show that a one standard deviation increase in inspection intensity led to a 29% reduction in the growth of the overall manufacturing employment shares, driven entirely by changes in formal employment. These findings highlight the complex role that regulatory frameworks play in shaping labor market adjustments in response to technological change.

To assess the broader economic implications and explore potential policy counterfactuals, I construct a general equilibrium model that builds upon the framework of Imbert and Ulyssea (2023). Specifically, to model labor reallocation, I extend the model to include two sectors—agriculture and manufacturing. Moreover, I assume households have non-homothetic preferences to account for income effects, which are important drivers of structural transformation (e.g., Kongsamut et al. 2001). In the model, the wage rate, labor allocation between sectors, and the size of the informal sector in manufacturing are endogenously determined.

I then calibrate the model to perform counterfactual simulations of the effects of labor-saving technical change in agriculture. The parameter representing the labor-saving technical changes is estimated using the agricultural production function and data on factor costs (Herrendorf et al. 2015). The counterfactual results confirm the main findings from the first difference analysis: the labor-saving technological change in agriculture leads to the reallocation of labor to manufacturing and a reduction in the share of informal employment within the manufacturing sector. The mechanism behind this is as follows: the labor-saving technical change reduces the demand for labor in the agricultural sector, which leads to a decrease in the equilibrium wage rate. The lower wages make formal operations more profitable for firms across all productivity levels, encouraging a shift toward formality.

In a second counterfactual, I examine the impact of intensifying labor regulation enforcement such that the share of informal employment in manufacturing is reduced by 50%. The results indicate that stricter enforcement leads to 4.5% less labor reallocation from agriculture to manufacturing than the baseline scenario. Furthermore, the decline in the informality rate within manufacturing is smaller. These findings suggest that while stricter enforcement aims to reduce informality, it may inadvertently slow down structural transformation by impeding labor movement into more productive sectors.

Finally, I analyze how reducing regulatory burdens associated with formal and informal firms affects labor reallocation in response to technological change. Specifically, I assess the effects of lowering the sunk entry cost and the fixed cost for formal firms. The results show that reducing these costs facilitates a greater shift of labor from agriculture to manufacturing and leads to more substantial declines in the informality rate within manufacturing. Interestingly, the mechanisms differ between reducing the entry cost and the fixed cost of formal firms. Reducing the entry cost results in a significant entry of new firms—both formal and informal—with many informal firms eventually choosing to formalize, thus decreasing the overall share of informal employment. In contrast, lowering the fixed cost for formal firms enhances the attractiveness of formal operations for potential entrants across all productivity levels. This shift encourages more firms to operate formally from the outset, leading to fewer informal entrants and, hence, fewer informal employment.

This paper contributes to the literature examining the effects of agricultural productivity shocks on other sectors and local economic outcomes, focusing on long-run changes arising from permanent shifts in technology or the environment (e.g., Foster and Rosenzweig 2004, 2007, Nunn and Qian 2011; Hornbeck and Keskin 2015; Henderson et al. 2017). Several studies have specifically investigated structural transformation with respect to labor reallocation (Bustos et al. 2016; Moscona 2019a; Albert et al. 2021; Liu et al. 2023). A few recent papers have combined spatial and temporal variation to analyze the impact of the Green Revolution in developing countries (Gollin et al. 2021; Moscona 2019b).

My contribution to this literature is twofold. First, I delve deeper into the nature of labor reallocation to manufacturing driven by technical change by distinguishing between formal and informal employment. I find that while positive agricultural productivity shock has led to a higher growth of formal manufacturing employment, it has led to a decline in informal manufacturing employment.

Second, I construct a two-sector model incorporating firm entry and the choice to comply with formal regulations, which I use to explore the role of job creation in the structural transformation process. By focusing on the labor demand side, I show that the release of agricultural labor due to labor-saving technical change can lead to formal employment creation in manufacturing. This paper is thus built on the extensive literature studying firms and informality (see Ulyssea 2020, for a review) and the growing body of work on firm dynamics and informality (e.g., D'Erasmo and Boedo 2012; Dix-Carneiro et al. 2021; Imbert and Ulyssea 2023).

Furthermore, I contribute to the broader literature on the consequences of labor market regulations and labor market rigidity (Besley and Burgess 2004; Botero et al. 2004; Aghion et al. 2008; Ahsan and Pagés 2009; Almeida and Carneiro 2012; Almeida and Poole 2017; Chaurey 2015). Specifically, I provide reduced-form evidence on how the intensity of labor regulation can slow down labor reallocation driven by agricultural technological advancements.

Moreover, a closely related study is Colmer (2021). They demonstrate that in response to temperature-driven agricultural productivity shock, labor reallocates to other sectors in more flexible labor markets, and thus, firms experience a relative increase in output. In contrast, firms in more rigid markets see contractions without labor reallocation. My paper is different in two aspects: first, I focus on long-run changes in agricultural productivity rather than short-term temperature-driven shocks. Second, I examine the role of enforcement intensity, which not only affects firms' flexibility in adjusting employment but also influences the types of jobs affected.

The remainder of the paper is organized as follows. Section 2 describes the data and institutional background. Section 3 presents the empirical strategy and results. Section 4 outlines the model. Appendix C explains the estimation of the labor-saving technical change. Section 5 details the calibration procedure and shows how the model fits data moments not targeted in the calibration. Section 6 presents the counterfactual results, and Section 7 concludes.

2 Institutional Background and Data

2.1 Agricultural Technical Change

The legalization and widespread adoption of genetically modified (GM) soy seeds in Brazil marked a significant technological advancement in the agricultural sector. This section outlines the institutional context surrounding the legalization and adoption of GM soybeans in Brazil and how it provides an exogenous shock to agricultural productivity for analyzing labor reallocation.

In the mid-1990s, advancements in agricultural biotechnology led to the development of genetically engineered crops. Notably, Monsanto's Roundup Ready soy seeds, the first generation of GM soy, were commercially released in the United States in 1996. These seeds are genetically modified to resist glyphosate, a broad-spectrum herbicide, allowing farmers to control weeds more efficiently without damaging the crop.

Brazil legalized the commercial cultivation of GM soybeans in 2003 through Law 10.688, following initial field tests approved by the National Technical Commission on Biosafety (CTNBio) in 1998. The adoption of GM soybeans in Brazil was swift and widespread. By 2006, GM soy adoption had surged to more than 40% of soy-planted areas, reaching approximately 85% by the 2011-2012 harvest season (IBGE 2006; United States Department of Agriculture (USDA) 2012).

The adoption of GM soybeans represents a significant labor-saving technological change in agriculture. Traditional soy cultivation involves labor-intensive soil preparation through tillage to remove weeds that compete with the crop for nutrients and water. In contrast, GM soybeans enable a shift to no-tillage practices. Farmers can use glyphosate to eliminate weeds selectively without harming the crop, reducing the need for repeated mechanical weed control and substantially lowering labor requirements. Data from the Agricultural Census indicate a marked reduction in labor intensity from 28.6 to 17.1 workers per 1,000 hectares between 1996 and 2006 (Bustos et al. 2016; IBGE 2006).

Following Bustos et al. (2016), to measure the exogenous variation in potential gains from adopting GM soybeans, I use the potential yield data for soybeans from the Food and Agriculture Organization's Global Agro-Ecological Zones (FAO-GAEZ) database. These estimates incorporate local soil, terrain, and climate conditions to predict maximum attainable yields, which result in variations across different geographical areas in Brazil. Moreover, a key feature of the data that allows me to measure the gains from GM soy is that it provides estimates of potential yields for different crops (including soybeans) under various input and management scenarios. Specifically, potential yield under "low-input" refers to the maximum attainable yields using *traditional crop varieties, labor-intensive techniques, and no application of fertilizers*. In contrast, "high-input" potential yield corresponds to the maximum attainable yields using *improved high-yielding crop varieties, full mechanization where possible, and optimum applications of nutrients and chemical pest, disease, and weed control*. The difference between these two captures the improvements in potential yields attributable to GM soy adoption. Crucially, these potential yields depend solely on exogenous agro-climatic factors and assumptions about the technology used, not actual farming practices or yields in Brazil. Figure A.1 shows substantial variations in the gains in potential yields across geographical regions due to differences in soil and weather characteristics.

2.2 Labor Regulation and Enforcement

Brazil's labor market is characterized by a stringent regulatory framework established in the Consolidação das Leis Trabalhistas (CLT) and further reinforced by the 1988 Federal Constitution. Formal employees work under regulated conditions, pay income taxes, and enjoy various benefits like pensions. In contrast, informal workers do not pay income or payroll taxes and are ineligible for these benefits. This category encompasses unregistered employees in non-compliant firms—which may employ both formal and informal workers—and most self-employed individuals.

In Brazil, every worker possesses a work card. When an employer signs a worker's work card, the hiring is officially reported to the government, and the individual is classified as a formal employee. However, formal hiring is costly, and although firms face penalties for not complying with labor laws, the chances of being caught are relatively low. As a result, informality continues to prevail at significant levels, even within nonfarm sectors, with approximately 26.9% of workers working informally between 2005 and 2009 (Gerard and Gonzaga 2021).

Furthermore, the high prevalence of informal workers also implies that enforcement of labor regulations is imperfect, revealing a discrepancy between official laws (*de jure* regulations) and their effective implementation (*de facto* regulations). Moreover, there is considerable heterogeneity in informality across Brazil's labor markets (Gerard and Gonzaga 2021), indicating substantial variation in enforcement capacity and intensity. This variation provides a unique opportunity to study the impact of *de facto* labor regulations on labor reallocation, as it allows for a more accurate measure of the regulatory burden firms face compared to *de jure* regulations.

To capture the variation in enforcement intensity across local labor markets in Brazil, I build on Almeida and Carneiro (2012) and use the number of inspections conducted between 1995 and 2003 in each municipality as a proxy for the predetermined intensity of labor regulation enforcement. I limit the measure to inspections conducted up to 2003 because the data is only available from 1995 onwards, and 2003 marks the year when genetically modified (GM) soy was legalized in Brazil.

Labor regulation enforcement is managed by the Ministry of Labor, which conducts inspections to ensure firms' compliance. The enforcement system is decentralized, with labor offices (delegacias) located in each state's capital and smaller local labor offices (subdelegacias) spread across municipalities within states. The number of subdelegacias in each state varies based on the state's size and economic significance (Almeida and Carneiro 2012). Labor inspectors are assigned to specific subdelegacias and travel by car to inspect companies within their jurisdiction. During these inspections, labor inspectors check whether companies comply with various aspects of the labor code, such as worker registration, payment of minimum wages, adherence to maximum working hours, and contributions to social security and severance pay funds (FGTS). Violations can lead to substantial fines (Almeida and Carneiro 2012).

2.3 Data Sources

This section outlines the three data sources used in the empirical analysis. The first source is the Brazilian Population Census for 1991, 2000, and 2010. The Census provides comprehensive information on individuals' socioeconomic characteristics and labor market outcomes of a sample representative at the municipal level. For my analysis, I primarily use the 2000 and 2010 Census data to construct measures of sectoral employment shares (both formal and informal) and baseline municipality control variables.

To calculate the employment share in agriculture and manufacturing, I divide the number of individuals who reported agriculture or manufacturing as the sector of their main job by the total number of individuals employed during the reference period. Employment is defined broadly as anyone who reported working during the reference week, regardless of whether the job was permanent or seasonal. This definition also encompasses individuals who worked without pay to assist someone in their household and those engaged in subsistence agriculture or fishing. Additionally, individuals temporarily away due to holidays, strikes, or leave are counted as employed.

For respondents who reported working during the reference period, information on the type of activity is also available. For example, whether they are a public servant or work for the military, employees with/without a formal contract, employers, or self-employed[2]. In this paper, for manufacturing employment, I define formal employment as private employees with a formal contract (work card signed by the employer) and informal employment as private employees without a formal contract plus self-employment. Formal/informal employment is defined similarly for agriculture. However, most of the farm establishments are family farms. As shown in Table 1, 84.4% of establishments in Brazil's agricultural sector in 2006 were family farms, which accounts for 74.3% of total personnel working in agriculture. Family members working on family farms are not required to hold a formal contract. Hence, the vast majority of employment in agriculture can be considered informal in this sense.

The sample is restricted to individuals aged 18 to 55 who were not attending school at the time of the Census. The original data, collected at the individual level, are aggregated to the municipality level using the individual sampling weights provided by the Brazilian Institute of Geography and

[2]Respondents' self-reports of being formal or informal workers is reliable because the Brazilian Institute of Geography and Statistics (IBGE) enforces strict confidentiality policies to ensure that personal information is not accessible to other government agencies for law enforcement or tax collection purposes.

Table 1: The Agricultural Sector in Brazil

	Num. of Establishments		Area of Land		Personnel Employed	
	(millions)	%	(millions ha)	%	(millions)	%
Total	5.18		333.68		16.57	
Family Farm	4.37	**84.4%**	80.10	24.0%	4.25	**74.3%**
Non-Family Farm	0.81	15.6%	253.58	76.0%	12.32	25.5%

Source: Agricultural Census (IBGE, 2006). Data are downloaded from SIDRA.

Statistics (IBGE) and further aggregated to the level of AMC (minimum comparable areas) based on a mapping developed by IPEA and IBGE.

The second data source is the FAO Global Agro-Ecological Zones (GAEZ) database, which provides estimates of potential yields for various crops across different geographical areas. These estimates incorporate local soil, terrain, and climate characteristics to predict the maximum attainable yields for each crop in a given area. The database also reports potential yields under different input and management assumptions. Potential yields under low-level inputs and traditional management are defined as those obtained using traditional crop varieties, labor-intensive techniques, and no application of fertilizers or chemicals. In contrast, high-level inputs and advanced management yields are achieved using improved high-yielding crop varieties, full mechanization where possible, and optimum applications of nutrients and chemical pest, disease, and weed control. The difference between these two potential yields serves as a measure of technological change in the production of soy and maize crops. The raw data is available at a 5 arc-minute resolution, which I aggregate to the municipality level. However, municipal borders often change, so to ensure comparability over time, IBGE has defined *Área Mínima Comparável* (AMC), or the minimum comparable areas, which I use as the unit of observation throughout the analysis. The average AMC is slightly larger than the average municipality. According to data from the 2000 population census, the average AMC has a population of 39,866 inhabitants, whereas the average municipality has 30,846 inhabitants (IBGE 2000).

The third data set contains administrative data from the Ministry of Labor related to enforcement activity. This dataset contains yearly information on the number of firms inspected by the municipality from 1995 to 2019, the sector of activity the firm is in, the number of inspectors responsible for the auditing process in each state of the country, and the locations of all labor offices. This data set is combined with the date of creation of each labor office (i.e., subdelegacia) collected by Ponczek and Ulyssea (2022) and the driving distance to the nearest labor office in each municipality, the distance to the state's capital and the number of inspectors at the state level compiled by Almeida and Carneiro (2012). Figure A.2 illustrates the regional variation in the number of inspections per hundred firms between 1995-2003, alongside the locations of all ninety-two local labor offices (subdelegacias) created before 1990 in Brazil.

Table 2 provides the descriptive statistics of the variables used in the analysis, which are all at the AMC level. Additional data are used for constructing data moments to estimate the parameters of the structural model, described in Section 5.

Table 2: Descriptive Statistics

Variable	**2000**		**2010**		**2000-2010**	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
% Agriculture Emp.	0.425	0.208	0.352	0.190	-0.072	0.081
% Formal Agric. Emp.	0.062	0.075	0.061	0.069	-0.00058	0.041
% Informal Agric. Emp.	0.363	0.219	0.291	0.194	-0.043	0.089
% Manufacturing Emp.	0.107	0.093	0.122	0.107	0.015	0.062
% Formal Manuf. Emp.	0.057	0.077	0.085	0.097	0.028	0.053
% Informal Manuf. Emp.	0.050	0.040	0.037	0.033	-0.013	0.032
Log population density	3.325	1.345				
Log Average Income	6.518	0.440				
Share of Urban Population	0.605	0.216				
Literacy Rate	0.812	0.11				

Variable	Mean	Std Dev
ΔA^{soy}	1.799	0.855
$\log$ Inspec.	1.284	1.163
Distance to the LO (per 100 km)	0.884	0.718

3 Local Effects of Labor-Saving Technical Change on Labor Reallocation

The empirical analysis is structured into two sections. The first section investigates the impact of technological advancements in agriculture on labor reallocation, with a particular emphasis on dissecting employment by formality status.

The equation to be estimated in this section is

$$EmpShare_{rt} = \delta_r + \delta_t + \beta A^{soy}_{rt} + \epsilon_{rt}, \tag{1}$$

where r indexes municipalities, t denotes time, δ_r and δ_t are municipality- and time-fixed effects respectively. The dependent variables, denoted as $EmpShare_{rt}$, represent the employment shares within municipality r at time t. Separate regressions are conducted for overall, formal, and informal employment shares of either agriculture or manufacturing. Given that the employment shares are derived from the 2000 and 2010 population censuses (i.e., $t = \{2000, 2010\}$), and fixed effects estimates are equivalent to first-difference estimates when only two periods are considered, I estimate Equation 1 using first differences. The independent variable A_{rt}^{soy} corresponds to the potential yields of soy. For each municipality r, A_{rt}^{soy} is assigned the estimates of potential yields under low inputs in 2000 and under high inputs in 2010. Therefore, taking the difference yields ΔA_r^{soy},which captures the potential gains from adopting GM soy in each municipality (Bustos et al. 2016).

A potential concern is that although the soil and weather characteristics that drive the variation in A_{rt}^{soy} across geographical areas are exogenous, they might be correlated with initial levels of development across Brazilian municipalities. To mitigate this concern, I incorporate a set of baseline municipality-level controls to capture differential trends across municipalities with varying initial characteristics. These controls include the logarithm of average household income, the logarithm of population density, the share of urban population, and literacy rate. The full specification is presented below:

$$\Delta EmpShare_{sr} = \Delta\delta + \beta\Delta A_{sr}^{soy} + \mathbf{X}'_{sr,2000}\omega + \gamma EmpShare_{1991,sr} + \alpha_s + \varepsilon_{sr} \tag{2}$$

The vector $\mathbf{X}'_{sr,2000}$ includes baseline municipality-level control variables measured in 2000. Additionally, state fixed effects α_s are included to account for state-level trends. To address potential "catch-up" effects, lagged sectoral employment shares from 1991 are included. It controls for the possibility that municipalities with initially lower manufacturing employment may experience faster growth independent of technological changes.

Table 3 presents the results from these regressions. Columns (1) and (5) show the results for municipality r's changes in agriculture and manufacturing employment shares between 2000 and 2010, respectively.[3] Columns (6) and (7) present the effects of ΔA_{sr}^{soy} on the share of formal and informal manufacturing employment shares, respectively. The results indicate that municipalities where the potential soy yields increased by one standard deviation would experience a 1.02 percentage points (17.9%) increase in the formal manufacturing employment share, which is larger than the 0.91 percentage points rise in the share of overall manufacturing employment. This might be due to the additional 0.15 percentage points (3%) decrease in the informal manufacturing employment

[3]These results replicate those from Bustos et al. (2016). In their study, in addition to GM soy, which they identify as a strongly labor-saving technological change, they also examine the introduction of a second harvesting season for maize, characterized as a land-augmenting technological change. They argue that the impact of agricultural production on industrialization significantly depends on the factor bias of technological change. While the regressions in this paper include the same ΔA^{maize} shock as a control, the estimates for maize are omitted from the main text to maintain focus but are included in the appendix for robustness.

share. Together, the results suggest that technological advancements in agriculture not only drive a shift of workers into the manufacturing sector but may also facilitate a reallocation from informal to formal employment within the industry.

Table 3: OLS-Changes in Sectoral Employment Shares, 2000-2010

	Agriculture				Manufacutring			
	Overall (1)	Formal (2)	Informal (3)	Inf. Rate (4)	Overall (5)	Formal (6)	Informal (7)	Inf. Rate (8)
ΔA^{soy}	-0.00860***	-0.00744***	-0.00946***	-0.00810	0.0107***	0.0119***	-0.00180*	-0.00914
	(0.00210)	(0.00135)	(0.00234)	(0.00834)	(0.00254)	(0.00226)	(0.00104)	(0.00620)
Observations	4251	4251	4251	4251	4251	4251	4251	4251
R^2	0.425	0.115	0.245	0.221	0.230	0.252	0.0955	0.133

Notes: Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Each observation corresponds to a minimum comparable area, analogous to a municipality, but remains consistent over time. The dependent variables in columns (1) to (3) are changes in the share of overall/formal/informal employment in agriculture between 2000 and 2010, while in column (4) is the change in informality rate in each sector (total informal agriculture employment/ total agriculture employment). Columns (5) - (8) are similar variables but for manufacturing. Informal workers are defined as those without a signed work card from their employer, while formal workers are those with a signed work card. ΔA^{soy} denotes the technical change in agriculture. For further details on data sources and variable construction, refer to Section 2.3. Baseline municipality controls include the share of urban population, log population density, log average household income, and literacy rate, all sourced from the 2000 Brazilian population census. Each regression also includes a set of state dummies to account for any state-level trends. Furthermore, to account for the potential "catch-up" effects, columns (1) and (5) also include the lagged sectoral employment shares in 1991, while columns (2) – (4) and (6) – (8) additionally include the lagged overall rate of informality in 1991. The regressions are also weighted by the population of each AMC in 2000.

Next, I investigate the role of regulatory enforcement by interacting ΔA^{soy}_{sr} with the logarithm of the total number of inspections conducted between 1995 and 2003—before the widespread adoption of GM soy seeds—in each state s and municipality r.[4] The regression model is specified as follows:

$$\begin{aligned}\Delta EmpShare_{sr} = \Delta\delta + \beta_1 \Delta A^{soy}_{sr} + \beta_2 \Delta A^{soy}_{sr} \times \log Inspec_{sr} \\ + \beta_3 \log Inspec_{sr} + \gamma EmpShare_{1991,sr} + \mathbf{X}'_{sr,2000}\omega + \alpha_s + \varepsilon_{sr}\end{aligned} \tag{3}$$

The coefficient of interest is β_2, which captures the extent to which regulatory enforcement moderates the impact of soy productivity shocks on labor reallocation. More specifically, it reflects whether municipalities with more stringent enforcement experience different labor market outcomes in response to technological change than those with weaker enforcement.

Table 4 presents the results for these regressions. Columns (1) to (4) of Table 4 focus on the agricultural sector. The interaction term $\Delta A^{soy} \times \log Inspec.$ in column (1) is positive but not statistically significant, suggesting that enforcement does not significantly impact the overall decline in agricultural employment induced by the technological shock. However, a more nuanced pattern emerges when I disaggregate agricultural employment by formality status. The positive and

[4] $\log Inspec_{sr}$ is weighted by the total number of firms in the municipality to account for the fact that larger municipalities with more firms may have more inspections conducted.

statistically significant estimates on the interaction term in column (2) show that in municipalities with more intensive regulatory enforcement, there is less reallocation of formal employment from agriculture.

Table 4: OLS-Changes in Sectoral Employment Shares, 2000-2010

	Agriculture				Manufacutring			
	Overall	Formal	Informal	Inf. Rate	Overall	Formal	Informal	Inf. Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔA^{soy}	-0.0116***	-0.00932***	-0.0121***	-0.00559	0.0174***	0.0180***	-0.00147	-0.0264***
	(0.00256)	(0.00145)	(0.00312)	(0.0103)	(0.00277)	(0.00243)	(0.00126)	(0.00741)
ΔA^{soy} × Log Inspec.	0.00147	0.000924*	0.000972	-0.00174	-0.00342***	-0.00290***	-0.000292	0.00866***
	(0.00109)	(0.000540)	(0.00126)	(0.00356)	(0.000983)	(0.000826)	(0.000503)	(0.00262)
Observations	4251	4251	4251	4251	4251	4251	4251	4251
R^2	0.426	0.117	0.250	0.221	0.235	0.259	0.0965	0.138

Notes: Robust standard errors are reported in parentheses, with ***, **, and * indicating significance at the 1%, 5%, and 10% levels, respectively. Each observation represents a minimum comparable area, which remains consistent over time, similar to a municipality. The dependent variables in columns (1) to (3) are changes in the share of overall/formal/informal agricultural employment from 2000 to 2010, while column (4) captures the change in agricultural informality (informal employment/total agricultural employment). Columns (5) to (8) present similar variables for manufacturing. Informal workers are those without a signed work card, while formal workers have one. ΔA^{soy} denotes technical change in agriculture, and "Log Inspec." refers to the log of inspections per 100 firms from 1995-2003, before GM soy legalization. Inspection data are from the Ministry of Labor. For more information on data sources and variable construction, refer to Section 2.3. All regressions include baseline municipality controls, such as urban population share, log population density, log average household income, and literacy rate, sourced from the 2000 Brazilian census. State dummies account for state-level trends. To address potential "catch-up" effects, columns (1) and (5) also include lagged sectoral employment shares from 1991, while columns (2) to (4) and (6) to (8) include the lagged informality rate from 1991. Regressions are weighted by each AMC's 2000 population.

Turning to the manufacturing sector, the main effect of ΔA^{soy}_{sr} on manufacturing employment in column (5) is positive and significant, indicating that technological improvements in soy lead to increased manufacturing employment. However, the interaction term is negative and significant, implying that this positive effect is weaker in municipalities with more intensive regulatory enforcement. Disaggregating further estimates from columns (6) and (7) show that regulatory enforcement dampens formal manufacturing employment growth while informal manufacturing employment remains largely unaffected.

These findings indicate that while increases in the potential yield of soy drive labor from agriculture to manufacturing, this reallocation is less pronounced in areas with more intensive enforcement. Moreover, enforcement intensity influences not only the extent of labor reallocation but also the type of employment created, with formal employment growth significantly constrained by more robust regulatory frameworks.[5].

However, using the number of inspections to measure enforcement intensity presents empirical challenges because enforcement is not randomly distributed across municipalities. Enforcement may be more stringent in areas with higher reports of labor violations or in municipalities with

[5] Almeida and Poole (2017) explores how trade openness impacted labor markets in Brazil during the 1999 currency crisis. They find that stricter enforcement of labor regulations reduces job creation and increases job destruction, particularly in small, labor-intensive, non-exporting plants.

stronger institutional frameworks. To address these issues, following Ponczek and Ulyssea (2022), I employ the distance to the nearest labor office (Dist_{sr}) and the interaction between Dist_{sr} and the number of inspectors at the state level (Inspector_s) as instruments for Log Inspec._{sr}.

As discussed in Section 2.2 and demonstrated by Almeida and Carneiro (2012), the level of enforcement of labor regulations in a city is influenced by two key factors: the proximity to the nearest local labor office and the number of inspectors per state. Greater distance to a labor office implies higher travel costs for inspectors, which result in lower inspection rates. Similarly, fewer inspectors means that each inspector must cover a larger area, leading to lower inspection frequency.

Table 5: First Stage - Inspections and Distance to LO

	Total	Agriculture	Manufacturing
Distance L.O.	-0.248***	-0.614***	-0.111*
	(0.0347)	(0.0776)	(0.0581)
Inspectors × Distance L.O.	0.000734***	0.000902	0.00187***
	(0.000260)	(0.000688)	(0.000409)
Observations	4251	4251	4251
R^2	0.349	0.210	0.291

Notes: Robust standard errors are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. Municipality controls include the share of urban population, log population density, log average income, and literacy rate, all based on the 2000 Brazilian census. The dependent variable in all columns is the log of total inspections per 100 firms in municipality r from 1995-2003 (before widespread GM soy adoption). Firm inspection data is from the Ministry of Labor. Column (1) covers all industries, while columns (2) and (3) focus on agriculture and manufacturing, respectively. Each column includes an interaction between the state-level number of inspectors (weighted by the total number of firms) and distance to the nearest labor office, as well as state dummies and all baseline municipality controls.

The first-stage results, presented in Table 5, confirm that the number of inspections per hundred firms decreases with increasing distance to labor offices and increases with the number of inspectors. This pattern holds when aggregating inspections targeted at firms across all sectors and within the manufacturing sector alone. Table 6 displays the two-stage least squares (2SLS) estimates. Consistent with the previous OLS results, the estimates in column (5) suggest that a one standard deviation increase in enforcement intensity reduces labor reallocation from agriculture to manufacturing by 29.3%. Additionally, column (6) shows that formal employment growth in the manufacturing sector decreases by 30.6%. These findings support the notion that regulatory constraints significantly shape the dynamics of labor market adjustments in response to technological change.

4 Structural Model

The findings from the previous section highlight the important role of regulatory enforcement in mediating the process of labor reallocation resulting from technological advancements in agriculture. To assess the broader economic implications and explore potential policy counterfactuals, I develop a model that builds on the frameworks of Hopenhayn (1992) and Ulyssea (2018). This model integrates heterogeneous firms' decisions to operate formally or informally under costly regulations within a two-sector framework encompassing agriculture and manufacturing.

4.1 The Agricultural Sector

The agricultural sector is characterized by a representative producer who operates outside the scope of labor regulations. This assumption is grounded in two key data observations: first, informal employment in agriculture accounts for approximately 75% of total employment across municipalities (Table 1); second, fewer than 5% of labor inspections conducted between 2000 and 2019 were on agricultural establishments. Moreover, to capture the factor-biased technical change associated with genetically modified (GM) soy, I employ the constant elasticity of substitution (CES) production function introduced by (Arrow et al. 1961):

$$Y_{At} = \left[\gamma(A_{Lt}L_t)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_{Tt}T_t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{4}$$

where A_{Lt} and A_{Tt} represent labor-augmenting and land-augmenting technical changes, respectively. The parameter γ denotes the relative weight on labor, and $\sigma > 0$ captures the elasticity of substitution between labor and land. Importantly, when the elasticity of substitution between land and labor is less than one, an increase in A_{Lt} leads to the reallocation of labor from agriculture to manufacturing.

4.2 The Manufacturing Sector

The manufacturing sector comprises a continuum of heterogeneous firms, each characterized by its idiosyncratic productivity level, z. These firms are subject to labor regulations and taxes; however, they can evade these costs by choosing to operate informally. Nevertheless, operating outside the regulatory framework incurs an increasing and convex informality penalty, denoted as $\tau_i(\ell)$.

Firms use the same production technology, with labor as the only input. The production function

Table 6: IV - Changes in Sectoral Employment Shares, 2000-2010

	Agriculture				Manufacturing			
	Overall	Formal	Informal	Informality Rate	Overall	Formal	Informal	Informality Rate
ΔA^{soy}	0.0132	-0.0136**	-0.00314	-0.0217	0.0532***	0.0612***	-0.00316	-0.0791***
	(0.0107)	(0.00554)	(0.00989)	(0.0253)	(0.0166)	(0.0174)	(0.00389)	(0.0268)
$\Delta A^{soy} \times$ Log Inspec.	0.0110**	0.000662	-0.00187	0.00511	-0.0134*	-0.0154*	0.00113	0.0216*
	(0.00549)	(0.00275)	(0.00500)	(0.0132)	(0.00797)	(0.00793)	(0.00188)	(0.0121)
Observations	4251	4251	4251	4251	4251	4251	4251	4251
R^2	0.376	-0.585	0.164	0.208	-1.654	-2.599	0.0782	-0.0669
Kleibergen-Paap rk LM statistic	49.01	47.74	47.74	47.74	58.52	55.24	58.61	66.06
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap rk Wald F statistic	15.20	15.11	15.11	15.11	15.45	14.08	15.64	18.21
Hansen J Test p-value	0.927	0.464	0.351	0.562	0.293	0.685	0.899	0.613

Notes: Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. This table reports the IV results from instrumenting Log Inspec.$_{sr}$ using the distance to labor office Dist$_{sr}$ and interaction between Dist$_{sr}$ and the number of inspectors at the state level (Inspectors$_s$) (Ponczek and Ulyssea 2022). Each observation corresponds to a minimum comparable area, analogous to a municipality, but remains consistent over time. The dependent variables in columns (1) to (3) are changes in the share of overall/formal/informal employment in agriculture between 2000 and 2010, while in column (4) is the change in the informality rate in agriculture (total informal agriculture employment/ total agriculture employment). The dependent variables from Columns (5) - (8) are similar but for manufacturing. Formal workers are measured as private employees whose work card is signed by the employer. Informal workers are measured as private employees whose work card is not signed or self-employed. ΔA^{soy} denotes the technical change in agriculture. Log Inspec.$_{sr}$ is equal to the log of the total number of inspections per hundred firms between 1995-2003 (before the legalization of GM soy). The inspection data are from the Ministry of Labor. For further details on data sources and variable construction, refer to Section 2.3. All regressions include baseline municipality controls, such as the share of urban population, log population density, log average household income, and literacy rate, all sourced from the 2000 Brazilian population census. Each regression also includes a set of state dummies to account for state-level trends. Furthermore, to account for the potential "catch-up" effects, columns (1) and (5) also include the lagged sectoral employment shares in 1991, while columns (2) – (4) and (6) – (8) additionally include the lagged overall rate of informality in 1991. The regressions are also weighted by the population of each AMC in 2000.

for a firm in sector M is given by:

$$y_M(z,\ell) = z\ell^{\alpha},$$

where z denotes the firm's idiosyncratic productivity, ℓ is the firm's employment, and $\alpha < 1$ is the decreasing returns to scale parameter. Labor is homogeneous, which implies that formal and informal firms pay the same wage.[6] Formal and informal firms produce a homogeneous good and face the same price in the competitive market.

The dynamics in this model are driven by the evolution of firms' idiosyncratic productivity, z. I assume that the idiosyncratic productivity z evolves according to the following AR(1) process:

$$\log z_{t+1} = \rho^z \log z_t + \sigma^z \epsilon^z_{t+1}, \quad \rho^z \in (0,1), \quad \epsilon^z \sim N(0,1), \tag{5}$$

where ρ^z_M is the persistence parameter, σ^z is the standard deviation of the productivity shocks, and ϵ^z is a standard normal random variable. The productivity process is assumed to be the same for formal and informal firms and independent across firms.[7]

Informal incumbents Informal firms can avoid paying taxes and complying with labor regulations. However, they face an informality cost, $\tau_i(\ell)$, defined as $\tau_i(\ell) = \frac{\ell^2}{b}$.[8] In this equation, ℓ represents employment, and b is a parameter that determines the rate at which the informality penalty increases with firm size.

Specifically, a lower value of b implies that the cost of informality rises more rapidly as the firm grows. Consequently, in equilibrium, this leads to a lower rate of informality or fewer informal firms, all else being equal. This relationship can be interpreted as a reflection of more stringent enforcement of labor regulations. Moreover, the increasing nature of $\tau_i(\ell)$ captures the reality that larger firms face greater challenges in evading government oversight. As firms expand, they become more visible and thus more susceptible to detection by labor inspectors. The parameter b is later calibrated and utilized in counterfactual exercises to analyze the impact of varying enforcement intensities on the effects of labor-saving technical change (A_L).

[6] This assumption is supported by the findings of Ulyssea (2018), who uses matched employer-employee data from the ECINF survey to show that the within-firm formal-informal wage gap becomes negligible and statistically insignificant once firm fixed effects are accounted for.

[7] As noted by Dix-Carneiro et al. (2021) and Ulyssea (2018), due to the lack of longitudinal data on informal firms in Brazil, this process cannot be separately estimated for formal and informal firms.

[8] The informality cost function, $\tau_i(\ell)$, serves as a "reduced-form" representation of the various potential costs associated with operating informally. These costs may include the risk of being detected by labor inspectors and the consequent financial penalties.

The profit function of an incumbent informal firm is defined as:

$$\pi_i(z,\ell) = p_M y(z,\ell) - w\ell - \bar{c}_i - \tau_i(\ell),$$

where p_M denotes the price of manufacturing output, and w denotes the wage rate, both taken as given by firms. The term $\bar{c}_i$ refers to the per-period fixed cost of operating as an informal firm, while $\tau_i(\ell)$ captures the informality cost associated with employment level ℓ.

In each period, incumbent firms decide whether to exit the market or continue operating. Informal firms have the additional option to formalize their status, whereas formal firms cannot revert to being informal. This is because evading regulation becomes significantly more difficult once a firm is registered and becomes visible to government authorities. Beyond endogenous exits, incumbents may also face exogenous shocks that compel them to exit. The probability of exogenous exits is denoted by δ_i for informal incumbents and δ_f for formal incumbents.

Hence, the value function of an incumbent informal firm is expressed as:

$$V_i(z,\ell_{-1}) = (1-\delta_i)\max\{0, V_i^{NE}(z,\ell_{-1}), V_i^F(z,\ell_{-1}) - c_{for}\} \tag{6}$$

Here, an incumbent informal firm receives 0 upon exiting the market, either exogenously or endogenously. Whereas $V_i^{NE}(z,\ell_{-1})$ is the value of continuing operations as an informal firm, and $V_i^F(z,\ell_{-1})$ denotes the value obtained if the informal firm decides to formalize. The term c^{for} represents the cost associated with formalization. They are written as follows:

$$V_i^{NE}(z,\ell_{-1}) = \max_{\ell}\{\pi_i(z,\ell) + \beta\mathbb{E}_{z'|z}V_i(z',\ell)\}$$
$$V_i^{F}(z,\ell_{-1}) = \max_{\ell}\{\pi_f(z,\ell) + \beta\mathbb{E}_{z'|z}V_f(z',\ell)\}$$

Solving Equation 6 yields three policy functions: the employment policy function $L_i'(z,\ell_{-1})$, the exit policy function $\chi_i(z,\ell_{-1})$, and the formalization policy function $\zeta_i(z,\ell_{-1})$.

Formal incumbents Formal firms, in contrast, are subject to payroll taxes and are prohibited from employing workers informally to circumvent these costs.[9] The profit function of formal firms is thus given by

$$\pi_f(z,\ell) = p_M y(z,\ell) - (1+\tau_w)w\ell - p_M\bar{c}_f$$

[9]Using Brazilian firm-level data, Ulyssea (2018) shows that the intensive margin of informality, that is, informal workers hired by formal firms, is both large and important. However, allowing only the extensive margin of informality should not affect the main results of this paper.

where ℓ denotes firms' current total employment, τ_w represents the payroll tax and $\bar{c}_f$ is a fixed cost of operation. The value function of a formal incumbent firm is expressed as:

$$V_f(z, \ell_{-1}) = (1 - \delta_f) \max\{0, \max_{\ell}\{\pi_f(z, \ell) + \beta \mathbb{E}_{z'|z} V_f(z', \ell)\}\} \tag{7}$$

where δ_f represents the probability that the firm experiences an exogenous shock that makes it exit.

Entrants The model also considers the entry of new firms into the manufacturing sector. In each period, there are M potential entrants who are ex-ante identical. After incurring a sunk cost c^e of entry, they observe their productivity z, drawn from the distribution $G(z)$. Based on their productivity, entering firms choose to operate as formal or informal entities or exit the market immediately. Formal and informal entrants start producing in the next period. The value at entry is, therefore, given by

$$V^e = \beta \mathbb{E}_{z'} \max\{V_f^e(z'), V_i^e(z'), 0\} \tag{8}$$

where the value function of entering as a formal firm is defined as

$$V_f^e(z) = \max_{\ell} \pi_f(z, \ell) + \beta \mathbb{E}_{z'|z} V_f(z', \ell)$$

and the value function of entering as an informal firm is given by

$$V_i^e(z) = \max_{\ell} \pi_i(z, \ell) + \beta \mathbb{E}_{z'|z} V_i(z', \ell)$$

Solving Equation 8 yields the entry policy functions. When the mass of entrants $M > 0$, the free entry condition requires that the value at entry equals the entry cost, that is:

$$V^e = c^e$$

4.3 Household

The economy is populated by an infinitely-lived representative household that owns the firms and supplies a fixed amount of labor each period, denoted by $\bar{L}$. The household's preferences are represented by:

$$\sum_{t=0}^{\infty} \beta^t u(c_{At}, c_{Mt})$$

where c_{At} and c_{Mt} denote the consumption of goods A and M at time t, respectively, and β is the discount factor. The household allocates all of its income to consumption, which is defined as:

$$I_t = w_t \bar{L} + \Pi_t + T_t + R_t$$

In this equation, $w_t \bar{N}$ represents total wage income, Π_t denotes total profits generated by firms, T_t refers to total tax revenues rebated to the household, and $R_t = r_t T_A$ is the total rental income from land. Moving forward, I consider a stationary economy and simplify the notation by dropping the time subscript. By abstracting from intertemporal decisions, the household's problem effectively becomes a sequence of static problems.

Preferences The household's instantaneous preferences over c_A and c_M are assumed to be non-homothetic, which generates shifts in sectoral demand associated with structural transformation (Kongsamut et al. 2001). These preferences are parametrized to fall within the Price-Independent Generalized Linear (PIGL) class, implicitly defined by the indirect utility function. I use a simplified version of the original formulation by Boppart (2014), as proposed by Eckert and Peters (2022):

$$v(p_A, p_M, e) = \frac{1}{\eta} \left(\frac{e}{p_A^{\phi} p_M^{1-\phi}} \right)^{\eta} - \nu \ln \left(\frac{p_A}{p_M} \right) \tag{9}$$

where $\eta, \phi \in (0, 1)$.

Applying Roy's Identity, the expenditure share allocated to each sectoral consumption $c \in \{A, M\}$ by the representative household with total spending $e = I$ is derived as:

$$\theta_A = \phi + \nu \left(\frac{I}{p_A^{\phi} p_M^{1-\phi}} \right)^{-\eta} \tag{10}$$

$$\theta_M = 1 - \theta_A = (1 - \phi) - \nu \left(\frac{I}{p_A^{\phi} p_M^{1-\phi}} \right)^{-\eta}$$

When both $\eta > 0$and $\nu > 0$, Equation 10 indicates that the share of expenditure allocated to agricultural goods, denoted as θ_A, decreases as income increases. Moreover, θ_A asymptotically approaches ϕ as incomes grow large. Conversely, if $\nu = 0$, preferences simplify to a standard Cobb-Douglas structure, resulting in constant expenditure shares on agriculture and manufacturing at ϕ and $1 - \phi$, respectively, regardless of income. The parameter η determines the responsiveness of demand to changes in real income. A larger value of η signifies greater sensitivity of demand to income variations.

4.4 Equilibrium

A stationary equilibrium is a set of allocations, wages, prices, and distributions $\{w, p_M, Y_A, Y_{Mj}, L_A, L_{Mj}, M, \mu_{Mj}\}$, where $j \in \{f, i\}$, that remain constant over time and satisfy the following conditions in every period:

1. Firms optimize:
   - Incumbent firms make optimal decisions regarding employment $\ell_j(z, \ell_{-1})$, exit $\chi_j(z, \ell_{-1})$, and formalization $\zeta_j(z, \ell_{-1})$ based on their productivity z and previous employment ℓ_{-1}.
   - New entrants make optimal entry and formality status decisions based on their initial productivity draw z.
   - The free entry condition holds with equality with positive entry: $V^e = c^e$ if $M > 0$.
2. Labor market clears: $L_A + \sum_j \int L_{Mj}(z, \ell_{-1})\, d\mu_{Mj}(z, \ell_{-1}) = \bar{L}$.
3. Product markets clear.
4. In a steady-state equilibrium, the distributions of states (z, ℓ) by sector and firm type, along with all aggregate variables, remain unchanged over time. This implies:
   - The number of firms entering the informal sector must equal the number of informal firms that either exit or formalize their business.
   - The number of new entrants to the formal sector plus the number of informal firms that formalize must equal the number of formal firms that exit (both endogenously or exogenously).

5 Model Calibration

The model is solved numerically using fixed-point iteration to determine the value functions and stationary distributions and least squares methods to solve for the equilibrium price and wage. This section outlines the calibration process of the model presented in Section 4. The calibration is conducted in two steps. First, a subset of parameters is calibrated externally based on aggregate data, estimates from existing literature, and statutory values of institutional parameters, such as sales and payroll taxes. Second, the remaining parameters are calibrated using the Simulated Method of Moments (SMM).

5.1 Externally Set Parameters

Externally set parameters are summarized in Table 7. Following Ulyssea (2018), the payroll tax rate is set to its statutory values: $\tau_w = 0.375$ [10]. The discount factor β is set at 0.9259, reflecting an annual discount rate of 8%, as per Heckman and Pagés (2000). The standard deviation of productivity shocks, σ^z, is set to 0.197, based on estimates by Dix-Carneiro et al. (2021) for manufacturing firms in Brazil[11]. The persistence parameter of the productivity process, ρ^z, is internally calibrated to target several moments of the formal and informal firm size distributions shown in Table 9. The elasticity of substitution between labor and land in the CES agricultural production function, σ, is set at 0.289, following Chirinko and Mallick (2017). Lastly, for the preference parameter ϕ, which corresponds to the asymptotic spending share on agricultural value added for very high incomes, I set it equal to 0.01, which is close to the agricultural employment share in the U.S. in 2020.

Table 7: Externally Calibrated Parameters

Parameter	Description	Source	Value
τ_w	Payroll tax	Ulyssea (2018)	0.375
β	Discount factor	Heckman and Pagés (2000)	0.9259
σ^z	Productivity AR(1) Process, Std. Dev. of Shock	Dix-Carneiro et al. (2021)	0.197
σ	elasticity of substitution in Agric. CES prod. function	Chirinko and Mallick (2017)	0.289
ϕ	Asymptotic Expenditure Share on Agriculture		0.01

5.2 Calibrated Parameters

The remaining parameters are jointly calibrated using the Method of Simulated Moments (SMM). Let Θ denote the vector of parameters to be calibrated:

$$\Theta = \{\alpha, \bar{c}_f, \bar{c}_i, \delta_f, \delta_i, b, c^e, c^{for}, \phi, \eta, \nu, \rho^z\}$$

, where α is the span of control parameter for firms in the manufacturing sector; $\bar{c}_f$ and $\bar{c}_i$ are the per-period fixed costs of operation for formal and informal firms, respectively; δ_f and δ_i represent the exogenous death shocks for formal and informal firms; b is the parameter that governs the informality penalty $\tau_i(\ell)$; c^e is the entry cost; c^{for} is the formalization cost that informal firms must pay if they choose to formalize; and ϕ, η, and ν are the parameters of the non-homothetic

[10] More Specifically, as described in Ulyssea (2018), τ_w represents the main taxes proportional to firms' wage bills, including the employer's social security contribution (20%), payroll tax (9%), and contributions to the severance indemnity fund, known as the *Fundo de Garantia do Tempo de Serviço* (FGTS) (8.5%).

[11] Following Dix-Carneiro et al. (2021), it is assumed that formal and informal firms in the manufacturing sector share the same productivity process.

preferences for consumption of the representative household.

The calibration procedure minimizes the distance between a set of moments generated by the model, $\mathbf{m}(\Theta)$, and their empirical counterparts, $\hat{\mathbf{m}}$:

$$\hat{\Theta} = \arg\min_{\Theta} ||\mathbf{m}(\Theta) - \hat{\mathbf{m}}|| \tag{11}$$

Moments and Identification Idea The targeted moments and their sources are summarized in Table 8. The parameter b, which dictates the cost of informality, is identified by observing how the share of informal firms varies with firm size. The function $\tau_i(\ell_i)$ increases with firm size, meaning that as firms grow larger, the cost of remaining informal also rises. Consequently, the share of informal firms decreases with increasing firm size. The rate at which the cost of informality escalates with firm size, and thus the rate at which the share of informal firms declines, is fundamentally determined by b. A lower value of b would indicate a steeper increase in the cost of informality with firm size, leading to a more rapid decline in the share of informal firms as they grow larger. Conversely, a higher value of b would suggest a more gradual increase in costs and a slower decline in the share of informal firms.

Table 8: Calibrated Parameters and Moments

	Description	Value	Moment	Source
α	Span of Control	0.75	% of Employment in Agric.	PNAD
$\bar{c}_f$	Fixed Cost, Formal	0.99	% Infor. Employment in Manuf.	PNAD
$\bar{c}_i$	Fixed Cost, Informal	0.74	Avg. Informal Manuf Firm Size	ECINF
δ_f	Exo. Exit Prob., Formal	0.044	% of Informal Firms Size ≥ 3	ECINF
δ_i	Exo. Exit Prob., Informal	0.073	Overall % of Informal Firms	Ulyssea (2018)
b	Inf. Penalty Parameter	13.1	Expenditure % on Agric.	ICP
c^e	Entry Cost	2.08	% of Agric. Value-Added	SEA 2014
c^{for}	Formalization Cost	0.001	Avg. Formal Manuf Firm Size	CEMPRE
η	Engel Elasticity	0.84	% of Formal Firms of Size $30-49$	CEMPRE
ν	PIGL Preference Parameter	0.099	% of Formal Firms of Size ≥ 50	CEMPRE
ρ^z	AR(1) Persistence Coeff.	0.92	Entry Rate of Formal in Manuf.	CEMPRE

Notes: The left panel summarizes the 11 structural parameters that are calibrated using the Method of Simulated Moments (SMM). The right panel lists the 11 moments used in the calibration and their respective sources. All moments except for the expenditure share on agriculture are measured using data from the year 2003. The expenditure share on agriculture is computed using data from the International Comparison Program (ICP) for 1996 and 2005.

The entry cost, c^e, influences the left tail of the size distribution of firms. A higher entry cost raises the productivity threshold required for entry, resulting in fewer small firms and a thinner left tail in the size distribution. The exogenous death probability for formal firms, δ_f, affects the right tail of the formal firms' size distribution. The model generates essentially no endogenous exit for the largest firms. Hence, they primarily exit due to these exogenous shocks, shaping the distribution's right tail.

Both the formalization cost c_{for} and informality penalty parameter b affect the right tail of the informal firm size distribution. A smaller value of b corresponds to a higher cost of operating in the informal sector for more productive firms whose optimal size is large. This leads to a thinner right tail in the size distribution of informal firms. On the other hand, a higher formalization cost c_{for} would make it more expensive for informal firms to formalize, leading to a thicker right tail in the size distribution of informal firms.

5.3 Discussion and External Validation

This section evaluates the model's fit to the data, focusing on targeted and untargeted moments. Table 9 compares the model-generated values of the eleven moments targeted during estimation and their empirical counterparts. Overall, the calibrated model replicates the targeted moments well.

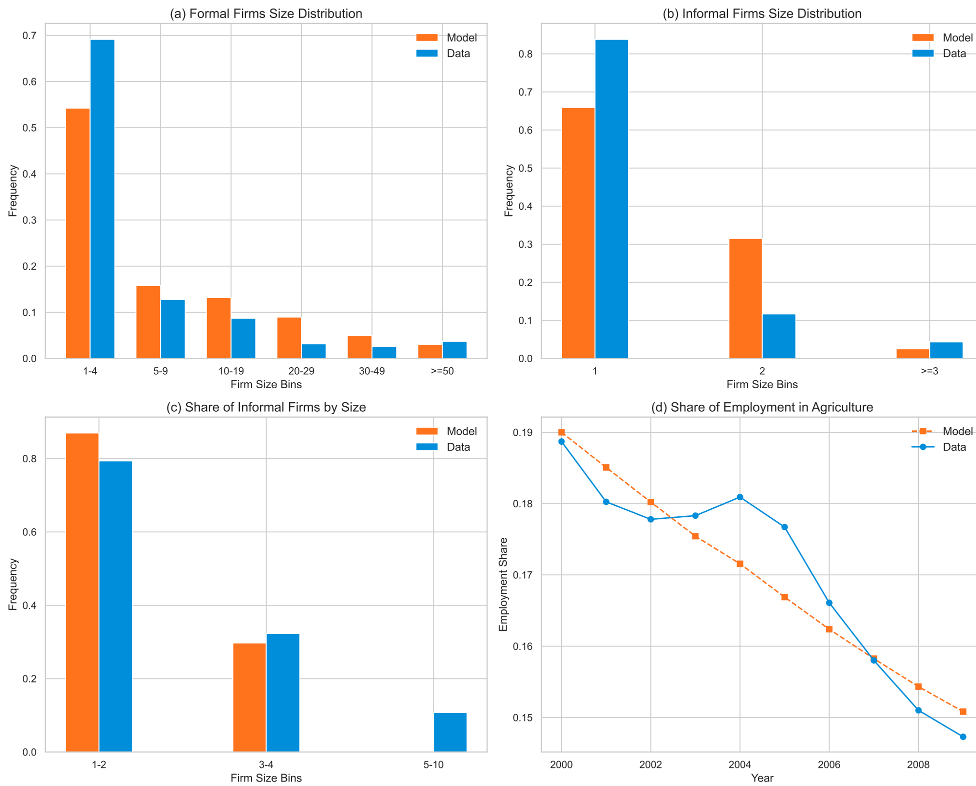
Table 9: Targeted Moments and Model Fit

	Moment	**Data**	**Model**
1	% of Employment in Agric.	0.18	0.19
2	% Informal Employment in Manuf.	0.31	0.32
3	Avg. Informal Manuf. Firm Size	1.42	1.30
4	% of Informal Firms Size $\geq$ 3 in Manuf.	0.043	0.061
5	Overall % of Informal Firms	0.69	0.78
6	Expenditure % on Agric.	0.19	0.10
7	% of Agric. Value-Added	0.18	0.22
8	Avg. Formal Manuf. Firm Size	10.27	10.00
9	% of Formal Firms of Size 30-49 in Manuf.	0.025	0.049
10	% of Formal Firms of Size ≥ 50 in Manuf.	0.037	0.029
11	Entry Rate of Formal Firm in Manuf.	0.063	0.097

Since the sorting of firms into formal or informal status largely depends on firm-specific productivity and size, I evaluate the validity of the calibrated model by demonstrating that the calibrated model closely replicates the distribution of firms observed in the data—a key aspect of the quantitative analysis. Figure 1 displays histograms showing the distribution of formal and informal firms by size and the proportion of informal firms across various size categories.

Panel (a) shows the share of formal firms in the manufacturing sector for each size category. The calibration targets the two largest bins (30-49 employees and 50 or more). It is reassuring that the model accurately matches the distribution of formal firms in the middle and lower size ranges.

Figure 1: Untargeted Moments and Model Fit



Consistent with the data, the share of firms decreases as size increases, indicating a left-skewed size distribution.

Panel (b) presents a similar histogram for informal firms in the manufacturing sector. The calibration targets explicitly the share of informal firms with three or more employees. While the model slightly underestimates the proportion of informal firms with only one employee and overestimates those with two employees, it generally captures the overall pattern of the informal firm size distribution.

Panel (c) illustrates additional non-targeted moments, which are the share of informal firms across different size categories. For instance, comparing the model to the data, the first two bars show the proportion of informal firms among all manufacturing firms with 1-2 employees. The model aligns closely with the data for the 1-2 and 3-4 employee bins but fails to accurately represent the 5-10 employee category due to a lack of informal firms in this range within the model. Nonetheless, the calibrated model correctly shows a declining share of informal firms as firm size increases. This trend is consistent with theoretical expectations, as larger firms are more likely to formalize to avoid the higher costs and risks associated with remaining informal at a larger scale. The model's ability to replicate this essential relationship between firm size and formality status highlights its robustness in capturing the key dynamics of firm behavior.

6 Counterfactuals

6.1 The Effect of Technical Change on Sectoral Reallocation

This section examines the impact of labor-saving technological change on reallocating labor from agriculture to manufacturing. The model predicts that such a technological change - represented as an increase in A_L in the agricultural production function - increases the marginal product of labor in the agricultural sector. Additionally, if the elasticity of substitution between land and labor is less than 1, this prompts a shift of labor toward manufacturing.

Values of A_L are estimated externally using the methodology developed by Herrendorf et al. (2015). To achieve this, I first express the labor augmenting technology parameter A_L as $\exp(\gamma_L t)$ and A_T as $\exp(\gamma_T t)$. Then, I derive a system of nonlinear equations from the first-order conditions of the representative firm's cost minimization problem, which I estimate using a nonlinear three-stage least squares procedure to determine the constant growth rates γ_L and γ_T. The detailed derivation of these nonlinear equations is provided in Appendix C, while Table 10 presents the estimated parameters along with their corresponding standard errors. The estimated growth rates for labor-saving and land-augmenting technical progress are $\gamma_L = 0.047$ and $\gamma_T = 0.0064$, respectively. For comparison, Herrendorf et al. (2015) estimated that $\gamma_L = 0.050$ using U.S. data, where their production function includes capital instead of land, yielding an estimated capital-augmenting growth rate of $\gamma_K = 0.023$, which is consistently lower than γ_L.

Table 10: Estimation Results

γ_L	γ_T
0.04685***	0.006443
(0.00614)	(0.00455)

Panel (d) of Figure 1 shows the time series of changes in the share of employment in agriculture, using data from the GGDC/UNU-WIDER Economic Transformation Database (Kruse et al. 2023). The model's line is calculated by first generating a series of values for A_L using the estimated value of γ_L from Table 10, assuming an initial value of A_L of 1 and that each period represents one year.

For each period, I solve for the steady-state equilibrium of the model using the corresponding value of A_L, then plot the equilibrium share of agricultural employment for each steady state. Given the assumption that the growth rate of technological change is constant, the model predicts a constant rate of decline in the share of agricultural employment over time. As a result, it does not capture the flattening observed in the empirical data. Nevertheless, the model successfully replicates the overall trend in the share of agricultural employment, particularly in the last observed period.

6.2 Technical Change with Informal Sector Reduced by 50%

In this section, I examine the effects of stricter enforcement of labor regulations. Specifically, I conduct a counterfactual exercise by lowering the value of b to achieve a 50% reduction in the equilibrium informality rate in manufacturing. Instead of modeling enforcement explicitly, I adopt a reduced-form representation of the informality penalty commonly used in the literature, defined as $\tau_i(\ell) = \frac{\ell^2}{b}$. Lowering the value of b makes the informality penalty function steeper, simulating increased enforcement on informal firms. This would correspond to a government crackdown on all informal firms, which results in a substantial reduction of informality within the sector.

For simplicity, in this and subsequent sections, I will compare steady states using the initial values of A_{L0} and A_{LT}, with $T = 10$. Let Y_0 represent the equilibrium outcomes in the steady state with A_{L0}, and Y_T represent those with A_{LT}. The changes due to technical change are defined as $\Delta Y = Y_T - Y_0$. Table 11 presents these ΔY values, with each row corresponding to a different variable. The first column displays the baseline results, identical to those discussed in Section 6.1. The second column shows the ΔY values for the counterfactual scenario with stricter regulation, while the third column presents the percentage differences between the baseline and counterfactual scenarios. The results indicate that stricter enforcement leads to 4.52% less labor reallocation from agriculture to manufacturing compared to the baseline economy.

Table 11: Counterfactual: Effect of Stricter Enforcement

Variable	Baseline	Stricter Enforcement	%Diff
Δ Share of Emp. in Agric.	-0.082	-0.079	-4.52
Δ Share Informal Worker in Manuf.	-0.017	-0.003	-80.08
Δ Number of Informal Workers	0.013	0.010	-23.62
Δ Number of Formal Workers	0.066	0.068	3.14
Δ Output	0.129	0.135	4.32
Δ Household Income	0.027	0.045	66.67
Δ Wage (Labor Income)	-0.013	-0.0067	-49.04
Δ Land Income	0.043	0.044	2.32
Δ Tax Revenue	0.012	0.019	58.3
Δ Total Firm Profits	-0.014	-0.011	-21.43

Furthermore, consistent with the findings presented in Tables 4 and 6, the decline in the informality rate within the manufacturing sector due to technical change is smaller when regulatory enforcement is more stringent. This outcome can be attributed to two main factors. First, in the counterfactual scenario, the informal sector in manufacturing is reduced by 50%, so achieving the same absolute reduction from a lower baseline necessitates a significantly larger increase in A_L. Second, stricter enforcement limits the reallocation of labor to the manufacturing sector. Consequently, although the number of formal workers increased slightly more in the counterfactual scenario, the overall change in the share of informal workers remains smaller.

Finally, the increase in output is larger under more intensive enforcement, aligning with findings in the literature (e.g., D'Erasmo and Boedo (2012) and Ulyssea (2018)). Enhanced enforcement eliminates many low-productivity informal firms, reallocating resources to more productive formal firms. The result indicates that this reallocation more than compensates for potential output losses due to the shutdown of informal firms. There is also a larger increase in household income under stricter enforcement, which is driven by the large increase in land rental income and tax revenue that is rebated to the household. However, the welfare implications should be considered cautiously. This counterfactual analysis focuses on steady-state equilibria and does not account for the adjustment costs involved in transitioning between steady states. Additionally, there are no reliable estimates of the implementation costs. Since informal firms are numerous, small in scale, and geographically dispersed, these costs are likely substantial and could significantly impact any welfare assessment.

6.3 Cost of Labor Regulation

In this section, I examine the effects of technical change on structural transformation by altering the costs associated with formal and informal firms, specifically focusing on regulatory burdens. The analysis compares the baseline with counterfactual scenarios with lower entry costs (c^e) and fixed costs for formal firms (c_f^f).

Table 12 presents the results of this counterfactual exercise. The findings suggest that reducing entry and fixed costs promotes greater reallocation of labor from agriculture to manufacturing and results in larger declines in the informality rate within the manufacturing sector compared to the baseline economy. Additionally, aggregate income increases more significantly when both costs are reduced. The counterfactual scenario also shows a substantial increase in the number of formal firms and a corresponding decrease in the number of informal firms. The mechanisms driving these changes differ between entry costs and fixed costs.

When the sunk entry cost is reduced, the number of entrants into both formal and informal sectors

Table 12: Counterfactual: Entry and Fixed Cost

	Baseline	Entry Cost Δc^e		Fixed Cost Δc_f^f	
	Δ	Δ	% Diff	Δ	% Diff
Share of Emp. in Agric.	-0.0823	-0.0834	1.34	-0.0916	11.3
Share Informal Worker in Manuf.	-0.017	-0.026	52.9	-0.031	82.4
Number of Informal Workers	0.013	-0.007	-153.8	-0.0034	-126.2
Number of Formal Workers	0.066	0.079	19.7	0.11	66.7
Aggregate Income	0.0273	0.0315	15.38	0.0409	49.81
Wage	-0.0132	-0.0106	-19.70	-0.0066	-50.23
Output	0.130	0.144	10.77	0.136	4.62
# of Formal firms	0.0044	0.0093	111.4	0.011	150.0
# of Informal firms	0.016	-0.0053	-133.1	-0.0058	-136.3
Mass of Entrants to Formal	0.0001	0.0002	43.6	0.0012	949.1
Mass of Entrants to Informal	0.0028	0.0031	10.7	-0.0009	-132.1
Formalization Rate	0.001	0.005	400.0	0.0013	30.0

increases significantly. This occurs because the lower entry cost makes entry more attractive for potential firms around the entry threshold, encouraging them to enter regardless of their choice to operate formally or informally. Despite more entrants, many of these firms eventually transition to formal status, leading to an overall reduction in the number of informal firms. This is reflected in the higher formalization rate of informal firms observed in the counterfactual scenario.

On the other hand, when the per-period fixed cost for formal firms (c_f^f) is lower, the number of entrants into the informal sector decreases. This shift occurs because the reduced fixed cost makes formal operations relatively more profitable for potential entrants at any given productivity level. Along with the increased formalization of informal firms, this leads to a more pronounced reduction in the mass of informal firms. The rise in formalization is likely driven by the decrease in wages resulting from the technical change in agriculture, which reduces labor demand in the agricultural sector. As a result, some higher-productivity informal firms that previously found it advantageous to remain informal under higher wages may choose to formalize when wages decline.

7 Conclusion

This paper examines how labor-saving technological advancements in agriculture influence labor reallocation between the formal and informal sectors of manufacturing in Brazil. Focusing on the introduction of genetically modified soybeans in the early 2000s, the analysis highlights the differential impacts of technological change on formal versus informal employment and the role of labor regulation enforcement. The findings indicate that agricultural technological progress leads to increased formal employment and a corresponding decline in informal employment in manufacturing, underscoring the importance of agricultural productivity as a catalyst for structural transformation.

Moreover, this paper reveals that labor regulation enforcement plays a significant role in mediating these effects. Municipalities with more stringent regulatory enforcement exhibit reduced labor reallocation from agriculture to manufacturing, resulting in slower growth of formal employment and less reduction in informal employment. This suggests that while labor regulations aim to improve worker protections, they may also impede the efficient movement of labor and structural transformation, particularly in contexts of technological change.

The structural model developed in this paper further supports these empirical findings by demonstrating how regulatory burdens and firm entry costs impact labor reallocation and informality. Policy counterfactuals suggest that reducing regulatory burdens for formal firms can enhance labor reallocation from agriculture to manufacturing and promote a larger decline in informality within the manufacturing sector. These insights highlight that policy efforts aimed at reducing informality should not solely focus on enforcement but also consider the regulatory cost of formal firms, thereby fostering an environment conducive to formal sector growth.

References

Aghion, Philippe, Robin Burgess, Stephen J Redding, and Fabrizio Zilibotti (2008). "The unequal effects of liberalization: Evidence from dismantling the License Raj in India". *American Economic Review* 98.4, pp. 1397–1412.

Ahsan, Ahmad and Carmen Pagés (2009). "Are all labor regulations equal? Evidence from Indian manufacturing". *Journal of Comparative Economics* 37.1, pp. 62–75.

Albert, Christoph, Paula Bustos, and Jacopo Ponticelli (2021). *The effects of climate change on labor and capital reallocation*. Tech. rep. National Bureau of Economic Research.

Almeida and Carneiro (Mar. 2009). "Enforcement of Labor Regulation and Firm Size". *Journal of Comparative Economics* 37.1, pp. 28–46.

– (July 2012). "Enforcement of Labor Regulation and Informality". *American Economic Journal. Applied Economics* 4.3, pp. 64–89.

Almeida and Poole (2017). "Trade and labor reallocation with heterogeneous enforcement of labor regulations". *Journal of Development Economics* 126, pp. 154–166.

Arrow, Kenneth, Hollis Chenery, Bagicha Singh Minhas, and Robert Solow (1961). "Capital-labor substitution and economic efficiency". *The review of Economics and Statistics*, pp. 225–250.

Besley, Timothy and Robin Burgess (2004). "Can labor regulation hinder economic performance? Evidence from India". *The Quarterly journal of economics* 119.1, pp. 91–134.

Boppart, Timo (Nov. 2014). "Structural Change and the Kaldor Facts in a Growth Model With Relative Price Effects and Non-Gorman Preferences: Structural Change and the Kaldor Facts". *Econometrica* 82.6, pp. 2167–2196.

Bosch, Mariano and Julen Esteban-Pretel (2012). "Job creation and job destruction in the presence of informal markets". *Journal of Development Economics* 98.2, pp. 270–286.

Botelho, Fernando and Vladimir Ponczek (2011). "Segmentation in the Brazilian labor market". *Economic Development and Cultural Change* 59.2, pp. 437–463.

Botero, Juan C, Simeon Djankov, Rafael La Porta, Florencio Lopez-de-Silanes, and Andrei Shleifer (2004). "The regulation of labor". *The Quarterly Journal of Economics* 119.4, pp. 1339–1382.

Bustos, Paula, Bruno Caprettini, and Jacopo Ponticelli (2016). "Agricultural productivity and structural transformation: Evidence from Brazil". *American Economic Review* 106.6, pp. 1320–1365.

Chaurey, Ritam (2015). "Labor regulations and contract labor use: Evidence from Indian firms". *Journal of Development Economics* 114, pp. 224–232.

Chirinko, Robert S and Debdulal Mallick (2017). "The substitution elasticity, factor shares, and the low-frequency panel model". *American Economic Journal: Macroeconomics* 9.4, pp. 225–253.

Colmer, Jonathan (2021). "Temperature, labor reallocation, and industrial production: Evidence from India". *American Economic Journal: Applied Economics* 13.4, pp. 101–124.

D'Erasmo, Pablo N and Hernan J Moscoso Boedo (2012). "Financial structure, informality and development". *Journal of Monetary Economics* 59.3, pp. 286–302.

Dix-Carneiro, Rafael, Pinelopi Koujianou Goldberg, Costas Meghir, and Gabriel Ulyssea (2021). “Trade and Informality in the Presence of Labor Market Frictions and Regulations”, p. 71.

Donovan, Kevin, Will Jianyu Lu, and Todd Schoellman (2022). “Labor Market Dynamics and Development”, p. 89.

Eckert, Fabian and Michael Peters (2022). *Spatial structural change*. Tech. rep. National Bureau of Economic Research.

Engbom, Niklas, Gustavo Gonzaga, Christian Moser, and Roberta Olivieri (2022). “Earnings inequality and dynamics in the presence of informality: The case of Brazil”. *Quantitative Economics* 13.4, pp. 1405–1446.

Foster, Andrew D and Mark R Rosenzweig (2004). “Agricultural productivity growth, rural economic diversity, and economic reforms: India, 1970–2000”. *Economic Development and Cultural Change* 52.3, pp. 509–542.

Gerard, François and Gustavo Gonzaga (2021). “Informal labor and the efficiency cost of social programs: Evidence from unemployment insurance in brazil”. *American Economic Journal: Economic Policy* 13.3, pp. 167–206.

Gollin, Douglas, Casper Worm Hansen, and Asger Mose Wingender (2021). “Two blades of grass: The impact of the green revolution”. *Journal of Political Economy* 129.8, pp. 2344–2384.

Heckman, James J and Carmen Pagés (2000). *The cost of job security regulation: Evidence from Latin American labor markets*.

Henderson, J Vernon, Adam Storeygard, and Uwe Deichmann (2017). “Has climate change driven urbanization in Africa?” *Journal of development economics* 124, pp. 60–82.

Herrendorf, Berthold, Christopher Herrington, and Akos Valentinyi (2015). “Sectoral technology and structural transformation”. *American Economic Journal: Macroeconomics* 7.4, pp. 104–133.

Hopenhayn (1992). “Entry, Exit, and Firm Dynamics in Long Run Equilibrium”. *Econometrica* 60.5, pp. 1127–1150.

Hornbeck, Richard and Pinar Keskin (2015). “Does agriculture generate local economic spillovers? Short-run and long-run evidence from the Ogallala Aquifer”. *American Economic Journal: Economic Policy* 7.2, pp. 192–213.

IBGE (2000). *Censo Demográfico 2000*. Rio de Janeiro: IBGE.

– (2006). *Censo Agropecuário 2006*. Rio de Janeiro: IBGE.

Imbert, Clement and Gabriel Ulyssea (2023). *Rural Migrants and Urban Informality: Evidence from Brazil*. Tech. rep. No. 18160. CEPR Discussion Papers.

Kambourov, Gueorgui (2009). “Labour market regulations and the sectoral reallocation of workers: The case of trade reforms”. *The Review of Economic Studies* 76.4, pp. 1321–1358.

Kongsamut, Piyabha, Sergio Rebelo, and Danyang Xie (2001). “Beyond balanced growth”. *The Review of Economic Studies* 68.4, pp. 869–882.

Kruse, Hagen, Emmanuel Mensah, Kunal Sen, and Gaaitzen de Vries (2023). “A manufacturing (re) naissance? Industrialization in the developing world”. *IMF Economic Review* 71.2, p. 439.

Kuznets, Simon (1973). “Modern economic growth: findings and reflections”. *The American economic review* 63.3, pp. 247–258.

Levy, Santiago (2008). “Good intentions, bad outcomes: Social policy, informality, and economic growth in Mexico”.

Lewis, W. Arthor (1954). “Economic Development with Unlimited Supplies of Labour”. *The Manchester School* 22.2, pp. 139–191.

Liu, Maggie, Yogita Shamdasani, and Vis Taraz (2023). “Climate change and labor reallocation: Evidence from six decades of the Indian Census”. *American Economic Journal: Economic Policy* 15.2, pp. 395–423.

Moscona, Jacob (2019a). “Agricultural development and structural change within and across countries”. *Unpublished manuscript*.

– (2019b). *Agricultural Development and Structural Change, within and across Countries*.

Nunn, Nathan and Nancy Qian (2011). “The potato’s contribution to population and urbanization: evidence from a historical experiment”. *The quarterly journal of economics* 126.2, pp. 593–650.

Ohnsorge, Franziska and Shu Yu (2022). *The long shadow of informality: Challenges and policies*. World Bank Publications.

Ponczek, Vladimir and Gabriel Ulyssea (Jan. 7, 2022). “Enforcement of Labour Regulation and the Labour Market Effects of Trade: Evidence from Brazil”. *The Economic Journal* 132.641, pp. 361–390.

Ulyssea, Gabriel (2018). “Firms, Informality, and Development: Theory and Evidence from Brazil”. *American Economic Review* 108.8, pp. 2015–2047.

– (2020). “Informality: Causes and consequences for development”. *Annual Review of Economics* 12.1, pp. 525–546.

United States Department of Agriculture (USDA) (2012). *Brazil: Agricultural Biotechnology Annual*. Tech. rep. Washington, DC: United States Department of Agriculture, Economic Research Service.

Appendices

Appendix A Table and Figures

Figure A.1: Increases in Potential Yield, Tons per Hectare

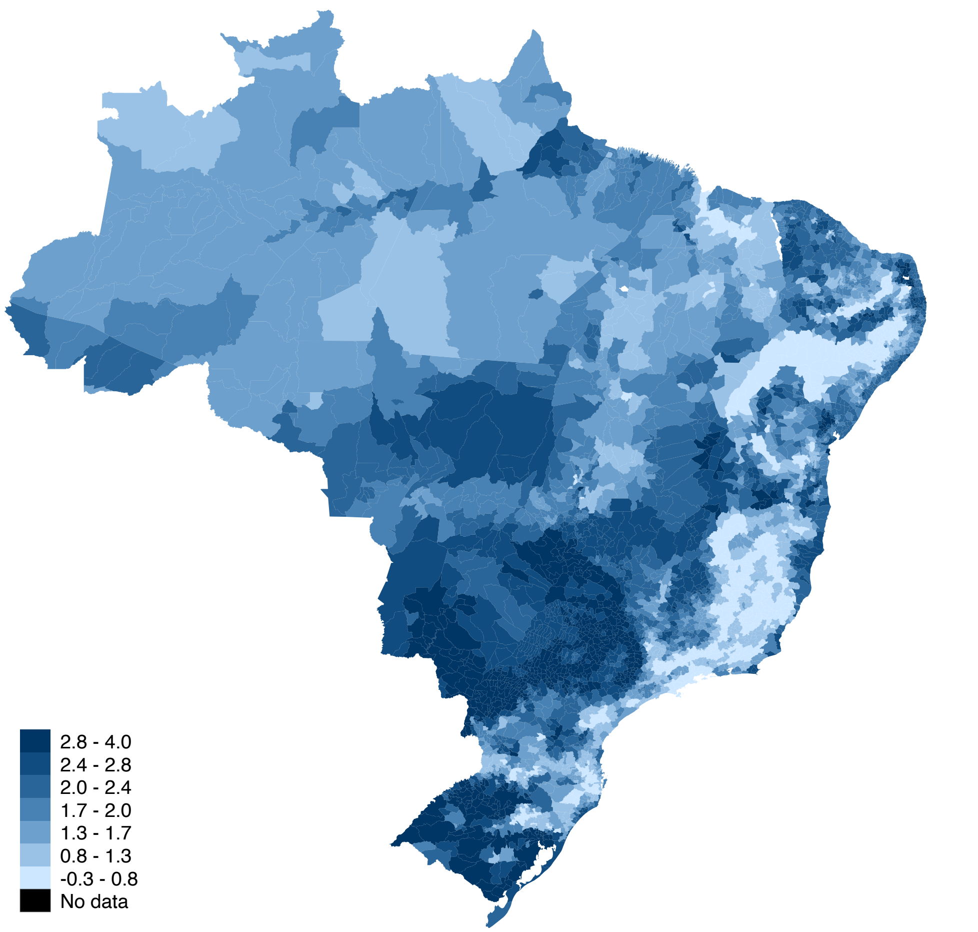


Figure A.2: Enforcement Intensity and Location of L.O.

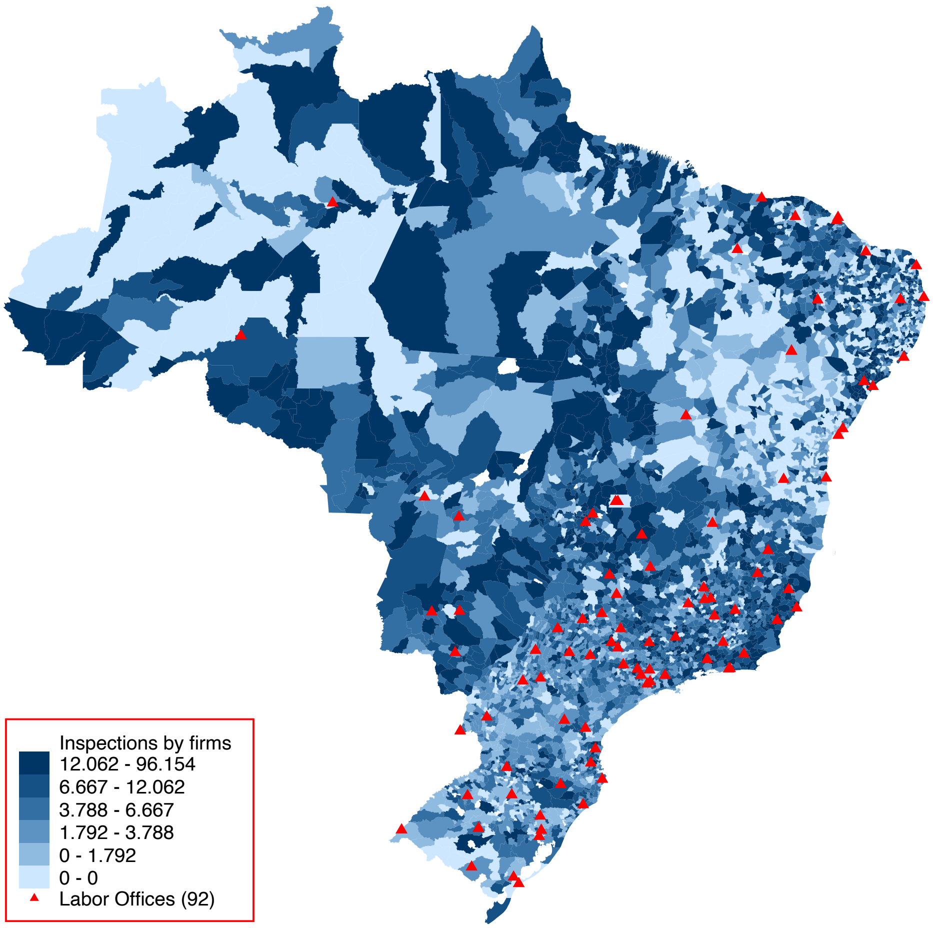


Table A.1: Net Migration Rate, 2010

	OLS		IV
	(1)	(2)	(3)
ΔA^{soy}	0.00636	0.000936	0.0301
	(0.00619)	(0.00700)	(0.0311)
ΔA^{soy} $\times$ Log Inspec.		0.00305	-0.00198
		(0.00246)	(0.0158)
Observations	4251	4251	4251
R^2	0.175	0.175	-0.257

Notes: Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. This table reports both the OLS and IV results on the net migration rate in 2010. ΔA^{soy} denotes the technical change in agriculture. Each observation corresponds to a minimum comparable area, analogous to a municipality but remains consistent over time. Log Inspec.$_{sr}$ is equal to the log of total number of inspections per hundred firms between 1995-2003 (before the legalization of GM soy). For further details on data sources and variable construction, refer to Section 2.3. All regressions include baseline municipality controls, including the share of urban population, log population density, log average household income, and literacy rate, all sourced from the 2000 Brazilian population census. Additionally, each regression also includes a set of state dummies.

Table A.2: Changes in Log Manufacturing Wages, 2000-2010

	OLS			IV
	(1)	(2)	(3)	(4)
ΔA^{soy}	-0.0294**	-0.0218	-0.0374**	-0.133**
	(0.0120)	(0.0138)	(0.0172)	(0.0642)
$\Delta A^{soy} \times$ Log Inspec.			0.0130**	0.0922*
			(0.00622)	(0.0509)
Observations	4212	4212	4212	4212
State-specific Trend		✓	✓	✓
Municipality Controls	✓	✓	✓	✓
Mean of Dep. Variable	0.285	0.285	0.285	0.285
Adjusted R^2	0.0559	0.0682	0.0687	0.00857
Kleibergen-Paap rk Wald F statistic				18.20

Notes: Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. This table reports both the OLS and IV results on the changes in the logarithm of average manufacturing wages between 2000 and 2010. Each observation corresponds to a minimum comparable area, analogous to a municipality but remains consistent over time. ΔA^{soy} denotes the technical change in agriculture. Log Inspec.$_{sr}$ is equal to the log of total number of inspections per hundred firms between 1995-2003 (before the legalization of GM soy). For further details on data sources and variable construction, refer to Section 2.3. All regressions include baseline municipality controls, including the share of urban population, log population density, log average household income, and literacy rate, all sourced from the 2000 Brazilian population census. Additionally, columns (2) - (4) also include a set of state dummies.

Appendix B The PIGL Demand Function

Consider the indirect utility function in Equation 9, Roy's Identity implies that the representative household's expenditure share of sector $k = \{A, M\}$' s output is given by the following formula:

$$\theta_k \equiv \theta_k(e_i, P_G, P_S) = -\frac{\frac{\partial V(e_i, P_G, P_S)}{\partial p_k} P_k}{\frac{\partial V(e_i, P_G, P_S)}{\partial e_i} e_i} \tag{12}$$

I compute the expenditure of goods $M = G$ first. The numerator can be written as:

$$\begin{aligned}
\frac{\partial V(e_i, P_G, P_S)}{\partial P_G} P_G &= \frac{\partial}{\partial P_G} \left[\frac{1}{\eta} \left(\frac{e_i}{p_G^{\phi} p_S^{1-\phi}} \right)^{\eta} - \nu \ln \left(\frac{p_G}{p_S} \right) \right] P_G \\
&= P_G \left[\frac{1}{\eta} \eta \left(\frac{e_i}{p_G^{\phi} p_S^{1-\phi}} \right)^{\eta - 1} \frac{(-\phi) e_i}{P_G^{1+\phi} P_S^{1-\phi}} - \nu \frac{1}{P_G} \right] \\
&= -\phi \left(\frac{e_i}{p_G^{\phi} p_S^{1-\phi}} \right)^{\eta} - \nu
\end{aligned}$$

The denominator can be written as:

$$\begin{aligned}
\frac{\partial V(e_i, P_G, P_S)}{\partial e_i} e_i &= \frac{\partial}{\partial e_i} \left[\frac{1}{\eta} \left(\frac{e_i}{p_G^{\phi} p_S^{1-\phi}} \right)^{\eta} - \nu \ln \left(\frac{p_G}{p_S} \right) \right] e_i \\
&= \left(\frac{e_i}{p_G^{\phi} p_S^{1-\phi}} \right)^{\eta}
\end{aligned}$$

Combining the two derivatives above using the expression in Equation (12) yields the expenditure share of goods

$$\theta_G = \phi + \nu \left(\frac{e_i}{p_G^{\phi} p_S^{1-\phi}} \right)^{-\eta} \tag{13}$$

Similarly, the expenditure share of services is given by

$$\theta_S = (1 - \phi) - \nu \left(\frac{e_i}{p_G^{\phi} p_S^{1-\phi}} \right)^{-\eta} \tag{14}$$

Appendix C Estimation of Labor-Saving Technical Change

This section details the equations used for estimating the growth rates of labor-augmenting (γ_L) and land-augmenting (γ_T) technical progress in the agricultural sector. The estimation is adapted from Herrendorf et al. (2015). These estimated growth rates will be utilized in subsequent counterfactual analyses to assess the impact of labor-saving technological change on structural transformation.

Rewriting the labor augmenting technology parameter A_L as $\exp(\gamma_L t)$ and A_T as $\exp(\gamma_T t)$, the production function of the agricultural sector becomes

$$F(T_{At}, L_{At}) = \left[\gamma(\exp(\gamma_L t)L_{At})^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(\exp(\gamma_T t)T_{At})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{15}$$

where T_{At} and L_{At} denote land and labor inputs, and σ is the elasticity of substitution. The representative firm's cost minimization problem can be formulated as:

$$\min_{L_{At}, T_{At}} wL_{At} + rT_{At} \qquad \text{s.t. } F(T_{At}, L_{At}) \geq Y_{At}, \tag{16}$$

where w_t and r_t are the wage rate and land rental rate, respectively. The first-order conditions for an interior solution are:

$$w_t = \gamma \exp(\gamma_l t)^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_{At}}{L_{At}}\right)^{\frac{1}{\sigma}} \tag{17}$$

$$r_t = (1-\gamma) \exp(\gamma_t t)^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_{At}}{T_{At}}\right)^{\frac{1}{\sigma}} \tag{18}$$

From these conditions, the income shares of labor and land can be expressed as:

$$\theta_{L_{At}} \equiv \frac{w_t L_{At}}{Y_{At}} = \gamma \left[\exp(\gamma_l t)\frac{L_{At}}{Y_{At}}\right]^{\frac{\sigma-1}{\sigma}} \tag{19}$$

$$\theta_{T_{At}} \equiv \frac{r_t T_{At}}{Y_{At}} = (1-\gamma) \left[\exp(\gamma_t t)\frac{T_{At}}{Y_{At}}\right]^{\frac{\sigma-1}{\sigma}} \tag{20}$$

For estimation purposes, it is advantageous to normalize the CES production function (Equation 15) so that the relative weights on land and labor match the average income shares, respectively. This normalization is achieved by dividing and multiplying each variable (except for time) by its geometric mean, resulting in the following expression:

$$F(T_{At}, L_{At}) = \bar{Y}\left[\gamma\left[\frac{\exp(\gamma_l t)\bar{L}}{\bar{Y}}\right]^{\frac{\sigma-1}{\sigma}}\left(\frac{\exp(\gamma_l t)L_{At}}{\exp(\gamma_l t)Y_{At}}\right)^{\frac{\sigma-1}{\sigma}}\right.$$
$$\left. + (1-\gamma)\left[\frac{\exp(\gamma_t t)\bar{T}_A}{\bar{Y}}\right]^{\frac{\sigma-1}{\sigma}}\left(\frac{\exp(\gamma_t t)T_{At}}{\exp(\gamma_t t)Y_{At}}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

where $\bar{Y}$, $\bar{L}$, and $\bar{T}_A$ represent the geometric averages of output, labor, and land, respectively. As a result of the normalization, the average income shares can be expressed as:

$$\bar{\theta}_L = \gamma\left[\exp(\gamma_L \bar{t})\frac{\bar{L}}{\bar{Y}}\right]^{\frac{\sigma-1}{\sigma}}$$
$$\bar{\theta}_{T_A} = (1-\gamma)\left[\exp(\gamma_T \bar{t})\frac{\bar{T}_A}{\bar{Y}}\right]^{\frac{\sigma-1}{\sigma}}$$

Given that income shares are observable, their geometric averages can be readily calculated. These calculated values can then be substituted into the production function before estimating the remaining parameters, yielding:

$$F(T_{At}, L_{At}) = \bar{Y}\left[\bar{\theta}_L\left(\frac{\exp(\gamma_l t)L_{At}}{\exp(\gamma_l t)Y_{At}}\right)^{\frac{\sigma-1}{\sigma}} + \bar{\theta}_{T_A}\left(\frac{\exp(\gamma_t t)T_{At}}{\exp(\gamma_t t)Y_{At}}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{21}$$

Define the normalized value added, labor, and land as $y_t \equiv Y_{At}/\bar{Y}$, $l_t \equiv L_{At}/\bar{L}$, and $t_t \equiv T_{At}/\bar{T}_A$ respectively. In terms of these normalized variables, the first-order conditions (Equation 17)-(Equation 18) can be expressed as:

$$w_t = \frac{\bar{\theta}_L \bar{Y}}{\bar{L}} \exp\left(\frac{\sigma-1}{\sigma}\gamma_L\left(t-\bar{t}\right)\right)\left(\frac{y_t}{l_t}\right)^{\frac{1}{\sigma}} \tag{22}$$
$$r_t = \frac{\bar{\theta}_T \bar{Y}}{\bar{T}_A} \exp\left(\frac{\sigma-1}{\sigma}\gamma_T\left(t-\bar{t}\right)\right)\left(\frac{y_t}{t_t}\right)^{\frac{1}{\sigma}} \tag{23}$$

The goal is to estimate the parameter values in (Equation 21)–(Equation 23). To achieve this, I introduce an error term into each equation, representing productivity shocks or measurement errors that might be correlated over time. By taking logs and rearranging them, I obtain:

$$\log\left(y_t\right) = \frac{\sigma}{\sigma-1}\log\left[\bar{\theta}_L\left(\exp\left(\gamma_L(t-\bar{t})\right)l_t\right)^{\frac{\sigma-1}{\sigma}} + \bar{\theta}_T\left(\exp\left(\gamma_T(t-\bar{t})\right)t_t\right)^{\frac{\sigma-1}{\sigma}}\right] + \epsilon_{yt} \tag{24}$$

$$\log(w_t) = \log\left(\frac{\bar{\theta}_L\bar{Y}}{\bar{L}}\right) + \frac{\sigma-1}{\sigma}\left[\gamma_L\left(t-\bar{t}\right)\right] + \frac{1}{\sigma}\left(\log(y_t) - \log(l_t)\right) + \epsilon_{wt} \tag{25}$$

$$\log(r_t) = \log\left(\frac{\bar{\theta}_T\bar{Y}}{\bar{T}_A}\right) + \frac{\sigma-1}{\sigma}\left[\gamma_T\left(t-\bar{t}\right)\right] + \frac{1}{\sigma}\left(\log(y_t) - \log(t_t)\right) + \epsilon_{rt} \tag{26}$$

where $(\epsilon_{yt}, \epsilon_{wt}, \epsilon_{rt})$ denote the errors.