working paper
1906

Structural Transformation, Industrial Specialization, and Endogenous Growth

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March 2019

CENTRO DE ESTUDIOS
MONETARIOS Y FINANCIEROS
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CEMFI Working Paper No. 1906
March 2019

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Abstract

The introduction of new technologies in agriculture can foster structural transformation by freeing workers who find occupation in other sectors. The traditional view is that this increase in labor supply in manufacturing can lead to industrial development. However, when workers moving to manufacturing are mostly unskilled, this process reinforces a country's comparative advantage in low-skill intensive industries. To the extent that these industries undertake less R&D, this change in industrial composition can lead to lower long-run growth. We provide empirical evidence of this mechanism using a large and exogenous increase in agricultural productivity due to the legalization of genetically engineered soy in Brazil. Our results indicate that improvements in agricultural productivity, while positive in the short-run, can generate specialization in less-innovative industries and have negative effects on productivity in the long-run.

JEL Codes: J43, O13, O14, O33, Q15, Q16.

Keywords: Agricultural productivity, skill-biased technical change, labor mobility, genetically engineered soy, Brazil.

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Acknowledgement

We received valuable comments from Donald Davis, Gene Grossman, Andres Rodriguez-Clare, Chris Tonetti, Chris Udry, Jose P. Vasquez, and seminar participants at CEMFI, CREI and University of Lugano. We are grateful to acknowledge financial support from the European Research Council Starting Grant 716338.

1 Introduction

Early development economists perceived the reallocation of workers from agriculture to "modern" sectors of the economy as fundamental for development and growth.[1] This reallocation of labor from agriculture to manufacturing is generally regarded as positive for aggregate productivity mainly because of two arguments. First, labor productivity is usually lower in agriculture than in the rest of the economy (Gollin, Parente, and Rogerson 2002, Lagakos and Waugh 2013 and Gollin, Lagakos, and Waugh 2014). Second, the manufacturing sector is characterized by economies of scale and on-the-job accumulation of human capital, such as learning-by-doing (Krugman 1987, Lucas 1988, Matsuyama 1992a). However, manufacturing productivity does not only depend on the size of the industrial sector but also on its composition. As shown in the work of Grossman and Helpman (1991a), the specific industrial sectors in which an economy specializes can determine its growth path. In this context, an inflow of low-skilled workers into manufacturing can induce a relocation of resources towards non-innovating industries, which can lead to lower long-run growth.

In this paper we study the effect of labor reallocation from agriculture to manufacturing on industrial specialization and productivity growth. Our empirical strategy exploits the legalization of genetically engineered (GE) soybean seeds in Brazil as a natural experiment. This new technology requires fewer but relatively high-skilled workers, generating an outflow of low skilled workers from the agricultural sector. Thus, it allows us to study the effect of a shock to the relative supply of skill on the composition of the local manufacturing sector.

To capture exogeneous variation in the adoption of this new technology across areas in Brazil, we use the difference between the potential soy yield in a particular area before and after the legalization of GE soybeans as in Bustos, Caprettini, and Ponticelli (2016).[2] This measure of technical change in soy is a function of weather and soil characteristics of different areas, and not of actual yields. In addition, we exploit detailed individual information from the Brazilian Population Census to trace the flow of workers with different education levels across sectors, as well as to construct wage measures adjusted for a large set of individual characteristics. Finally, we use data from the Brazilian Manufacturing Survey and the Technological Innovation Survey to construct measures of manufacturing productivity and expenditure in innovative activities.

We start by providing evidence that the introduction of GE soy led to a decrease in

[1]For instance, Lewis (1954) argued that the movement of workers from a "subsistence" sector with negligible productivity to a capitalist sector was at the core of the process of economic development, whereas Kuznets (1973) identified the shift of resources away from agriculture into non-agricultural sectors as one of the six main characteristics of modern economic growth.

[2]Our geographical unit of observation are Brazilian micro-regions. Micro-regions consist of a group of municipalities and can be thought of as small open economies that trade in agricultural and manufacturing goods but where production factors are immobile.

local demand for unskilled labor and a reallocation of low-skilled workers towards the manufacturing sector.[3] Our estimates indicate that microregions with a one standard deviation higher increase in soy technical change experienced a 8.4 larger decrease in unskilled employment in agriculture, and no differential change in high-skilled employment. We also find that micro-regions more exposed to the introduction of the GE soy technology experienced a larger increase in the skill premium – i.e. the wage paid to high- relative to low-skilled workers – consistent with the new technology leading to a reduction in the local demand for unskilled labor. Despite the outflow of low-skilled workers from agriculture, their average wages increased in regions more exposed to the new technology. This trend is consistent with the agricultural sector retaining its best workers, while those leaving agriculture being negatively selected, not only in terms of education, but also in terms of unobservable characteristics.[4]

Second, we study the consequences of this reallocation of unskilled labor from agriculture to manufacturing for industrial specialization. From the point of view of the manufacturing sector, this reallocation of workers amounts to an increase in the relative supply of unskilled labor. Indeed, we document that the manufacturing industries which expanded were unskilled-labor-intensive, as predicted by the Rybczynski theorem. In addition, these industries are less involved in innovative activities as measured by expenditure in research and development (R&D). Finally, we find that the increased supply of low-skilled workers was partly absorbed through changes in factor intensity usage within industries. In particular, we find that in microregions more exposed to soy technical change low-skilled intensive manufacturing industries experienced higher reductions in skill intensity of production technologies. Thus, our evidence suggests that the increase in the relative supply of unskilled labor not only generated industrial specialization into less innovative industries, but also the adoption of less skill-intensive production techniques within industries.

We rationalize our findings in light of an endogenous growth, open economy model with three sectors: agriculture, high-skilled intensive manufacturing, and low-skilled intensive manufacturing. To study the effect of skill-biased agricultural technical change, we consider an agricultural sector employing high- and low-skilled workers, and land. We model the introduction of GE soy seeds as a skilled-labor-augmenting technical change in agriculture. We show that when high- and low-skilled workers are imperfect substitutes, but land and labor are strong complements, this type of technical change leads to an absolute decrease in the demand for low-skilled labor in agriculture. As a result, and as long as agriculture is not much more intensive in unskilled labor than the most unskilled in-

[3] We classify skilled workers as those who completed the 8th grade, which is equivalent to graduating from middle school in the US.

[4] Note that all our results on wages are obtained after netting out from raw wages a large set of worker-observable characteristics in Mincerian regression (age, race), to obtain a measure of how much each labor type is paid.

tensive manufacturing industry, low-skilled workers reallocate towards the manufacturing sector.[5]

Next, we analyze the implications of this increase in the relative supply of low-skilled workers into manufacturing in light of the Grossman and Helpman (1991a) model. In our model, the manufacturing sector has two industries. In the first industry, innovation leads to an expansion of the inputs (which we think as ideas) available for production. Innovating is profitable because entrepreneurs keep the profits from the inputs introduced. All these inputs are the knowledge in the economy. In the other industry, firms produce homogeneous goods using unskilled labor more intensively. When low-skilled workers are released from agriculture low-skilled workers enter the low-skill intensive manufacturing industry and shrink the size of the R&D, high-skill intensive one. As a result, in the long run, the economy conducts less R&D, exports more homogeneous products in exchange for high-skilled, high R&D good, and its total output grows more slowly.

The negative dynamic effect of agricultural productivity growth discussed above may mitigate the positive static gains of structural transformation identified in the prior literature. We show evidence consistent with this idea using data from the Annual Industrial Survey (PIA). The data allows us not only to directly observe the response of manufacturing firms to changes in the local supply of unskilled labor, but also to assess whether these changes led to lower productivity in the manufacturing sector. We show that microregions more exposed to technical change in soy production experienced faster employment growth in low-skill intensive manufacturing industries in the short-run and lower labor productivity in manufacturing in the long-run. As predicted by our model, this decrease in manufacturing productivity is driven exclusively by high-skill intensive industries, and hence it is not simply due to a composition effect.

Overall, our empirical findings indicate that unskilled labor-saving technical change in agriculture can lead to a reallocation of labor towards low-skilled manufacturing industries. This leads to an expansion of the industrial sectors with lower R&D intensity in the economy, thus lowering manufacturing productivity in the long run. We interpret this result as a cautionary tale on the effects of structural change on productivity growth. Positive productivity shocks in agriculture may result in static productivity gains in the primary sector and negative dynamic effects in manufacturing productivity.

Our findings suggest that different forces driving structural transformation can lead to different types of industrial specialization. In most countries, the process of labor reallocation from agriculture to manufacturing can be ascribed to one of two forces: "push" forces, such as new agricultural technologies that push workers out of agriculture, or "pull" forces, such as industrial productivity growth, that pull workers into manufactur-

[5] If agriculture is much more intensive in low-skilled labor than all the manufacturing industries, then Heckscher - Ohlin international trade forces would make the economy specialize in agriculture and heavily draw resources from all other sectors of activity.

ing. We show that when labor reallocation from agriculture to manufacturing is driven by labor-saving *and* skill-biased agricultural productivity growth – rather than manufacturing labor demand – it can generate an expansion in those manufacturing sectors with the lowest potential contribution to aggregate productivity. In this sense, our results are informative for low- to middle-income countries where a large share of the labor force is employed in agriculture, and who import new agricultural technologies from more developed countries with high-skilled intensive agricultural sectors. Our results suggest that positive agriculture productivity shocks coming from technology adoption may be more effective if coupled with industrial development or education policies.

Related Literature

There is a long tradition in economics of studying the links between agricultural productivity and industrial development. Nurkse (1953), Schultz (1953), and Rostow (1960) argued that agricultural productivity growth was an essential precondition for the industrial revolution. Classical models of structural transformation formalized their ideas by proposing two main mechanisms through which agricultural productivity can speed up industrial growth in closed economies. First, agricultural productivity growth increases income, which can increase the relative demand for manufacturing goods, driving labor away from agriculture and into manufacturing (see Murphy, Shleifer, and Vishny 1989, Kongsamut, Rebelo, and Xie 2001, Gollin et al. 2002). Second, if productivity growth in agriculture is faster than in manufacturing and these goods are complements in consumption, the relative demand for agricultural goods does not grow as fast as productivity and labor reallocates toward manufacturing (Baumol 1967, Ngai and Pissarides 2007).[6] Note that these two mechanisms are not operative in open economies, where high agricultural productivity induces a reallocation of labor towards agriculture, the comparative advantage sector (Matsuyama (1992b)). However, Bustos et al. (2016) show that, if agricultural technical change is labor-saving, increases in agricultural productivity can lead to a reallocation of labor towards the industrial sector, even in open economies.

Several scholars argue that reallocating agricultural workers into manufacturing can increase aggregate productivity. First, there might be large static productivity gains when labor reallocates from agriculture to manufacturing. Sizable productivity and wage gaps between agriculture and manufacturing have been measured in several studies and have been shown to be larger in developing economies (e.g., Caselli 2005, Restuccia, Yang, and Zhu 2008, Lagakos and Waugh 2013, Lagakos and Waugh 2013, Gollin et al. 2014). To the extent that these gaps arise from the existence of inefficiencies and frictions in the economy, a reallocation of labor from agriculture to the other sectors of the economy is

[6]See also: Caselli and Coleman 2001, Acemoglu and Guerrieri 2008, Buera, Kaboski, and Rogerson 2015.

both productivity- and welfare-enhancing.[7] Second, there can be dynamic productivity gains when labor reallocates towards manufacturing if this sector is subject to agglomeration externalities and knowledge spillovers (Krugman 1987, Lucas 1988, Matsuyama 1992a).

In this paper, we take a different perspective based on endogenous growth theory, which stresses that manufacturing productivity growth not only depends on the size of the industrial sector, but also on its composition. In particular, we focus on understanding whether a reallocation of unskilled agricultural workers into the manufacturing sector might discourage innovation and technology adoption as argued in Grossman and Helpman (1991a) and how this affects the longer-run evolution of productivity in the manufacturing sector.

Finally, this paper builds upon the literature on the effects of agricultural technical change, particularly those papers that provide evidence that technological advancements in agriculture are skill-biased. For instance Foster and Rosenzweig (1996), who study the effects of the introduction of high-yield varieties in India, show that technological innovations in agriculture increased the relative demand for skill in agriculture and thus returns to primary schooling.[8] We contribute to this literature by showing that the recent introduction of GE soy was also skill-biased. More importantly, we study the implications of skill-biased agricultural technical change for industrialization, which have not previously been explored.

The rest of the paper is organized as follows. Section 2 describes the institutional background and the data used in the empirical analysis. Section 3 describes the theoretical framework. Section 4 explains our identification strategy and empirical results. Finally, section 5 contains our final remarks.

2 Institutional Background and Data

2.1 Background

This section describes the technological change introduced in Brazilian agriculture by GE soybean seeds and some basic stylized facts on soy production in Brazil. GE soy seeds are genetically engineered in order to resist a specific herbicide (glyphosate). The main advantage of this technology relative to traditional seeds is the reduction in production

[7]More recently, Herrendorf and Schoellman (2018) measure and compare agricultural wage gaps in countries in different stages of the structural transformation process. They find that the implied barriers to labor reallocation from agriculture are smaller than usually thought in the macro-development literature, and argue that labor heterogeneity and selection are important drivers of such gaps. Other scholars emphasize that structural change can be growth-enhancing or growth-reducing depending on the correlation between changes in employment shares and productivity levels (McMillan and Rodrik (2011) and McMillan, Rodrik, and Sepulveda (2017)).

[8]In related recent work, Bragança (2014) shows that investments in soybean adaptation in Central Brazil in the 1970s induced positive selection of labor in agriculture.

costs. In particular, the use of GE soybean seeds allows farmers to spray their fields with a specific herbicide (glyphosate) without harming soy plants. Thus, the use of GE soybean seeds reduces labor requirements for weed control.[9] The planting of traditional seeds is usually preceded by soil preparation in the form of tillage, the operation of removing the weeds in the seedbed that would otherwise crowd out the crop or compete with it for water and nutrients. In contrast, the planting GE soy seeds requires no tillage, as the application of herbicide selectively eliminates all unwanted weeds without harming the crop. As activities related to weed control are mostly performed by unskilled workers, the introduction of GE soy seeds should displace unskilled labor relatively more than skilled labor.

The first generation of GE soy seeds (Monsanto's Roundup Ready) was commercially released in the U.S. in 1996 and legalized in Brazil in 2003.[10] The 2006 Brazilian agricultural census reports that, only three years after their legalization, 46.4% of Brazilian farmers producing soy were using GE seeds with the "objective of reducing production costs" (IBGE 2006, p.144). According to the Foreign Agricultural Service of the USDA, by the 2011-2012 harvesting season, GE soy seeds covered 85% of the area planted with soy in Brazil (USDA 2012).

Panel (a) of Figure 1 documents that the legalization of GE soy seeds was followed by a fast expansion of the area planted with soy, which increased from 11 to 19 million hectares between 2000 and 2010.[11] Panel (b) of Figure 1 documents that, in the same period, the number of workers employed in the soy sector decreased substantially. This is consistent with GE soybean seeds decreasing the number of agricultural workers per hectare required to cultivate soy. Bustos et al. (2016) document that labor intensity in soy production fell from 29 workers per 1000 hectares in 1996 to 17 workers per 1000 hectares in 2006. Finally, in panel (c) of Figure 1, we decompose the decrease in employment in the soy sector between skilled workers and unskilled workers, where a worker is considered as skilled if it has completed at least the 8^{th} grade. As shown, the decrease in employment in the soy sector is entirely driven by low-skilled workers, while the skilled ones were retained. This is consistent with GE soy seeds being a unskilled labor saving technology.

Figure 1 goes around here

[9] Other advantages of GE soy seeds are that they require fewer herbicide applications (Duffy and Smith 2001; Fernandez-Cornejo, Klotz-Ingram, and Jans 2002), allow a higher density of the crop on the field (Huggins and Reganold 2008) and reduce the time between cultivation and harvest.

[10] See law 10.688 of 2003 and law 11.105 – the New Bio-Safety Law – of 2005 (art. 35).

[11] According to the two most recent agricultural censuses, the area planted with soy increased from 9.2 to 15.6 million hectares between 1996 and 2006 (IBGE 2006, p.144).

2.2 Data

The four main data sources used in this paper are the FAO-GAEZ database, the Brazilian Population Census, the Annual Industrial Survey (*PIA*), and the Industrial Survey of Technological Innovation (*PINTEC*) which we describe in detail in this section. In our analysis, we use microregions as our unit of observation. Microregions are statistical units defined by the Brazilian Statistical Institute (IBGE) and consist of a group of municipalities. There are 557 microregions in Brazil, with an average population of around 300,000 inhabitants. We use microregions as an approximation of the local labor market of a Brazilian worker. They can be thought of as small, open economies that trade in agricultural and manufacturing goods but where production factors are immobile.[12]

To construct our measure of technical change in soy production, we use estimates of potential soy yields across microregions from the FAO-GAEZ database. This dataset reports the maximum attainable yield for a specific crop in a given geographical area. In addition, it reports maximum attainable yields under different technologies or input combinations. Yields under the *low* technology are described as those obtained planting traditional seeds, with no use of chemicals or mechanization. Yields under the *high* technology are obtained using improved high-yielding varieties, with optimum application of fertilizers and herbicides, and mechanization.

Following Bustos et al. (2016), we define technical change in soy production as the difference in potential yields between high and low technology. This measure aims to capture the effect on soy yields of moving from traditional agriculture to the use of improved seeds and optimum weed control, among other characteristics. Technical change in soy production in microregion k is therefore defined as:

$$\Delta A_k^{soy} = A_k^{soy,High} - A_k^{soy,Low}$$

where $A_k^{soy,Low}$ is equal to the potential soy yield under the low technology and $A_k^{soy,High}$ is equal to the potential soy yield under the high technology. Figure 2 shows the geographical variation in our measure of technical change in soy across microregions.

Figure 2 goes around here

We obtain information on employment, wages and other worker characteristics from the Brazilian population census conducted by the IBGE. We focus on the two most recent surveys of the census (2000 and 2010), which respectively precede and follow the 2003 legalization of GE soybeans. Note that the population census collects information on

[12]In Table A2 of the Appendix we show that internal migration did not respond to the shock. This is in line with evidence from Brazil's lack of internal migration responses documented also in Dix-Carneiro and Kovak (2019) and Costa, Garred, and Pessoa (2016).

both formal and informal workers, and therefore provides a more accurate description of employment in each microregion than social security data, which is only available for formal workers.

In the population census, we focus on individuals with strong labor force attachment. In particular, we include individuals aged between 25 and 55 that work more than 35 hours a week.[13] Moreover, we only consider individuals not enrolled in the education system at the time of the survey. For each individual, we define the sector of occupation as the sector of their main job during the last week. The population census also provides information on the number of hours worked during the last week and the monthly wage. Therefore, we compute hourly wages as the monthly wage divided by 4.33 times the hours worked last week. For each microregion, we compute employment shares as the number of workers in each sector divided by total employment.[14]

We use information on education from the population census to categorize individuals as unskilled or skilled. We define a worker as skilled if they have completed at least the 8^{th} grade. This level should be attained when an individual is 14 or 15 years old and is equivalent to graduating from middle school in the US. We define unskilled individuals as those who have not completed the 8^{th} grade. We use this data to characterize manufacturing industries by their skill intensity. In particular, we split manufacturing industries into two groups: low-skill-intensive industries and high-skill-intensive industries. To this end, we first compute the share of skilled workers over total workers in each industry in the baseline year (2000). Then, we split the distribution of industries at the median, weighting industries by the total number of workers, so that each of the two groups has roughly 50% of the total manufacturing employment in Brazil.

Table 1 goes around here

Table 1 reports summary statistics of individual level characteristics for workers operating in agriculture, low-skill manufacturing, high-skill manufacturing and services.[15] As shown, there is large heterogeneity in skill intensity of workers across these broad sectors. As much as 93.5% of workers in agriculture had not completed the 8^{th} grade in 2000,

[13]In order to deal with extreme observations, we focus on individuals whose absolute and hourly wages are between the 1st and the 99th percentile for the distribution of wages in their respective year, and who work less than the 99th percentile of hours.

[14]Each worker is weighted according to their respective sampling weights.

[15]We define agriculture, manufacturing and services by following the classification of the CNAE Domiciliar of the 2000 census. Agriculture includes Sections A and B (agriculture, cattle, forestry, and fishing). Manufacturing includes Section D, which corresponds to the transformation industries. Services include: construction, commerce, lodging and restaurants, transport, finance, housing services, domestic workers, and other personal services. We exclude the following sectors because they are mostly under government control: public administration, education, health, international organizations, extraction, and public utilities.

against the 80.7% in low-skill manufacturing, 61.8% in high-skill manufacturing, and 69% in services.

We use data from the population census to compute "composition-adjusted" wages (i.e., wages net of observable worker's characteristics). To this end, we estimate a Mincerian regression of log hourly wages on observable characteristics for the two census years of 2000 and 2010, as follows:

$$ln(w_{ikt}) = \gamma_{kt} + H_{ikt}\beta_{Ht} + \varepsilon_{ikt} \quad \textit{for t=2000, 2010} \tag{1}$$

where $ln(w_{ijkt})$ is the log hourly wage of individual i, working in sector j in microregion k at time t, and γ_{kt} is a microregion fixed effect, while H_{ijkt} is a vector of individual characteristics, which includes dummies for sector, skill group, age group, race, and all the interactions between these variables. We estimate the previous Mincerian regression for each microregion and for each broad sector separately. Also, we estimate these regressions constraining the sample to either unskilled or skilled labor only, recovering the unit price of labor in each microregion for each type of labor in both cross sections. Since the existing literature documented how Brazil has experienced a considerable reduction in its gender pay gap (Ferreira, Firpo, and Messina 2017), we estimate equation (1) only for male workers. Observations are weighted by their corresponding population census weight. Next, we use the microregion fixed effects estimated above as the unit price of labor for a given skill group in a given microregion, and we compute the change in unit prices of labor in microregion k between 2000 and 2010 as $\Delta\gamma_k = \gamma_{k,2010} - \gamma_{k,2000}$, which gives us the change in the composition-adjusted wages at microregion level.

Table 2 goes around here

Table 2 provides summary statistics for the main variables used in the empirical analysis at microregion level. For each variable, we report the mean and standard deviation of their level in the baseline year (2000) and of their change between 2000 and 2010.

Finally, we use data from the two different manufacturing surveys mentioned above to investigate the dynamic effects of labor reallocation on industrial output. To construct our measure of R&D expenditure per worker in manufacturing we source data on R&D expenditure from the Industrial Survey of Technological Innovation (*PINTEC*) – which is designed to capture innovation activities of Brazilian firms – and data on number of workers in manufacturing from the Population Census. Specifically, we use the 2000 and 2008 waves of the PINTEC survey to construct aggregate measures of R&D expenditure per worker by industry.

To study the dynamic effect of labor reallocation on employment and value added per worker we use data on number of workers and value added from the Annual Industrial

Survey (*PIA*).[16] This data comes aggregated at micro-region level and is constructed using manufacturing firms with more than 30 employees. Since firms with 30 or more employees are sampled with probability one in the PIA survey, we have a representative sample at the microregion level. We focus on firms operating in manufacturing as defined by the CNAE 1.0 classification (codes between 15 and 37) and use the aggregate microregion-level data from 2000 to 2009. For both PINTEC and PIA, we map their industry classification to our definition of low-skill-intensive industries and high-skill-intensive industries explained above.

3 Model

3.1 General setting

In this section we describe the theoretical framework that guides our empirical exercise. For this we combine the key insights from the theoretical work in Bustos et al. (2016) – extended to two labor types in agriculture production using Acemoglu (2002) – and an open economy version of Romer (1990), which is inspired in Chapter 6 of Grossman and Helpman (1991a).[17] The combination of these two open economy models gives rise to a number of predictions that are useful to interpret the evidence that we present below. In this section we discuss these insights in some depth. We provide further details of the model and prove the different results in Appendix B.

The model has infinitely lived consumers that maximize life-time utility. To make things simple, we assume that consumers have Constant Relative Risk Aversion flow utility given by $u(c) = \frac{c^{1-\eta}-1}{1-\eta}$. c is just a composite of consumption of the three goods in the economy: the agricultural good, and two manufacturing goods. Time is continuous. Life-time utility is given by $\int e^{-\rho t} u(c(t))dt$, where ρ is the discount factor. The budget constraint is given by $p(t)c(t) + I(t) \leq p(t)Q(t)$, where $Q(t)$ is the vector of total output in the economy and $p(t)$ is the vector of prices.[18] $I(t)$ denotes savings which are the same as investment. In what follows we omit explicitly showing time t when it does not lead to a confusion.

The model has three sectors and three factors of production: agriculture, low-skill

[16] We construct our measure of employment based on the aggregation of variable V0194, which is defined in the original documentation as: Total pessoal ocupado em 31/12 or end-of-year number of workers and value added as the difference between output value and production costs. Specifically, the value of output is defined as the sum of revenue from industrial sales, the value of production used for investment and the changes in inventories, whereas production costs are equal to the sum of the cost of industrial operations and the cost of materials used.

[17] We simplify Grossman and Helpman (1991a) and Romer (1990) using Chapter 3 of Aghion and Howitt (2008).

[18] We define total output by $Q = (Q_a, Q_m^\ell, (Q_m^h - (\int^{K_t} x_k^{1-\alpha} dk))$, where Q_j is output in sector j and $(\int^{K_t} x_k^{1-\alpha} dk)$ are the inputs used in the high-skill manufacturing sector. $p(t) = (p_a(t), p_m^\ell(t), p_m^h(t))$ is the vector of prices. We assume that p_m^h is the numeraire.

intensive manufacturing, and high-skill intensive manufacturing that use land, low- and high-skilled workers. Hence, it is a three-factor, three-sector model, where prices of final goods are determined by world markets. To talk more easily about structural transformation – which we define as the movement of resources away from agriculture – we denote by high- and low-skilled intensive *industries* the two sectors in manufacturing.

The agricultural sector produces combining labor and land in a constant elasticity of substitution (CES) production function. In turn, labor is a CES composite of high- and low-skilled labor. In equations, the local agricultural production function is defined by:

$$Q_a = K_t A_N[\gamma(A_L L_a)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_T T_a)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where A_N is a Hicks-neutral technology shifter, γ governs the weight of labor in the production function, A_L and A_T are labor-augmenting and land-augmenting technologies, respectively, and σ is the elasticity of substitution between labor (L_a) and land (T_a). K_t is the knowledge in the local economy which is driven by high-skilled intensive manufacturing output as we discuss below. The main difference between this production function and the one in Bustos et al. (2016) is that, in our context, L_a is not just raw labor, but rather a CES aggregate of high- and low-skilled labor:

$$L_a = [\theta(A_U U_a)^{\frac{\varepsilon-1}{\varepsilon}} + (1-\theta)(A_S S_a)^{\frac{\varepsilon-1}{\varepsilon}}]^{\frac{\varepsilon}{\varepsilon-1}} \tag{3}$$

where θ is the weight of low-skilled labor and ε is the elasticity of substitution between high- and low-skilled labor.

In this model there are two manufacturing industries. In the first industry, which we call high-skilled intensive or heterogeneous input industry, final output is produced combining high- and low-skilled labor and intermediates according to:

$$Q_m^h = A_m^h F_m^h(U_m^h, S_m^h)^\alpha (\int^{K_t} x_k^{1-\alpha} dk) \tag{4}$$

Where K_t is the total amount of varieties or ideas in the industry at time t. We also refer to K_t as the knowledge in the economy.[19] Note that by investing in R&D activities this industry can expand the set of inputs used in production and hence total production.

In the other industry, which we call the low-skill intensive manufacturing industry, firms produce a homogeneous good under conditions of perfect competition according to:

$$Q_m^\ell = K_t A_m^\ell F_m^\ell(U_m^\ell, S_m^\ell) \tag{5}$$

Both sectors combine low- and high-skilled labor. The only difference across industries is that industry h is relatively more intensive in high-skilled labor than the homogeneous

[19] We assume that knowledge in the economy affects productivity in agriculture and low-skilled manufacturing. This guarantees balanced-growth across sectors.

good industry ℓ.

We define the gross domestic output of the economy as: $GDP = p_a K_t A_a F_a + p_m^\ell K_t A_m^\ell F_m^\ell + A_m^h \left(F_m^h\right)^\alpha \left(\int^{K_t} x_k^{1-\alpha}\right) - \left(\int^{K_t} x_k^{1-\alpha}\right)$, i.e. total output minus inputs, and the long-run growth rate of the economy as $g = \frac{G\dot{D}P}{GDP}$, where the dot indicates the derivative with respect to time.

3.2 Structural transformation

With the agricultural production function introduced before we can apply the results in Bustos et al. (2016) and Acemoglu (2002) to think about the relative and absolute demands for low-skilled labor in the primary sector. Hence, we first investigate how agricultural technical change affects the distribution of high- and low-skilled workers between agriculture and manufacturing. To do so, we proceed in two steps. We first look at the *relative* demand and then at the *absolute* demand for low-skilled labor in agriculture.

Theorem 1. *An increase in A_s in agriculture, leads to an increase in the relative demand for high skilled workers in agriculture if and only if the elasticity of substitution between high- and low-skilled workers is greater than one ($\varepsilon > 1$).*

Proof. See Appendix B. □

This result essentially follows from Acemoglu (2002). When it is relatively easy to substitute low- for high-skilled labor, then when the latter becomes more productive firms want to hire relatively more skilled labor.

Note that, at the same time, this increase in A_S makes the whole CES aggregate L_a increase its output, which is akin to the increase in the productivity of labor A_L studied in Bustos et al. (2016). That paper shows that an increase in A_L leads to a relocation of labor from agriculture to manufacturing, provided that the elasticity between land and labor (σ) is smaller than the share of land in production. Thus, by combining the insights in Acemoglu (2002) and Bustos et al. (2016) we obtain, under certain conditions, that a technology which improves the productivity of high-skilled workers in agriculture leads to the relocation of low-skilled workers away from agriculture.

Theorem 2. *Whether an increase in A_s in agriculture leads to an absolute decrease in the demand for low skilled workers in agriculture depends on whether labor and land are strong complements ($\sigma < \varepsilon\Gamma$).*

Proof. See Appendix B. Note that $\Gamma = \left(\frac{(1-\gamma)(A_T T_a)^{\frac{\sigma-1}{\sigma}}}{\gamma (A_L L_a)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_T T_a)^{\frac{\sigma-1}{\sigma}}} \right)$ is the share of land in agricultural production, and ε is the elasticity of substitution between high- and low-skilled workers. □

Theorem 2 extends the logic of Bustos et al. (2016) to two labor types and in doing so we obtain interesting new insights. With only labor and land in agriculture, labor augmenting technical change may lead to a decrease in the demand of labor only if land and labor are sufficiently strong complements. When there are two labor types, the argument is a little bit more nuanced. If one of the labor types becomes more productive, then on the one hand we would like to use more of it if it can substitute the other type of labor. On the other hand, however, we want to use less labor overall if labor and land are strong complements. As a result, when skill-biased-factor-augmenting technologies (A_s) improve, as may be the case in many developing countries when importing technologies from more developed countries, the demand for unskilled labor in agriculture decreases if high- and low-skilled workers are good substitutes and land and labor are strong complements. With two labor types, strong complementarity is weaker than with just one labor type. The reason for that is that part of the adjustment takes place within labor.

3.3 Industrial specialization and economic growth

From the view point of the manufacturing sector, the release of low-skilled workers from agriculture essentially looks like an exogenous increase in the relative supply of labor. Hecksher-Ohlin forces imply that this increase in low-skilled workers into manufacturing expands the industries that use low-skilled labor more intensively. Industrial specialization matters for economic growth because its composition determines the long-run growth rate of the economy. We explain these two points in what follows.

We start by analyzing industrial specialization. We can summarize our results with the following theorem.

Theorem 3. *An increase in skilled-biased-factor-augmenting technology in agriculture (A_s), leads to an expansion of low-skill intensive manufacturing industries, provided that:*

1. *High- and low-skilled workers are imperfect substitutes (i.e. when $\varepsilon > 1$)*
2. *Land and labor are strong complements (i.e. when $\sigma < \varepsilon\Gamma$)*
3. *Agriculture is not much more intensive in low-skilled labor than the low-skill intensive industry.*

Proof. In Appendix B we provide a proof of this theorem assuming that the economy is inside the factor price equalization set. □

The intuition for this result follows, essentially, from standard Hecksher-Ohlin international trade theory. In a two sector Hecksher-Ohlin world (think now about the high- and low-skilled manufacturing industries), an exogenous increase in low-skilled workers expands the low-skilled intensive industry more than proportionately and shrinks the high-intensive industry. The reason for that is that if all low-skilled workers enter the low-skilled intensive industry, total output would increase by more than if they were put in the high-skilled intensive one. Given our assumption of a small open economy, prices are fixed. Hence, if output of the high-skilled intensive good does not change and all the extra low-skilled labor enters the low-skill intensive sector, the marginal product of high-skilled labor would be higher in the low-skilled intensive industry. This means that some high-skilled labor would want to leave the high-skilled intensive industry towards the low-skilled intensive one. As a result, the high-skill intensive industry shrinks and all the low-skilled labor released from agriculture plus some high-skilled labor from the high-skill intensive industry enter the low-skilled intensive industry, expanding its size. In our context we have three sectors (agriculture, low-skilled intensive manufacturing and high-skill intensive manufacturing), instead of two. In this case, if agriculture was very low-skill intensive (much more than the other two sectors), Rybczynski forces would push the "freed labor" from skilled-biased-factor-augmenting technological progress back into agriculture. If these forces are not too strong, which occurs when agriculture is not much more intensive in low-skilled labor than low-skill intensive manufacturing, low-skilled labor finds accommodation into low-skilled intensive manufacturing industries.

The final result in this section relates industrial composition and economic growth. In particular, we show that:

Theorem 4. *When the following conditions hold:*

1. *High- and low-skilled workers are imperfect substitutes (i.e. when $\varepsilon > 1$)*
2. *Land and labor are strong complements (i.e. when $\sigma < \varepsilon\Gamma$)*
3. *Agriculture is not much more intensive in low-skilled labor than the low-skill intensive industry.*

An exogenous change in skill-biased-factor-augmenting technology (A_s), results in:

1. *Static gains from increased productivity in the agricultural sector.*
2. *Dynamic losses shaped by the decrease in the size of the R&D, high-skilled intensive manufacturing industry.*

In particular, the growth rate of consumption is given by:

$$g_C = \frac{\chi A_m^h F_m^h(U_m^h, S_m^h) - \rho}{\eta} \tag{6}$$

where $\chi > 0$ is a constant defined in Appendix B. And the change in gross domestic output is given by:

$$\frac{\partial \ln GDP_t}{\partial A_s} = \underbrace{\omega_a \frac{\partial \ln p_a A_a F_a}{\partial A_s} + \omega_m^\ell \frac{\partial \ln p_m^\ell A_m^\ell F_m^\ell}{\partial A_s} + \omega_m^h \frac{\partial \ln A_m^h F_m^h}{\partial A_s}}_{\textit{Static gains/losses}} + \underbrace{\frac{\chi}{\eta} \frac{\partial A_m^h F_m^h}{\partial A_s} t}_{\textit{Dynamic gains/losses}} \tag{7}$$

where $\omega_j = \frac{p_j A_j F_j}{p_a A_a F_a + p_m^\ell A_m^\ell F_m^\ell + \varsigma A_m^h F_m^h}$.

Proof. See Appendix B. □

To provide some intuition for this result we just need to note that output in the high-skill intensive industry can expand if K_t expands. The level of knowledge, K_t, expands if it is profitable to do so. In our model, this is so because entrepreneurs can invest in developing a new variety and become the monopoly owners of the profits derived from the new variety they invent.

Under suitable assumptions, which we detail in Appendix B, we have that both total production, profits, and net production in the sector (i.e. total output minus the output used for intermediates), are all proportional to $A_m^h F_m^h(U_m^h, S_m^h)$. This, in turn, has the convenient feature that the rate of return of investment is itself proportional to $A_m^h F_m^h(U_m^h, S_m^h)$, and given by $\chi A_m^h F_m^h(U_m^h, S_m^h)$.

In steady state, total output depends on the sectoral composition and the economy grows based on the size of the high-skilled intensive sector. We can then apply theorems 1 to 3 to obtain the result that skill-biased-factor-augment technological change in agriculture leads, under the three conditions stated in theorem 4, to the expansion of the low-skilled intensive industry and a contraction of the high-skill intensive one. This movement of resources into the "wrong" industries lowers the long-run growth rate, something that we labeled as *dynamic loses*. On impact, however, total output increases since there are productivity gains in agriculture and employment gains in low-skill intensive manufacturing. This is what we labeled as *static gains*, which is different from the static gains emphasized in prior literature and that we abstract from in the model.[20]

We provide a qualitative illustration of theorem 4 in Figure 3, where we abstract from transition dynamics. The left-graph of the figure shows the evolution of total output in the economy under two scenarios. Shown in a solid line, total output keeps increasing over time (log) linearly at the steady state growth rate. If A_s increases (permanently) at a point in time (denoted by $t = 0$ in the graph), then total output increases instantaneously, as shown by the dashed line. This instantaneous increase is the result of the higher productivity in agriculture and the increased output in manufacturing due to the entry of

[20]Previous literature, see Caselli 2005, Restuccia et al. 2008, Lagakos and Waugh 2013, Lagakos and Waugh 2013, or Gollin et al. 2014, argues that there are frictions to mobility from agriculture to manufacturing that impede workers to move across sectors. Instead, in this paper we observe patterns that are in-line with relatively flexible cross-sector mobility, and the static gains come exclusively from increases in agricultural productivity.

low-skilled workers into the sector. However, because the sector that absorbs labor is the low-skilled intensive manufacturing industry and some high-skilled workers leave the high-skilled intensive industry, the new equilibrium growth rate decreases, shown in the graph as a lower trend in the dashed line. The increase in total output in manufacturing is lower than the increase in total output, as shown in the right-graph of Figure 3, because total output in manufacturing only increases on impact because of the reallocation of workers away from agriculture and not because of technological progress. After the initial increase in manufacturing output, industrial specialization lowers the trend in manufacturing output in exactly the same way as it lowers the trend in overall output.

Figure 3 goes around here

In what follows, we explore how these theoretical insights can help us understand the patterns in the data.

4 Empirics

This section describes our identification strategy and reports the main empirical results of the paper. We start by discussing our identification strategy in section 4.1. In sections 4.2 and 4.3, we study the effect of soy technical change on the reallocation of low-skilled and high-skilled workers across sectors, as well as its effect on the wages of these two types of workers. Finally, in section 4.5, we focus on the effect of soy technical change on labor allocation across industries within the manufacturing sector, and its impact on manufacturing productivity.

4.1 Identification Strategy

To estimate the effect of soy technical change on our outcomes of interest, we estimate the following equation:

$$\Delta Y_k = \alpha + \beta \Delta A_k^{soy} + \varphi X_k + \varepsilon_k \tag{8}$$

where ΔY_k is the change in the outcome of interest in microregion k between 2000 and 2010, ΔA_k^{soy} corresponds to our exogenous measure of technical change in soy described in section 2.2, and X_k is a vector of controls of microregion k. Our identification strategy relies on the fact that the new GE soybeans seeds were legalized in Brazil in 2003, and that this new technology disproportionately favored microregions with certain soil and weather characteristics (as captured by ΔA_k^{soy}), something that was not anticipated as of 2000.

In our baseline specification, we include as controls the share of rural population in 1991 and a measure of technical change in maize. The lagged share of rural population captures differential trends in the outcome variable between urban and rural microregions, whereas the technical change in maize captures the differential impact across microregions of new maize production methods that were introduced in this period.[21] In our extended specification, we also control for the initial level of income per capita, alphabetization rate, and population density, all observed in 1991 and sourced from the Population Census. These controls are meant to capture differential trends across microregions with different initial levels of income and human capital.

4.2 Effect of Technical Change on Labor Reallocation and Skill Intensity

In this section we start by establishing that soy technical change introduced by GE seeds was labor-saving. Microregions that could benefit more from the new technology experienced a reallocation of workers from the agricultural sector to the manufacturing and services sectors. Next, we document that soy technical change was not only labor-saving, but also skill-biased. In particular, with the introduction of this new technology, high-skilled workers had relatively more opportunities in the agricultural sector than low-skilled workers. This led low-skilled workers to leave agriculture. As argued in Section 3, the skill-biased nature of technical change in agriculture affects the type of industrial specialization of the economy as a whole.

We start in Table 3 by documenting that soy technical change generated a reallocation of labor from agriculture into manufacturing, i.e. it led to structural transformation. This is shown in columns (3) to (8) of Table 3. We find that microregions with higher exposure to soy technical change experienced a decrease in the share of workers employed in agriculture and an increase in the share of workers employed in manufacturing and services. Notice that – as shown in column (2) – soy technical change had only small and not significant effects on total employment. Thus, the employment changes that we document in what follows are not driven by migration between microregions or by changes in the total number of workers employed, but by movement of workers across sectors within microregions. The estimate presented in column (4) indicates that microregions with a one standard deviation larger increase in soy technical change experienced a 2.4 percentage points lower change in agricultural employment share. This estimate is stable to the inclusion of controls, as can be observed when comparing Columns (3) and (4). These agricultural workers displaced by the new soy technology relocated into manufacturing and services. Manufacturing employment shares increased by 1.7 percentage points and

[21] This new production methods – and in particular second-season maize – might have affected some of the outcomes and are partially correlated with the soy shock. See Bustos et al. (2016) for a detailed discussion of second-season maize.

services employment share by 0.7 percentage points for a standard deviation difference in soy technical change, hence absorbing the bulk of workers released from agriculture. In sum, the results presented in Table 3 show that soy technical change was labor-saving and led to structural transformation, which is the main finding documented in Bustos et al. (2016).[22]

Table 3 goes around here

Next, in Table 4, we investigate whether the soy technical change was skill-biased. More specifically, we investigate whether the workers who left agriculture were high- or low-skilled. To do so, we proceed in two steps. First, we study whether regions most favorably affected by the shock gained or lost total employment in each skill type. Next, we trace the movement across sectors of workers of each skill type within the microregion.

We start by discussing the results reported in Panel A of Table 4. Columns (1) and (2) show that soy technical change had negative – although not precisely estimated – effects on the total employment of low-skilled workers. Columns (3) to (8) investigate the effect of soy technical change on the reallocation of low-skilled workers across sectors. In particular, as shown in Columns (4) and (6), microregions more exposed to soy technical change experienced a larger reallocation of low-skilled workers from agriculture to manufacturing.[23]

Table 4 goes around here

Panel B of Table 4 repeats the exercise of Panel A for high-skilled workers. Contrary to what happened with low-skill employment, microregions positively affected by the soy shock experienced an increase in total high-skilled employment, as shown in Columns (1) and (2), something that is not driven by internal migration as we documented in Table A2 in the Appendix, but rather through increased local employment. Columns (3) to (8) explore whether the share of high-skilled workers employed in each sector was affected by soy technical change. The estimates in columns (3) and (4) indicate that,

[22] Bustos et al. (2016) find that soy technical change had a positive and significant effect on the employment share in manufacturing but no significant effect on the employment share in the services sector. Table 3 in this paper documents that microregions more exposed to soy technical change experienced an increase in employment share in both manufacturing and services. There are two reasons behind this difference in results when the outcome is the employment share in the services sector. The first is that, in this paper, we focus on remunerated labor – i.e. workers receiving a wage – whereas Bustos et al. (2016) also included workers who helped household members without receiving a payment or worked in subsistence agriculture. The second is the unit of observation, which is a microregion in Table 3, a municipality in Bustos et al. (2016).

[23] Table A1 in the Appendix shows the results using as an outcome the total number of unskilled workers instead of shares.

in microregions more exposed to the shock, the share of high-skilled workers employed in agriculture decreased. As shown in Table A1 in the Appendix – which report the same regression when the outcome is total number of skilled workers – the decrease in the share of high-skilled workers in agriculture is driven by the total increase in high-skill employment in microregions more exposed to the soy shock, and not by an overall decrease in the total number of high-skilled workers employed in agriculture, which was not significantly affected by soy technical change (see column (4) of Table A1). On the other hand, we observe that manufacturing gained relatively more high-skilled workers, while services also gained high-skilled workers, but at the average of the microregion. Taken together, our estimates show that manufacturing gained both high- and low-skilled employees, whereas agriculture lost low-skilled workers.

To explore whether the soy shock affected the skill intensity of the different regions and sectors within these microregions, in Panel C we estimate the effect of soy technical change on skill intensity, measured as the (log) ratio of high-skilled workers over low-skilled workers. Consistently with Panels A and B, microregions positively affected by the soy shock became more skill-intensive, a consequence of the increase in high-skill employment. In columns (3) to (8) we study the effect on skill intensity by sector. In particular, we use as an outcome the change in skill intensity in a given sector relative to the change in skill-intensity in the whole microregion. The results show that, in regions more exposed to soy technical change, manufacturing experienced lower increases in skill intensity relative to the other sectors.

In sum, Table 4 documents that regions more exposed to soy technical change experienced faster increase in high-skilled employment and a reallocation of low-skilled workers out of agriculture and into manufacturing. This reallocation of labor across sectors is consistent with the predictions of the model presented in Section 3 in response to skilled labor-augmenting technical change. It is crucial, thus, to understand how these workers that moved into manufacturing were absorbed across industries within the manufacturing sector. Before showing these results, however, we investigate wage changes.

4.3 Effect of Technical Change on Wages and Skill Premia

In section 4.2 we presented evidence consistent with regions more exposed to soy technical change experiencing a decline in the absolute demand for low-skilled labor and a relative increase in the demand for high-skill labor in agriculture. If labor supply across sectors or microregions is imperfectly elastic, some of these results should also be observable in wage changes. Instead, if workers mobility across sectors is high, we should not observe substantial differences in wage changes across sectors. This is what we investigate in this section.

Following the structure in Tables 3 and 4, we first look at what happens to the average worker in the local economy and then we distinguish between high-skilled and low-skilled workers. Table 5 shows that microregions with higher exposure to soy technical change experienced larger increases in wages. As shown in Columns (3) and (4), these wage gains are driven by the agricultural sector. It is important to remember that our outcome variable is the change in composition-adjusted wages, computed as explained in Section 2.2. This means that we always net out all the observable characteristics of workers using Mincerian regressions in order to obtain a measure of how much each labor type is paid.

Table 5 goes around here

Given the evidence presented in section 4.2, we expect important differences across labor types. We investigate this in Table 6. As before, we first study each labor type separately. Next, we study relative wages between high-skilled and low-skilled workers (skill premia).

The results reported in Panel A, Columns (1) and (2), show no significant effects of soy technical change on average wages of low-skilled workers. When splitting workers by sector, we find that low-skilled agricultural workers experienced higher wage growth in microregions more exposed to the soy shock. We interpret this result as evidence that only the "best" low-skilled workers – in terms of unobservable characteristics – stayed in agriculture. In other words, the low-skilled workers that moved into manufacturing were negatively selected both in terms of observable characteristics, as documented in the previous section, and possibly in terms of unobservable characteristics.[24]

Table 6 goes around here

In Panel B of Table 6, we focus on wages of high-skilled workers as an outcome. Consistent with the increase in employment of high-skill workers, wages of high-skilled workers increased faster in microregions more exposed to soy technical change. Although this result holds across sectors, the effect is larger in agriculture. This is in line with the idea that agriculture experienced a relative increase in the demand for high-skilled workers, which is partly observable in employment and partly in wages.

Finally, in Panel C, we investigate whether the increase in the relative demand for high-skilled workers in agriculture led to systematic differences in the relative wages across types of workers in the different sectors of the economy. As can be seen in this panel, the

[24] The fact that there is selection in unobservable characteristics has been used in previous literature to explain cross-sectoral results: For an example, see Autor, Dorn, and Hanson (2013). Monras, Vazquez-Grenno, and Elias (2018) show that there is selection in "observables" and "unobservables" that goes in the same direction in labor market adjustments induced by a large amnesty program. They also introduce a model of the labor market with heterogenously productive low-skilled labor that rationalizes this fact.

estimates in each sector are similar in magnitude, which is consistent with the idea that labor reallocation across sectors is relatively elastic.

In sum, the evidence from wage regressions is consistent with what we learn from the employment responses, consistently with soy technical change being both labor-saving and skill-biased. The results in this section also imply that readjustment across sectors was, over this period, quite flexible, which suggests that it may be particularly interesting to further investigate labor reallocation within sectors. We turn to this point in the following section.

4.4 Reallocation Across Industries within Manufacturing

As discussed in Section 3, the way in which the excess supply of low-skilled workers in agriculture is absorbed into manufacturing is likely to have important consequences for industrial specialization and long-term economic growth. In this section, we document which industries absorbed the low-skilled workers release from agriculture due to technological innovation in soy production.

To investigate this point, we distinguish between low-skill-intensive and high-skill intensive industries within manufacturing. As explained in more detail in section 2.2, we split overall employment in manufacturing between industries above the median level of skill-intensity, defined as the share of skilled workers over total workers in the baseline year of 2000. We also present results splitting manufacturing industries by R&D intensity, which is measured as R&D expenditures as a share of sales in the baseline year. Table A3 reports the full list of industries by skill-intensity and R&D intensity, while Figure A.1 reports the correlation between skill intensity and R&D intensity at industry level.

Table 7 reports the main results of this section. We start in panel A by estimating equation (8) when the outcome variable is the share of unskilled labor employed in manufacturing over total unskilled labor in a given microregion. Column (1) shows that microregions more exposed to soy technical change experienced a larger increase in the share of low-skilled workers employed in manufacturing. In columns (2) and (3) we split the manufacturing sector into low-skill-intensive and high-skill-intensive industries. The estimated coefficients indicate that the increase in low-skilled manufacturing employment driven by soy technical change is concentrated exclusively in low-skill-intensive manufacturing industries. In columns (4) and (5) we replicate the same exercise splitting the manufacturing sector into low versus high R&D intensive industries. We find results consistent with low skilled workers released from agriculture being absorbed mostly by low R&D intensive manufacturing industries. In terms of magnitudes, the estimated coefficients in columns (2) and (4) indicate that microregions with a one standard deviation larger increase in soy technical change experienced a 2 percent higher change in low-skilled manufacturing employment share in low-skilled-intensive or low R&D industries.

Table 7 goes around here

Next, in Panel B of Table 7, we focus on the share of high-skilled labor employed in manufacturing over total skilled labor in a given microregion as an outcome. Column 1 shows that manufacturing gained high-skilled employment in response to soy technical change. However, as shown in columns (2) and (3), we do not find significant differences in this effect between manufacturing industries with different skill-intensities. When splitting manufacturing industries by R&D intensity, we find that, if anything, some high-skilled workers moved into low-R&D-intensive industries, consistent with the Rybczynski logic that the two-factor types move to the same type of sectors.

Finally, in Panel C of Table 7, we study the effect of soy technical change on the skill intensity of the manufacturing sector. The outcome variable in all columns is the change in skill intensity of manufacturing workers in deviation from the change in overall skill intensity in a given microregion. Column (1) shows that microregions more exposed to soy technical change experienced a larger decrease in the ratio of high-skilled to low-skilled workers in the manufacturing sector. This change in the relative use of high vs low skilled workers in manufacturing is consistent with the effect of soy technical change on their relative wages documented in Panel C of Table 6. Next, we study the effect of soy technical change on skill intensity separately for low-skill intensive and high-skill intensive industries. Columns (2) and (3) show that, in response to the soy shock, low-skill intensive industries accommodated to a greater extent the excess supply of low-skilled labor leaving agriculture. Thus, they became relatively more low-skill-intensive. We find similar results when splitting manufacturing industries by R&D intensity in Columns (4) and (5), although high-R&D intensive industries also seem to have experienced a decrease in skill-intensity in response to soy technical change.

Table 7 shows that low-skilled labor is absorbed into low-skill intensive manufacturing. So far, we have split manufacturing into two industries making sure that half of total manufacturing employment is assigned to each industry. This is, however, an arbitrary split of the manufacturing sector. In fact, the model suggests that low-skill intensive manufacturing expands only if the unskill-intensity of the sector is sufficiently close to that of agriculture. To investigate this further, we split manufacturing into four industries, ranked by their skill intensity, concentrating one fourth of total manufacturing employment, instead of just two and we none-parametrically estimate which of the four groups absorbs low-skilled labor. To do so we use the following equation:

$$\Delta \frac{L_{m,ik}}{L_k} = \alpha + \beta_i \Delta A_k^{soy} \times \gamma_i + \gamma_i + \varepsilon_{ik} \tag{9}$$

where i indexes quartiles of skill intensity at industry level and k indexes microregions. The outcome variable in this regression is the change in manufacturing employment in each quartile of industry skill-intensity as a share of total employment in a given microregion. For example, $\Delta\frac{L_{m,1k}}{L_k}$ is the change in manufacturing workers employed in industries belonging to the lowest quartile of initial skill-intensity divided by total workers in a given microregion. When estimating equation (9) we include the standard set of controls at microregion level interacted with quartiles of skill intensity at industry level (γ_i).

Figure 4 shows the results. In this Figure we report the estimated coefficients on soy technical change by quartile of industry skill-intensity. The Figure shows that the effect of soy technical change on the change in manufacturing employment share documented in Table 3 is concentrated in industries in the lowest quartile of skill-intensity. We obtain similar results when splitting industries by R&D intensity, as shown in Figure 5.

Figures 4 and 5 go around here

Overall, the results presented in Figures 4 and 5 show that soy-driven increases in manufacturing employment are concentrated in the lowest skill-intensive and R&D intensive industries. This is fully in line with the model introduced Section 3. Only when the skill intensity in manufacturing is not too far from that of agriculture we should observe that industries can absorb the excess supply of low-skilled labor "freed" from agriculture. These is in line with the logic of the classical Heckscher-Ohlin theory of international trade. In addition, the fact that these effects are concentrated in low R&D manufacturing industries has implications for long-run growth potential. As argued in section 3, we view these findings as a cautionary note on the potential benefits of structural change. When structural change is driven by "push" factors, the workers leaving agriculture may be negatively selected, and may, thus, favor the expansion of sectors in manufacturing with lower innovation-intensity. We test the implications of this result on manufacturing productivity in what follows.

4.5 Development Dynamics

In section 4.4 we showed that technical change in soy production led to a reallocation of low-skilled workers into low-skill intensive and low-R&D intensive manufacturing industries. A key implication of the theoretical framework presented in section 3 is that this type of industrial specialization may push the economy towards a lower GDP growth path in the long run. In this section we provide empirical evidence consistent with this argument.

The empirical analysis presented in this section relies on data from the Annual Industrial Survey (PIA), described in detail in Section 2.2. There are two main advantages of the PIA data. First, it provides detailed information on labor and value added for the universe of manufacturing firms above a certain employment threshold operating across

Brazilian microregions. Second, because the data is reported annually, it allows us to study the effect of soy technical change on manufacturing employment and productivity at a yearly frequency. The main draw-back of these data is that we cannot distinguish between high- and low-skilled workers as we did with Census data.

To exploit the yearly variation in the data and visualize the evolution of outcomes of interest, we first estimate the following event-type equation:

$$\ln y_{k,t} = \delta_t + \delta_k + \sum_{j=2001}^{j=2009} \beta_j \Delta A_k^{soy} + \gamma X_{k,t} + t \times X'_{k,1991}\omega + \varepsilon_{k,t} \tag{10}$$

where ΔA_k^{soy} is the change in our exogenous measure of technical change in soy in microregion k as defined in section 2.2, and $\ln y_{k,t}$ is an outcome of interest in microregion k at time t. δ_k and δ_t are microregion and year fixed effects, respectively, and $X_{k,t}$ are time-varying controls and $X_{k,1991}$ are baseline controls interacted with a time trend.[25] β_j estimates the effect of the change in the productivity of soy in each year between 2000 and 2009, using 2000 as the omitted category.[26] Thus, we flexibly allow β_j to capture the effect of soy ten year technical change on the outcomes of interest in each year. Given that genetically modified soy was introduced in 2003, we expect significant effects of our exogenous measure of technical change on the outcomes of interest starting around 2003. This type of specification is also informative on the persistence of these effects.

We use equation 10 to study the effect of soy technical change on two main outcomes: manufacturing employment and manufacturing productivity. For each of these outcomes we separately study the effects in low-skill intensive industries and high-skill intensive industries. For each outcome we plot the estimated β_j in equation 10 for each year between 2000 and 2009, along with the 95 percent confidence interval around the point estimates.

Figure 6 goes around here

We start by studying the yearly effect of soy technical change on manufacturing employment. Figure 6 reports the results when the outcome variables are employment in low-skill intensive manufacturing industries (Figure 6a) and in high-skill intensity manufacturing industries (Figure 6b). We find that in regions more affected by soy productivity increases, more labor enters low-skilled manufacturing industries, while there are no differential effects of soy technical change on employment in high-skill intensive industries.[27]

[25] $X_{k,t}$ controls for technical change in maize.

[26] When estimating equation 10 in the data we additionally control for the change in maize technical change interacted with year fixed effects as well as for the standard set of microregion level controls used in previous tables, interacted with time fixed effects.

[27] Notice that PIA data does not report information on workers' education. Therefore, in this section we cannot separate high and low-skilled workers accurately, which is why we have used Census data in the previous sections.

In addition, the amount of labor entering low-skill intensive industries starts to increase substantially after 2003, consistent with the timing of introduction of GE soybean seeds. These results are also consistent with those presented in section 4.4 and 4.2 using Census data, which showed that the workers entering manufacturing following the soy shock were mainly low-skilled, and that they tended to be absorbed by low-skill intensive industries.

Figure 7 goes around here

Next, we investigate the effect of soy technical change on manufacturing productivity. Ideally, we would like to use total factor productivity in manufacturing as an outcome. However, due to data limitations in the reporting of book value of physical capital in the Annual Industrial Survey, we use value added per worker in a given micro-region as a proxy for manufacturing productivity. We define labor productivity in a micro-region as the sum of value added of all firms in that region divided by their total employment. Figure 7 shows the differential dynamics in labor productivity as a function of the change in soy technical change. The graph shows that micro-regions more exposed to the soy shock experienced a relative decline in labor productivity. The effect becomes statistically significant in 2005, two year after the legalization of GE soybean seeds, and increases in magnitude over the decade.

While Figure 7 seems to confirm the predictions of the model, it could also be explained by labor productivity decreasing in manufacturing purely as a result of a composition effect. If labor productivity is lower in low-skill intensive industries, then the movement of workers towards these industries necessarily results in lower aggregate labor productivity in manufacturing. Our model highlights instead that manufacturing productivity decreases because the incentives to innovate in high-skill-intensive sectors decrease. To investigate this, we split manufacturing between high- and low-skill-intensive industries, as we did in Figure 6. The results are reported in Figure 8. As predicted in our model, the decrease in manufacturing productivity is concentrated in high-skill-intensive industries.

Figure 8 goes around here

We quantify the estimates shown in Figures 7 and 8 in Table 8. To this end we use the following regression:

$$\ln y_{k,t} = \delta_t + \delta_k + \beta A^{soy}_{k,t} + \gamma X_{k,t} + t \times X'_{k,1991}\omega + \varepsilon_{k,t}$$

where $A^{soy,t}$ is defined as potential soy yield under high inputs for the years between 2003 and 2009, and the potential soy yield under low inputs for the years between 2000 and 2002. δ_k and δ_t are microregion and year fixed effects, respectively, and $X_{k,t}$ are time-varying controls and $X_{k,1991}$ are baseline controls interacted with a time trend.[28] Hence, β is the (continuous) difference-in-difference estimate obtained from comparing microregions before and after 2003.[29]

Table 8 goes around here

In line with the figures, in the first column of Table 8 we show that aggregate employment in manufacturing increased after the legalization of GE soybeans. This table uses data from PIA – which does not let us distinguish between high- and low-skilled workers –, but confirms that irrespective of the data set used we observe that manufacturing disproportionately gains employment in soy-shock regions. Columns 3 and 5 show that the manufacturing industries that gained employment are the low-skilled intensive ones.

Columns 2, 4, and 6 report results on labor productivity. Column 2 shows that labor productivity in manufacturing declined in soy-shock regions, as predicted by the model introduced in section 3. This estimate could be the result of increased employment in industries with low labor productivity. Our model, however, suggests a different mechanism. In the model manufacturing productivity declines because investing in high-skilled intensive industries is less profitable. Hence, the model predicts that manufacturing productivity decreases because it decreases in the high-skilled intensive industries. Columns 4 and 6 show that this is exactly what we also observe in the data.

In sum, Figures 7 and 8, and Table 8 provide empirical evidence consistent with one of the key implications of the model discussed in Section 3. An increase in agricultural productivity due to the introduction of new technologies can benefit the local economy in the short-run. However, when these technologies are skilled biased they tend to displace low-skilled workers into manufacturing, expanding the least productive manufacturing industries. Thus, compared to a counterfactual where workers leaving agriculture enter the most vibrant and R&D intensive sectors, our evidence suggests that structural transformation may not lead the economy from a "subsistence" sector with negligible productivity to a capitalist and high growth potential sector, as argued by Lewis (1954) and Kuznets (1973).[30] Depending on the circumstances, the workers leaving agriculture may expand the "wrong" industries, leading to lower productivity growth in the long-run than what was believed in the previous literature.

[28] $X_{k,t}$ controls for technical change in maize and is defined as potential maize yield under high inputs for the years between 2003 and 2009, and potential maize yield under low inputs for the years between 2000 and 2002.

[29] In this table we use a balanced panel of microregions that includes all the microregions for which we have observations in each year of the decade.

[30] In Appendix C we quantify how much our mechanism affected aggregate R&D.

5 Conclusions

The reallocation of labor from agriculture into manufacturing is generally regarded as positive in economic development literature. Several studies have documented that the manufacturing sector has, on average, higher productivity and pays higher wages. However, little is known about which type of workers are released from the agricultural sector and which manufacturing industries absorb them during the process of structural transformation.

Our paper contributes to the literature by showing that the forces driving structural transformation can shape the type of industries in which a country specializes. In most countries, the process of industrialization can be ascribed to one of two forces: "push" forces, such as new agricultural technologies that push workers out of agriculture, or "pull" forces, such as industrial growth that pull workers into manufacturing. We show that when labor reallocation from agriculture to manufacturing is driven by labor-saving agricultural productivity growth – rather than manufacturing labor demand – it can generate an expansion in those manufacturing sectors with the lowest potential contribution to aggregate productivity.

We guide our empirical analysis through the lenses of an open economy, three sector endogenous growth model. The model suggests that the low-skilled labor released from agriculture should find accommodation in the low-skilled intensive manufacturing industries, which leads to lower productivity growth. We use yearly data on labor productivity to show that the data fully supports the predictions of the model.

Taken together, our findings indicate that structural transformation obtained through labor-saving and skill-biased technical change in agriculture – which may be quite common when developing countries adopt agricultural technologies from more developed ones – can attenuate the standard gains from reallocation into manufacturing emphasized by the existing literature.

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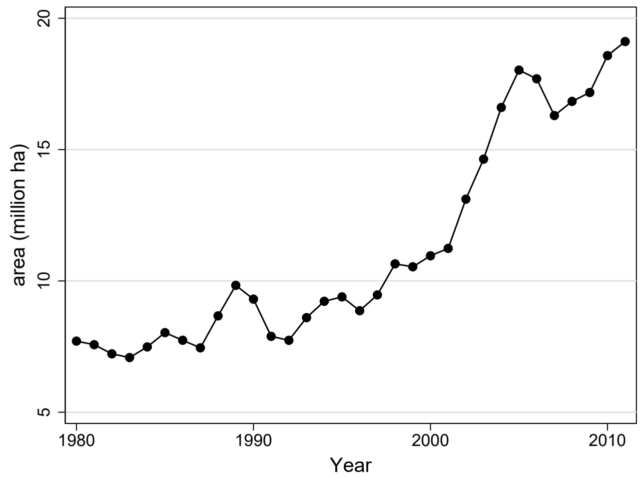
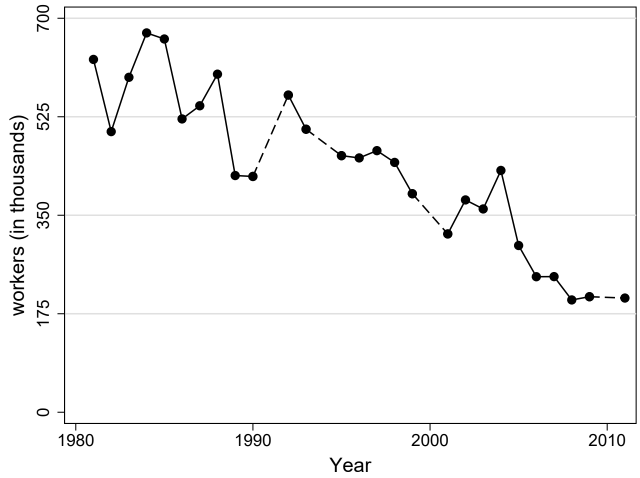
6 Figures and Tables

Figure 1: Soy Production and Employment

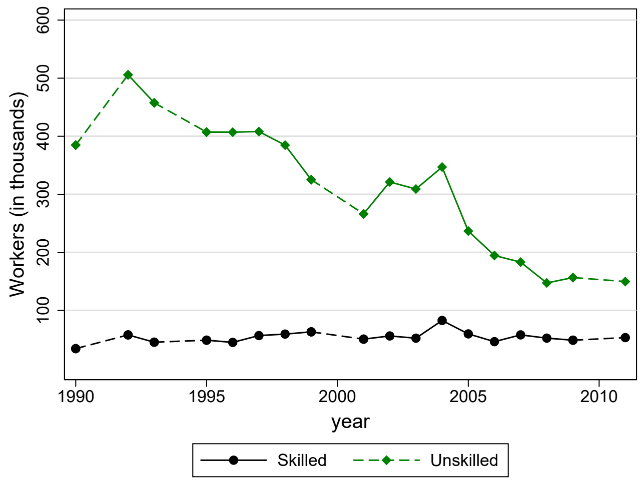
(a) Soy: Area planted



(b) Soy: Employment

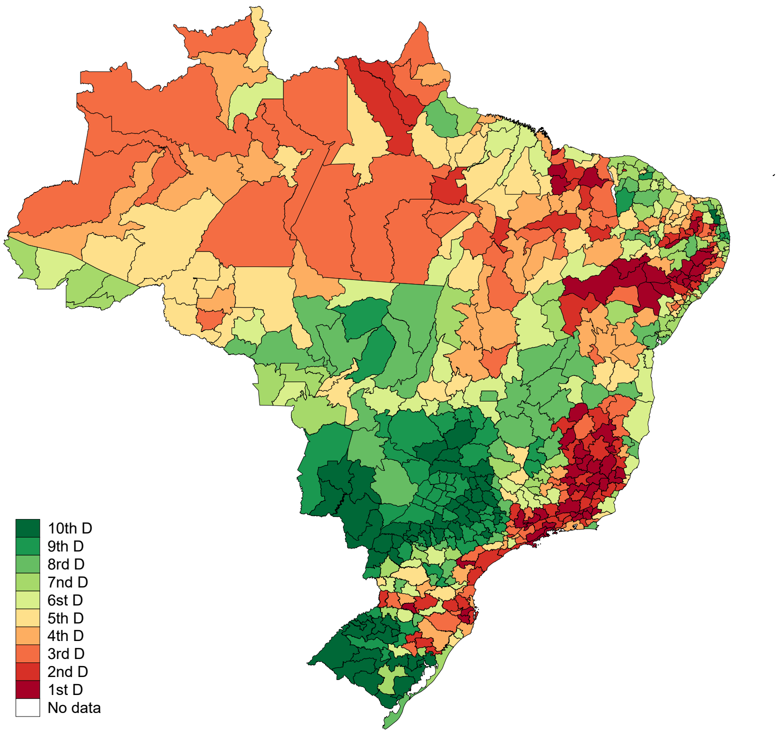


(c) Soy: Employment by Skill Group



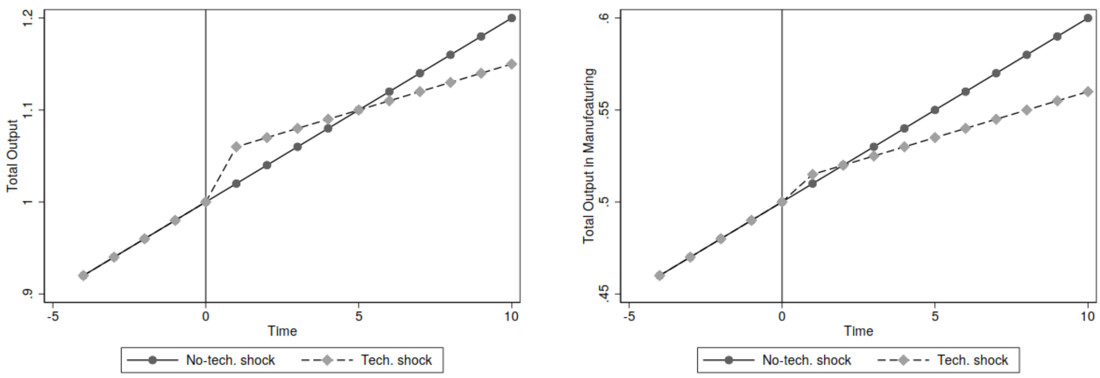
Notes: First two figures taken from Bustos et al. (2016). Data sources of Panel A is CONAB and of Panel B and C is PNAD. The states of Rondonia, Acre, Amazonas, Roraima, Pará, Amapá, Tocantins, Mato Grosso do Sul, Goias, and Distrito Federal are excluded due to incomplete coverage by PNAD in the early years of the sample. In Panel C, an individual is classified as skilled if it has at least completed the 8^{th} grade. This level should be attained when an individual is 14 or 15 years old and is equivalent to graduating from middle school.

Figure 2: Δ in Potential Soy Yield 2000-2010



Notes: Authors' calculations from FAO-GAEZ data. Technical change in soy production for each microregion is computed by deducting the average potential yield under low inputs from the average potential yield under high inputs.

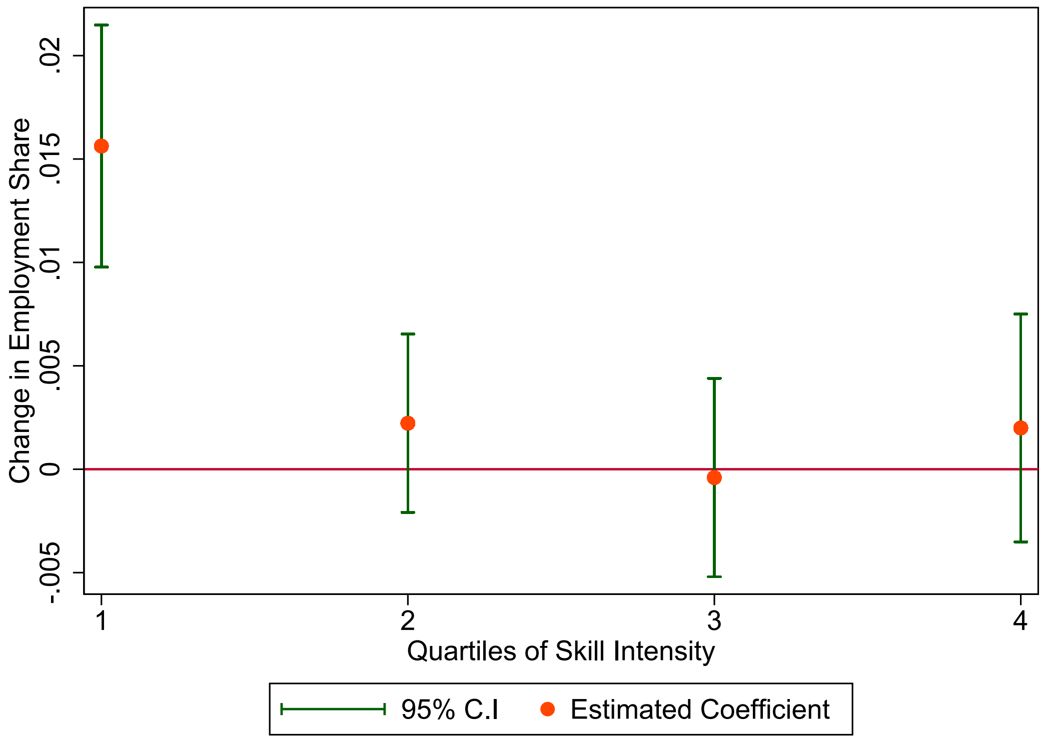
Figure 3: Evolution of output given an increase in A_s



Total Output **Total Output in Manufacturing**

Notes: This figure shows the qualitative theoretical evolution of total output (left panel) and total output in manufacturing (right panel) implied by our model when at time $t = 0$ skilled-biased-factor-augmenting technology (A_s) in agriculture increases. The figure displays the evolution of the economy both with (dashed line) and without (solid line) the technological change.

Figure 4: Employment Share Growth by Quartile of Skill Intensity

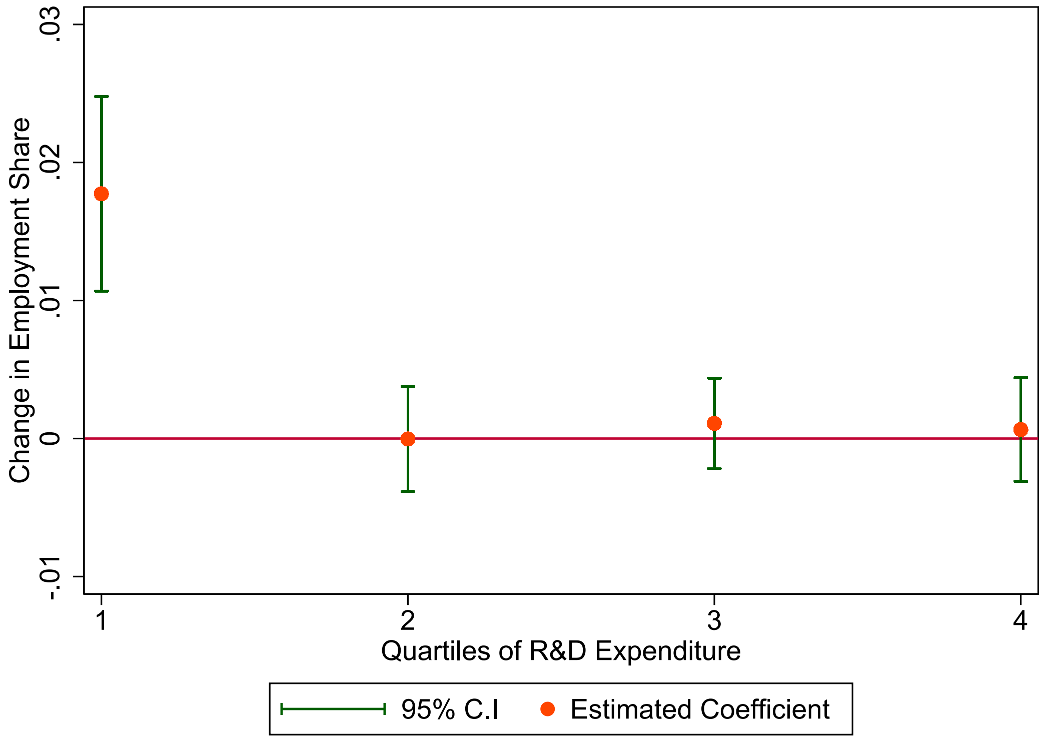


Notes: The plot shows the β_i coefficients of the following regression:

$$\Delta \frac{L^k_{m,i}}{L^k} = \alpha + \beta_i \Delta A_{soy} \times \gamma_i + \theta_i \Delta A_{mze} \times \gamma_i + \gamma_i + \varphi X_{k,1991} + \varepsilon^i_k$$

for $i = 1, 2, 3, 4$ where γ_i is a dummy for the different quartiles of skill intensity. We are splitting splitting manufacturing industries in quartiles according to their level of skill intensity in such a way that roughly 25% of the Brazilian manufacturing employment is in each group. Changes in dependent variables are calculated over the years 2000 and 2010 (source: Population Censuses). We define skill intensity as the share of skilled individuals in a particular industry in Brazil at baseline and we source it from the 2000 Population Census.

Figure 5: Employment Share Growth by Quartile of R & D Expenditure

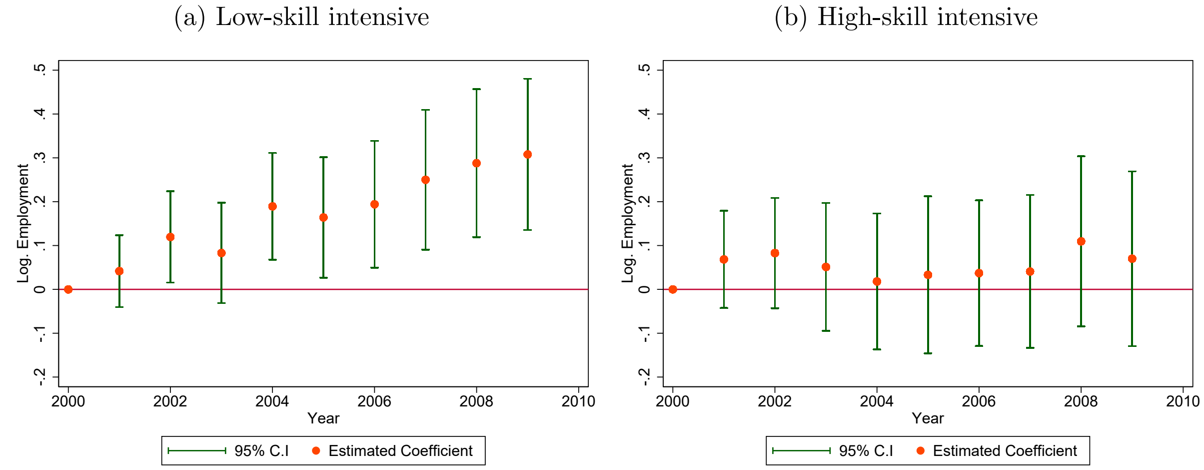


Notes: The plot shows the β_i coefficients of the following regression:

$$\Delta \frac{L^k_{m,i}}{L^k} = \alpha + \beta_i \Delta A_{soy} \times \gamma_i + \theta_i \Delta A_{mze} \times \gamma_i + \gamma_i + \varphi X_{k,1991} + \varepsilon^i_k$$

for $i = 1, 2, 3, 4$ where γ_i is a dummy for the different quartiles of R&D activity. We are splitting splitting manufacturing industries in quartiles according to their level of R&D activity in such a way that roughly 25% of the Brazilian manufacturing employment is in each group. Changes in dependent variables are calculated over the years 2000 and 2010 (source: Population Censuses). Our measure of R&D activity is R&D expenditure as a share of total sales at baseline and we source it from from the 2000 *Pesquisa de Inovação Tecnológica* (PINTEC).

Figure 6: Effect of the Soy Shock on Manufacturing Employment by Type of Industry

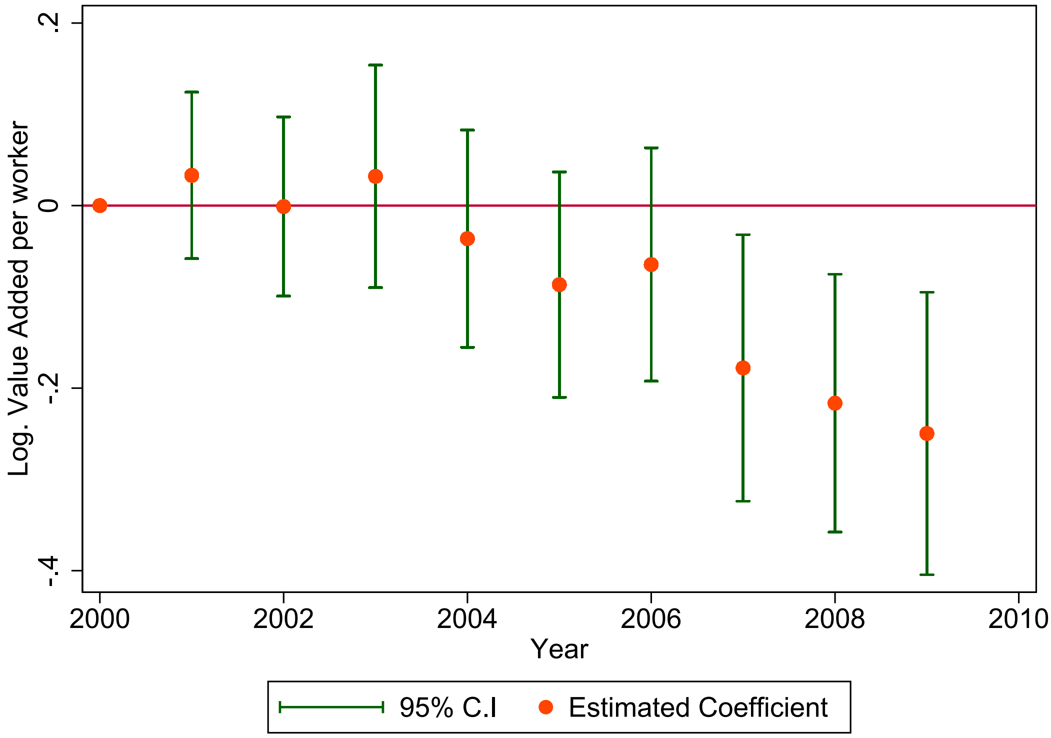


Notes: The plot shows the point estimates and the 95% confidence intervals for the estimates of the β_j coefficients of the following regression:

$$\ln y_{k,t} = \delta_t + \delta_k + \sum_{j=2001}^{j=2009} \beta_j \Delta A_k^{soy} + \sum_{j=2001}^{j=2009} \gamma_j \Delta A_k^{mze} + tX'_{k,1991}\omega + \varepsilon_{k,t}$$

Standard errors are clustered at the microregion level. $\ln y_{k,t}$ corresponds to aggregate log. employment in microregion k at the end of year t for each group of industries (Source: PIA). We are splitting manufacturing industries across the median according to their level of skill intensity at baseline in such a way that roughly 50% of the Brazilian manufacturing employment is at both sides of the median.

Figure 7: Effect of the Soy Shock on Manufacturing Productivity



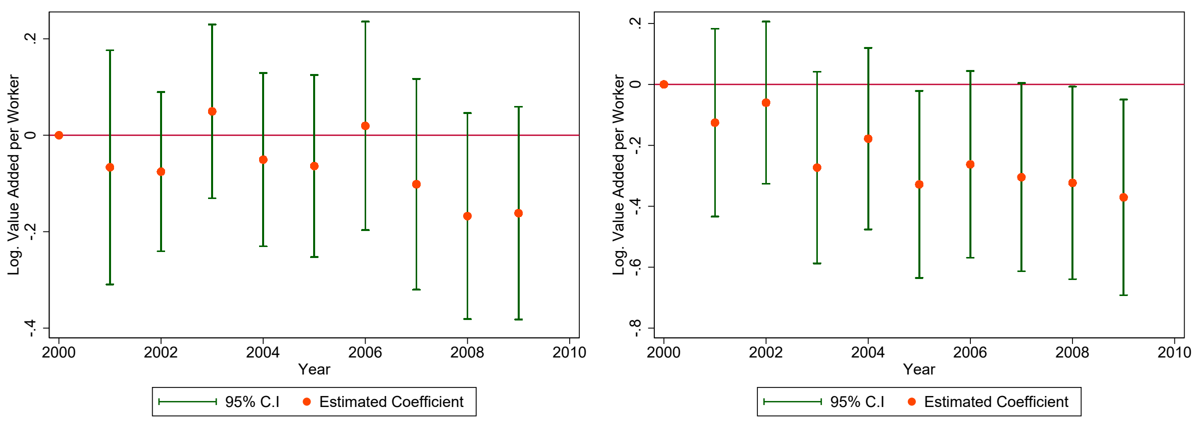
Notes: The plot shows the point estimates and the 95% confidence intervals for the estimates of the β_j coefficients of the following regression:

$$\ln y_{k,t} = \delta_t + \delta_k + \sum_{j=2001}^{j=2009} \beta_j \Delta A_k^{soy} + \sum_{j=2001}^{j=2009} \gamma_j \Delta A_k^{mze} + tX'_{k,1991}\omega + \varepsilon_{k,t}$$

Standard errors are clustered at the microregion level. $\ln y_{k,t}$ corresponds to aggregate log. value added per worker in microregion k at the end of year t for manufacturing industries (Source: PIA).

Figure 8: Effect of the Soy Shock on Manufacturing Productivity by Type of Industry

(a) Low-skill intensive (b) High-skill intensive



Notes: The plot shows the point estimates and the 95% confidence intervals for the estimates of the β_j coefficients of the following regression:

$$\ln y_{k,t} = \delta_t + \delta_k + \sum_{j=2001}^{j=2009} \beta_j \Delta A_k^{soy} + \sum_{j=2001}^{j=2009} \gamma_j \Delta A_k^{mze} + tX'_{k,1991}\omega + \varepsilon_{k,t}$$

Standard errors are clustered at the microregion level. $\ln y_{k,t}$ corresponds to aggregate log. value added per worker in microregion k at the end of year t for each group of industries (Source: PIA). We are splitting manufacturing industries across the median according to their level of skill intensity at baseline in such a way that roughly 50% of the Brazilian manufacturing employment is at both sides of the median.

Table 1: Summary Statistics of the Sample of Individuals by Sector

	2000	2010
Agriculture		
Age	38.0	39.0
Male (% of the Total)	89.3	81.2
White (% of the Total)	55.4	48.6
Education level (highest degree obtained)		
Less than Middle School (% of the Total)	86.1	72.7
Completed Middle School (% of the Total)	7.4	13.8
High School Graduates (% of the Total)	5.2	11.4
University Graduates (% of the Total)	1.3	2.1
Average log real hourly wage	0.81	1.06
For skilled labor	1.39	1.38
For unskilled labor	0.71	0.95
Low-Skill Manufacturing		
Age	36.7	37.3
Male (% of the Total)	61.1	61.0
White (% of the Total)	62.2	54.0
Education level (highest degree obtained)		
Less than Middle School (% of the Total)	61.8	43.5
Completed Middle School (% of the Total)	18.9	21.5
High School Graduates (% of the Total)	16.5	30.4
University Graduates (% of the Total)	2.9	4.5
Average log real hourly wage	1.23	1.41
For skilled labor	1.51	1.54
For unskilled labor	1.06	1.25
High-Skill Manufacturing		
Age	36.4	37.0
Male (% of the Total)	80.0	72.4
White (% of the Total)	65.9	56.5
Education level (highest degree obtained)		
Less than Middle School (% of the Total)	40.2	26.6
Completed Middle School (% of the Total)	21.5	19.9
High School Graduates (% of the Total)	28.8	43.1
University Graduates (% of the Total)	9.4	10.4
Average log real hourly wage	1.78	1.73
For skilled labor	2.03	1.84
For unskilled labor	1.40	1.42
Services		
Age	37.1	37.8
Male (% of the Total)	67.3	62.1
White (% of the Total)	58.9	50.8
Education level (highest degree obtained)		
Less than Middle School (% of the Total)	51.1	36.0
Completed Middle School (% of the Total)	17.9	19.3
High School Graduates (% of the Total)	23.4	34.3
University Graduates (% of the Total)	7.6	10.4
Average log real hourly wage	1.42	1.51
For skilled labor	1.77	1.67
For unskilled labor	1.01	1.24

Notes: The data comes from the Population Censuses for years 2000 and 2010. These summary statistics come from our final sample of individuals as detailed in 2.2. An individual is classified as skilled if it has at least completed the 8^{th} grade. This level should be attained when an individual is 14 or 15 years old and is equivalent to graduating from middle school. Manufacturing industries are classified according to their skill intensity at baseline. We are splitting manufacturing industries across the median according to their level of skill intensity in such a way that roughly 50% of the Brazilian manufacturing employment is at both sides of the median. We define of skill intensity as the share of skilled individuals in a particular industry in Brazil at baseline and we source it from the 2000 Population Census.

Table 2: Summary Statistics of the Sample of Microregions

		2000		2000-2010		
	Source:	**Mean**	**SD**	**Mean**	**SD**	**Observations**
Potential Yields	*FAO-GAEZ*					
Soy		0.286	0.135	1.787	0.740	557
Maize		1.847	0.9984	3.082	1.639	557
Employment Shares	*Population Census*					
Agriculture		0.279	0.140	-0.050	0.055	557
Low-Skill Manufacturing		0.100	0.055	-0.009	0.037	557
High-Skill Manufacturing		0.048	0.047	0.016	0.021	557
Services		0.573	0.118	0.044	0.057	557
Skill Intensity $\frac{S}{S+U}$	*Population Census*					
Local Economy		0.289	0.089	0.165	0.039	557
Agriculture		0.13	0.70	0.127	0.053	557
Low-Skill Manufacturing		0.305	0.101	0.191	0.091	557
High-Skill Manufacturing		0.446	0.147	0.153	0.134	557
Services		0.376	0.866	0.176	0.042	557
Log. Employment	*Population Census*					
Agriculture		8.268	0.890	0.122	0.249	557
Low-Skill Manufacturing		7.353	1.346	0.154	0.382	557
High-Skill Manufacturing		6.359	1.287	0.746	0.522	554
Services		9.194	1.887	0.404	0.175	557

Notes: The data comes from the Population Censuses for years 2000 and 2010. These summary statistics represent the mean values for the different variables of the set of 557 Brazilian microregions defined by the IBGE. Changes in the variables are calculated over the years 2000 and 2010. An individual is classified as skilled if it has at least completed the 8^{th} grade. This level should be attained when an individual is 14 or 15 years old and is equivalent to graduating from middle school. Manufacturing industries are classified according to their skill intensity at baseline. We are splitting manufacturing industries across the median according to their level of skill intensity in such a way that roughly 50% of the Brazilian manufacturing employment is at both sides of the median. We define of skill intensity as the share of skilled individuals in a particular industry in Brazil at baseline and we source it from the 2000 Population Census.

Table 3: Effect of technical change in soy on employment shares

VARIABLES	(1) Δ Log. L	(2) Δ Log. L	(3) $\Delta \frac{L_a}{L}$	(4) $\Delta \frac{L_a}{L}$	(5) $\Delta \frac{L_m}{L}$	(6) $\Delta \frac{L_m}{L}$	(7) $\Delta \frac{L_s}{L}$	(8) $\Delta \frac{L_s}{L}$
ΔA_{soy}	-0.033**	-0.011	-0.034***	-0.033***	0.020***	0.023***	0.014***	0.009**
	[0.015]	[0.013]	[0.005]	[0.005]	[0.004]	[0.005]	[0.005]	[0.004]
Observations	557	557	557	557	557	557	557	557
R-squared	0.023	0.154	0.218	0.242	0.086	0.107	0.251	0.311
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Changes in dependent variables are calculated over the years 2000 and 2010 (source: Population Censuses). The unit of observation is the micro-region. All the regressions include the baseline specification controls which are the share of rural population in 1991 and a measure of technical change in maize. The regressions with all controls also include income per capita (in logs), population density (in logs), literacy rate, all observed in the 1991 Population Census. Robust standard errors reported in brackets. Significance levels: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 4: Effect of technical change in soy on employment shares by skill group

Panel A: Reallocation of Unskilled Labor

VARIABLES	(1) Δ Log. U	(2) Δ Log. U	(3) $\Delta \frac{U_a}{U}$	(4) $\Delta \frac{U_a}{U}$	(5) $\Delta \frac{U_m}{U}$	(6) $\Delta \frac{U_m}{U}$	(7) $\Delta \frac{U_s}{U}$	(8) $\Delta \frac{U_s}{U}$
ΔA_{soy}	-0.062***	-0.023	-0.033***	-0.033***	0.025***	0.028***	0.008*	0.005
	[0.017]	[0.014]	[0.006]	[0.006]	[0.005]	[0.005]	[0.005]	[0.004]
Observations	557	557	557	557	557	557	557	557
R-squared	0.136	0.301	0.106	0.120	0.092	0.100	0.117	0.142
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Reallocation of Skilled Labor

VARIABLES	(1) Δ Log. S	(2) Δ Log. S	(3) $\Delta \frac{S_a}{S}$	(4) $\Delta \frac{S_a}{S}$	(5) $\Delta \frac{S_m}{S}$	(6) $\Delta \frac{S_m}{S}$	(7) $\Delta \frac{S_s}{S}$	(8) $\Delta \frac{S_s}{S}$
ΔA_{soy}	0.032*	0.052***	-0.015***	-0.016***	0.012**	0.013**	0.002	0.003
	[0.019]	[0.017]	[0.004]	[0.004]	[0.005]	[0.005]	[0.005]	[0.005]
Observations	557	557	557	557	557	557	557	557
R-squared	0.301	0.446	0.030	0.043	0.057	0.076	0.032	0.069
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	No	Yes	No	Yes	No	Yes	No	Yes

Panel C: Log. of Skill Intensity

VARIABLES	(1) $\Delta \log \frac{S}{U}$	(2)	(3) $\Delta \log \frac{S_a}{U_a} - \Delta \log \frac{S}{U}$	(4)	(5) $\Delta \log \frac{S_m}{U_m} - \Delta \log \frac{S}{U}$	(6)	(7) $\Delta \log \frac{S_s}{U_s} - \Delta \log \frac{S}{U}$	(
ΔA_{soy}	0.094***	0.075***	0.010	0.007	-0.086***	-0.100***	-0.025***	-0
	[0.017]	[0.016]	[0.028]	[0.030]	[0.027]	[0.026]	[0.009]	[0.
Observations	557	557	557	557	556	556	557	5
R-squared	0.174	0.213	0.065	0.074	0.021	0.041	0.131	0.
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
All Controls	No	Yes	No	Yes	No	Yes	No	Y

Notes: Changes in dependent variables are calculated over the years 2000 and 2010 (source: Population Censuses). The unit of observation is the micro-regio the regressions include the baseline specification controls which are the share of rural population in 1991 and a measure of technical change in maize. The regre with all controls also include income per capita (in logs), population density (in logs), literacy rate, all observed in the 1991 Population Census. In columns ((6) of Panel C, because there are no unskilled manufacturing workers in our sample in the microregion of Amapá (IBGE ID 16002) in 2010. Robust standard reported in brackets. Significance levels: $^{***}p < 0.01$,$^{**}p < 0.05$,$^{*}p < 0.1$.

Table 5: Effect of technical change in soy on wages by sector

VARIABLES	(1) Overall	(2) Overall	(3) Agriculture	(4) Agriculture	(5) Manufacturing	(6) Manufacturing	(7) Services	(8) Services
ΔA_{soy}	0.012	0.023***	0.044***	0.048***	0.014	0.016	0.004	0.018*
	[0.009]	[0.008]	[0.012]	[0.012]	[0.012]	[0.011]	[0.010]	[0.009]
Observations	557	557	557	557	557	557	557	557
R-squared	0.035	0.177	0.121	0.179	0.039	0.087	0.023	0.195
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Changes in dependent variables are calculated over the estimates of the Mincerian regression detailed in Section 2.2 using the male individuals working in each sector in our sample: $\Delta\gamma_k = \gamma_{k,2010} - \gamma_{k,2000}$. The unit of observation is the micro-region. All the regressions include the baseline specification controls which are the share of rural population in 1991 and a measure of technical change in maize. The regressions with all controls also include income per capita (in logs), population density (in logs), literacy rate, all observed in the 1991 Population Census. We recover the estimates of the dependent variable from a first stage Mincerian regression in which we estimate a regression of the log. hourly wage on a microregion fixed effect, and a vector of individual characteristics that includes dummies for the sector, for skill group, age group, race, and all the interactions between these variables. Naturally, when we estimate this regression for a particular sector we do not include the sector dummy. Robust standard errors reported in brackets. Significance levels: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 6: Effect of technical change in soy on wages by skill group

Panel A: Wages of Unskilled Labor

VARIABLES	(1) Overall	(2) Overall	(3) Agriculture	(4) Agriculture	(5) Manufacturing	(6) Manufacturing	(7) Services	(8) Services
ΔA_{soy}	-0.011	0.010	0.038***	0.045***	0.004	0.007	-0.004	0.011
	[0.009]	[0.009]	[0.012]	[0.012]	[0.014]	[0.013]	[0.010]	[0.010]
Observations	557	557	557	557	556	556	557	557
R-squared	0.181	0.262	0.118	0.170	0.027	0.068	0.018	0.169
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Wages of Skilled Labor

VARIABLES	(1) Overall	(2) Overall	(3) Agriculture	(4) Agriculture	(5) Manufacturing	(6) Manufacturing	(7) Services	(8) Services
ΔA_{soy}	0.033***	0.036***	0.115***	0.070***	0.052***	0.050***	0.028**	0.037***
	[0.011]	[0.010]	[0.021]	[0.020]	[0.019]	[0.018]	[0.012]	[0.012]
Observations	557	557	557	557	555	555	557	557
R-squared	0.063	0.164	0.058	0.164	0.034	0.070	0.030	0.157
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	No	Yes	No	Yes	No	Yes	No	Yes

Panel C: Skill Premia

VARIABLES	(1) Overall	(2) Overall	(3) Agriculture	(4) Agriculture	(5) Manufacturing	(6) Manufacturing	(7) Services	(8) Services
ΔA_{soy}	0.043***	0.025***	0.077***	0.025	0.052**	0.042**	0.033***	0.026***
	[0.009]	[0.009]	[0.020]	[0.019]	[0.022]	[0.020]	[0.010]	[0.010]
Observations	557	557	557	557	554	554	557	557
R-squared	0.081	0.121	0.028	0.098	0.012	0.014	0.018	0.025
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: In Panels A and B, changes in dependent variables are calculated over the estimates of the Mincerian regression detailed in Section 2.2 using the male individuals working in each sector in our sample: $\Delta\gamma_k = \gamma_{k,2010} - \gamma_{k,2000}$. In Panel C, we use our estimates for the unit price of skilled and unskilled labor and we define the skill premia at period t as Skill Premia$_{k,t} = \gamma^S_{k,t} - \gamma^U_{k,t}$, so that our dependent variable is ΔSkill Premia$_k$. All the regressions include the baseline specification controls which are the share of rural population in 1991 and a measure of technical change in maize. The regressions with all controls also include income per capita (in logs), population density (in logs), literacy rate, all observed in the 1991 Population Census. In columns (4) and (5) of Panel A, we have one observation less because there are no unskilled manufacturing workers in our sample in the microregion Amapá (IBGE ID 16002) in 2010. In columns (4) and (5) of Panel B, we have two we have one observation less because there are no skilled male manufacturing workers in our sample in the microregions of Japurà (IBGE ID 13002) and Chapadas Das Mangabeiras (IBGE ID 21021) in 2000. The missing observations in columns (4) and (5) of Panel C follow from the above. We recover the estimates of the dependent variable from a first stage Mincerian regression in which we estimate a regression of the log. hourly wage on a microregion fixed effect, and a vector of individual characteristics that includes dummies for the sector, for skill group, age group, race, and all the interactions between these variables. Naturally, when we estimate this regression for a particular sector and skill level we do not include the sector and skill group dummies. Robust standard errors reported in brackets. Significance levels: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 7: Reallocation of Labor to Manufacturing by Skill Group

Panel A: Unskilled Labor $\Delta \frac{U_M}{U}$

VARIABLES	(1) $\Delta \frac{U_m}{U}$	(2) $\Delta \frac{U_M}{U}$ Skill Intensity=Low	(3) $\Delta \frac{U_M}{U}$ Skill Intensity=High	(4) $\Delta \frac{U_M}{U}$ R&D Expenditure=Low	(5) $\Delta \frac{U_M}{U}$ R&D Expenditure=High
ΔA_{soy}	0.028***	0.025***	0.002	0.024***	0.004
	[0.005]	[0.004]	[0.002]	[0.004]	[0.003]
Baseline Controls	Yes	Yes	Yes	Yes	Yes
All Controls	Yes	Yes	Yes	Yes	Yes
Observations	557	557	557	557	557
R-squared	0.100	0.103	0.034	0.120	0.031

Panel B: Skilled Labor $\Delta \frac{S_M}{S}$

VARIABLES	(1) $\Delta \frac{S_m}{S}$	(2) $\Delta \frac{S_M}{S}$ Skill Intensity=Low	(3) $\Delta \frac{S_M}{S}$ Skill Intensity=High	(4) $\Delta \frac{S_M}{S}$ R&D Expenditure=Low	(5) $\Delta \frac{S_M}{S}$ R&D Expenditure=High
ΔA_{soy}	0.013**	0.006	0.007**	0.013***	0.000
	[0.005]	[0.004]	[0.003]	[0.004]	[0.003]
Baseline Controls	Yes	Yes	Yes	Yes	Yes
All Controls	Yes	Yes	Yes	Yes	Yes
Observations	557	557	557	557	557
R-squared	0.076	0.051	0.038	0.053	0.056

Panel C: Skill Intensity $\Delta \log \frac{S_M}{U_M} - \Delta \log \frac{S}{U}$

VARIABLES	(1) $\Delta \log \frac{S_m}{U_m}$	(2) $\Delta \log \frac{S_m}{U_m}$ Skill Intensity = Low	(3) $\Delta \log \frac{S_m}{U_m}$ Skill Intensity=High	(4) $\Delta \log \frac{S_m}{U_m}$ R&D Expenditure=Low	(5) $\Delta \log \frac{S_m}{U_m}$ R&D Expenditure=High
ΔA_{soy}	-0.100***	-0.157***	0.011	-0.105**	-0.054
	[0.026]	[0.034]	[0.050]	[0.041]	[0.037]
Baseline Controls	Yes	Yes	Yes	Yes	Yes
All Controls	Yes	Yes	Yes	Yes	Yes
Observations	556	556	544	551	552
R-squared	0.041	0.034	0.063	0.022	0.036

Notes: Changes in dependent variables are calculated over the years 2000 and 2010 (source: Population Censuses). The unit of observation is the micro-region. All the regressions include the baseline specification controls which are the share of rural population in 1991 and a measure of technical change in maize. The regressions with all controls also include income per capita (in logs), population density (in logs), literacy rate, all observed in the 1991 Population Census. In Panel C, we lose observations because of the logs. In these regressions, we are splitting manufacturing industries across the median according to their level of skill intensity and R&D activity in such a way that roughly 50% of the Brazilian manufacturing employment is at both sides of the median. We define of skill intensity as the share of skilled individuals in a particular industry in Brazil at baseline and we source it from the 2000 Population Census. Our measure of R&D activity is R&D expenditure as a share of total sales at baseline and we source it from from the 2000 *Pesquisa de Inovação Tecnológica* (PINTEC). Robust standard errors reported in brackets. Significance levels: $^{***}p < 0.01$,$^{**}p < 0.05$,$^{*}p < 0.1$.

Table 8: Effect of technical change in soy on manufacturing productivity

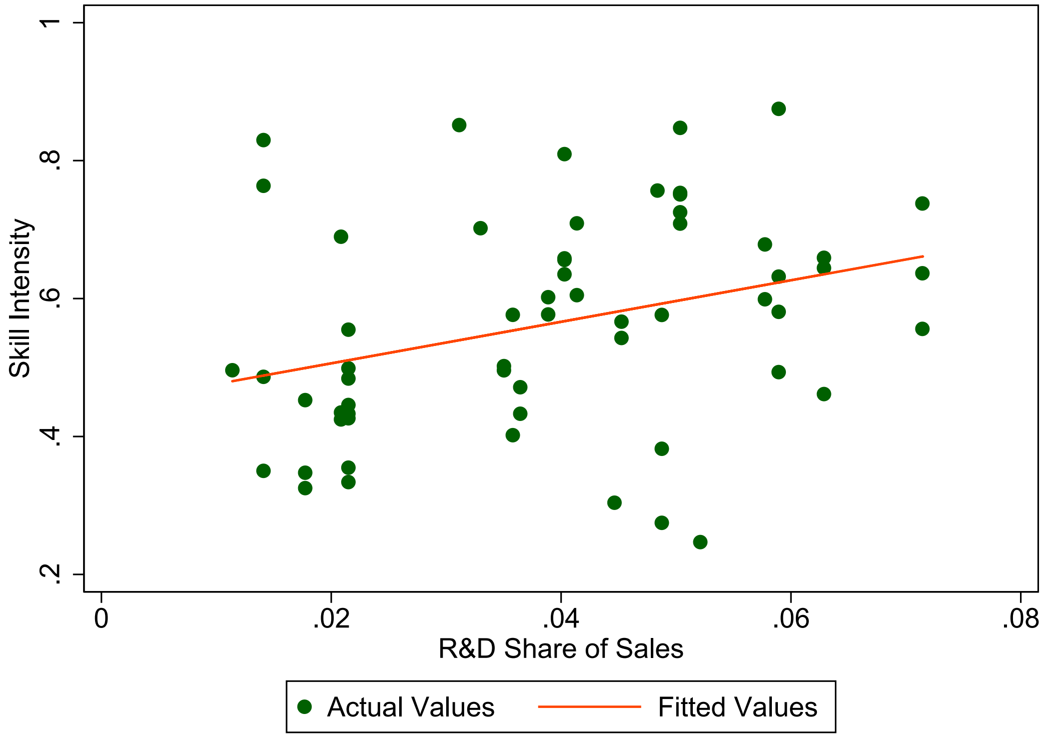
	Aggregate		Low skill intensity		High skill intensity	
	Log L	L-productivity	Log L	L-productivity	Log L	L-productivity
	(1)	(2)	(3)	(4)	(5)	(6)
A^{soy}	0.119***	-0.105**	0.152***	-0.019	0.016	-0.199**
	[0.034]	[0.047]	[0.049]	[0.055]	[0.063]	[0.078]
Observations	3,350	3,350	3,350	3,350	3,350	3,350
R-squared	0.976	0.864	0.954	0.769	0.960	0.814
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variables correspond to aggregate log. employment in microregion at the end of each year, L-productivity is labor-productivity measured by log. value added per worker (Source: PIA). We use aggregate information from PIA at the microregion level for the time period comprehended between 2000-2009. We include only those microregions that have both, low-skill intensive and high-skill intensive, industries for all the years in the sample. A^{soy} is defined as potential soy yield under high inputs for the years between 2003 and 2009, and the potential soy yield under low inputs for the years between 2000 and 2002. A^{mze} is defined as potential maize yield under high inputs for the years between 2003 and 2009, and potential maize yield under low inputs for the years between 2000 and 2002. We include time and microregion fixed effects in all the regressions. All the regressions include the baseline specification controls which are the share of rural population in 1991 and a measure of technical change in maize. The regressions with all controls also include income per capita (in logs), population density (in logs), literacy rate, all observed in the 1991 Population Census. Since these controls do not vary over time they are interacted with a linear trend. The unit of observation is the microregion. Standard errors clustered at the microregion level reported in parentheses. Significance levels: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

A Appendix: Empirics

A.1 Figures and Tables

Figure A.1: Correlation between Skill Intensity and R & D Expenditure



Notes: We define skill intensity as the share of skilled individuals in a particular industry in Brazil at baseline and we source it from the 2000 Population Census. Our measure of R&D activity is R&D expenditure as a share of total sales at baseline and we source it from from the 2000 *Pesquisa de Inovação Tecnológica](PINTEC)*. The correlation between these variables is approximately 0.33.

Table A1: Effect of technical change in soy on Log. Employment by Sector

Panel A: Employment of Unskilled Labor

VARIABLES	(1) Δ Log. U	(2) Δ Log. U	(3) Δ Log. U_a	(4) Δ Log. U_a	(5) Δ Log. U_m	(6) Δ Log. U_m	(7) Δ Log. U_s	(8) Δ Log. U_s
ΔA_{soy}	-0.062***	-0.023	-0.154***	-0.113***	0.117***	0.172***	-0.033*	-0.006
	[0.017]	[0.014]	[0.025]	[0.024]	[0.032]	[0.033]	[0.017]	[0.016]
Observations	557	557	557	557	556	556	557	557
R-squared	0.136	0.301	0.077	0.129	0.033	0.095	0.276	0.431
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Employment of Skilled Labor

VARIABLES	(1) Δ Log. S	(2) Δ Log. S	(3) Δ Log. S_a	(4) Δ Log. S_a	(5) Δ Log. S_m	(6) Δ Log. S_m	(7) Δ Log. S_s	(8) Δ Log. S_s
ΔA_{soy}	0.032*	0.052***	-0.050	-0.031	0.123***	0.148***	0.036*	0.057***
	[0.019]	[0.017]	[0.038]	[0.039]	[0.036]	[0.036]	[0.020]	[0.018]
Observations	557	557	557	557	557	557	557	557
R-squared	0.301	0.446	0.178	0.217	0.086	0.100	0.298	0.481
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Changes in dependent variables are calculated over the years 2000 and 2010 (source: Population Censuses). The unit of observation is the micro-region. All the regressions include the baseline specification controls which are the share of rural population in 1991 and a measure of technical change in maize. The regressions with all controls also include income per capita (in logs), population density (in logs), literacy rate, all observed in the 1991 Population Census. In columns (5) and (6) of Panel C, because there are no unskilled manufacturing workers in our sample in the microregion of Amapá (IBGE ID 16002) in 2010. Robust standard errors reported in brackets. Significance levels: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table A2: Internal migration

VARIABLES	(1) Net Migration: ALL	(2) In-Migration: ALL	(3) Out-Migration: ALL	(4) Net Migration: S	(5) In-Migration: S	(6) Out-Migration: S	(7) Net Migration: U	(8) In-Migration: U	(9) Out-Migration: U
ΔA_{soy}	-0.000	0.004	0.004	-0.006	-0.000	0.006	0.008	0.012**	0.005
	[0.009]	[0.005]	[0.006]	[0.010]	[0.005]	[0.007]	[0.008]	[0.005]	[0.006]
Observations	557	557	557	557	557	557	557	557	557
R-squared	0.496	0.307	0.541	0.442	0.307	0.532	0.535	0.292	0.526
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are calculated for 2010 (source: Population Censuses). The unit of observation is the micro-region. These regressions compute the 5 year internal migration rate between 2005 and 2010, using the microregion of residence 5 years prior to the Census 2010. All the regressions include the baseline specification controls which are the share of rural population in 1991 and a measure of technical change in maize. The regressions with all controls also include income per capita (in logs), population density (in logs), literacy rate, all observed in the 1991 Population Census. . Robust standard errors reported in brackets. Significance levels: $^{***}p < 0.01$,$^{**}p < 0.05$,$^{*}p < 0.1$.

Table A3: Classification of Manufacturing Industries by Skill Intensity

IBGE Code	Description	Skill Intensity	R&D Share of Sales
20000	Wooden products	0.247	0.052
26091	Ceramic products	0.275	0.049
37000	Recycling	0.304	0.045
19011	Tanning and other preparations of leather	0.325	0.018
15041	Manufacturing and refining of sugar	0.334	0.021
19020	Footwear	0.348	0.018
23400	Alcohol production	0.350	0.014
15010	Slaughtering and preparation of meat and fish	0.355	0.021
26092	Miscellaneous products of non-metallic minerals	0.382	0.049
36010	Pieces of furniture	0.402	0.036
18001	Making of clothing articles and accessories - except on order	0.425	0.021
15043	Other food products	0.426	0.021
17002	Manufacturing of textile objects based on cloth - except for garments	0.433	0.036
15030	Dairy products	0.433	0.021
18002	Making clothing articles and accessories - on order	0.435	0.021
15022	Vegetable fat and oil	0.446	0.021
19012	Leather objects	0.453	0.018
27003	Foundries	0.462	0.063
17001	Processing of fibers, weaving and cloth making	0.471	0.036
15021	Preserves of fruit, vegetables and other vegetable products	0.484	0.021
23010	Coke plants	0.487	0.014
35010	Construction and repair of boats	0.493	0.059
28001	Metal products - except machines and equipment	0.496	0.035
16000	Tobacco products	0.496	0.011
15042	Roasting and grinding of coffee	0.499	0.021
28002	Foundries, stamping shops, powder metallurgy and metal treatment services	0.502	0.035
25020	Plastic products	0.543	0.045
15050	Beverages	0.555	0.021
34003	Reconditioning or restoration of engines of motor vehicles	0.556	0.071
25010	Rubber products	0.567	0.045
26010	Glass and glass products	0.576	0.049
36090	Miscellaneous products	0.576	0.036
21002	Corrugated cardboard, packaging, and paper and cardboard objects	0.577	0.039
35090	Miscellaneous transportation equipment	0.581	0.059
31002	Electrical material for vehicles	0.599	0.058
21001	Pulp, paper and smooth cardboard, poster paper and card paper	0.602	0.039
29001	Machines and equipment - except appliances	0.605	0.041
35020	Construction and assembly of locomotives, cars and other rolling stock	0.632	0.059
24090	Miscellaneous chemical products	0.635	0.040
34002	Cabins, car bodies, trailers and parts for motor vehicles	0.637	0.071
27002	Non-ferrous metals	0.644	0.063
24010	Paints, dyes, varnish, enamels and lacquers	0.656	0.040
24030	Soap, detergents, cleaning products and toiletries	0.658	0.040
27001	Steel products	0.659	0.063
31001	Machines, equipment and miscellaneous electric material - except for vehicles	0.678	0.058
18999	Making of clothing articles and accessories - on order or not	0.690	0.021
22000	Editing, printing and reproduction of recordings	0.702	0.033
33004	Equipment, instruments and optical, photographic and cinematographic material	0.709	0.050
29002	Appliances	0.709	0.041
33002	Measuring, testing and control equipment - except for controlling industrial processes	0.725	0.050
34001	Manufacturing and assembly of motor vehicles	0.738	0.071
33005	Chronometers, clocks and watches	0.751	0.050
33001	Medical equipment	0.753	0.050
32000	Electronic material and communications equipment	0.757	0.048
23020	Products in oil refining	0.763	0.014
24020	Pharmaceutical products	0.809	0.040
23030	Production of nuclear fuels	0.830	0.014
33003	Machines, equipment for electronic systems for industrial automation, and control	0.848	0.050
30000	Office machines and data-processing equipment	0.852	0.031
35030	Construction, assembly and repair of airplanes	0.875	0.059
	Median	0.432	0.035

Notes: The industry codes correspond to the CNAE-Domiciliar, the industry classification used in the 2000 Population Census. Industries are sorted by their skill intensity at baseline. We define skill intensity as the share of skilled individuals in a particular industry in Brazil at baseline and we source it from the 2000 Population Census. Our measure of R&D activity is R&D expenditure as a share of total sales at baseline and we source it from from the 2000 *Pesquisa de Inovação Tecnológica* (PINTEC). The correlation between these variables is approximately 0.33. We are splitting manufacturing industries across the median according to their level of skill intensity and R&D activity in such a way that roughly 50% of the Brazilian manufacturing employment is at both sides of the median. Thus, industries below the median are classified as low and the ones above the median as high.

B Appendix: Theory

In this appendix we provide the proofs of Theorems 1 to 4.

Preliminaries

We assume that Brazil is a collection of microregions interpreted as small open economies with segmented labor markets. There are three sectors, namely agriculture, low-skill-intensive manufacturing that produces a homogeneous good, and high-skill-intensive industry that uses both labor and intermediates. We assume that the economy is populated by U unskilled workers and S skilled workers, supplying labor inelastically. The agriculture sector also uses land which is fixed at T. Finally, we assume that for any set of wages, the low-skill intensive industry is uses unskilled labor more intensively. We can express this more precisely in terms of the unit factor demands in each industry. Defining $\omega = \frac{w_s}{w_u}$ we have that the following condition holds:[31]

$$\frac{a_{U_m^h}(\omega)}{a_{S_m^h}(\omega)} < \frac{a_{U_m^\ell}(\omega)}{a_{S_m^\ell}(\omega)}$$

In what follows, we assume that we are in the Factor Price Equalization set.

Theorem 1. *An increase in A_s in agriculture, leads to an increase in the relative demand for high skilled workers in agriculture if and only if the elasticity of substitution between high- and low-skilled workers is greater than one ($\varepsilon > 1$).*

Proof. Take the agriculture sector. Solving for the inner nest we get that the conditional factor demands $S_a(w_s, w_u, L_a)$, $U_a(w_s, w_u, L_a)$ and the cost function $C(w_s, w_u, L_a)$ for agriculture labor L_a are given by:

$$S_a(w_s, w_u, L_a) = \frac{\left(\frac{w_s}{A_s}\right)^{-\varepsilon} L_a}{A_s \left[w_s^{1-\varepsilon} A_s^{\varepsilon-1} + w_u^{1-\varepsilon} A_u^{\varepsilon-1}\right]^{\frac{\varepsilon}{\varepsilon-1}}} \tag{12}$$

$$U_a(w_s, w_u, L_a) = \frac{\left(\frac{w_u}{A_u}\right)^{-\varepsilon} L_a}{A_u \left[w_s^{1-\varepsilon} A_s^{\varepsilon-1} + w_u^{1-\varepsilon} A_u^{\varepsilon-1}\right]^{\frac{\varepsilon}{\varepsilon-1}}} \tag{13}$$

$$C(w_s, w_u, L_a) = L_a \left[\left(\frac{w_s}{A_s}\right)^{1-\varepsilon} + \left(\frac{w_u}{A_u}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \tag{14}$$

Thus, the relative demand for skilled workers in agriculture is given by:

[31] In particular for the manufacturing sectors since the monopolistic sector is more intensive in skilled labor, this means that for any $\omega = \frac{w_s}{w_u}$:

$$\det \begin{pmatrix} a_{U_m^\ell}(\omega) & a_{U_m^h}(\omega) \\ a_{S_m^\ell}(\omega) & a_{S_m^h}(\omega) \end{pmatrix} > 0 \tag{11}$$

$$\frac{S_a}{U_a} = \left(\frac{w_u}{w_s}\right)^{\varepsilon} \left(\frac{A_s}{A_u}\right)^{\varepsilon-1} \tag{15}$$

$\square$

Theorem 2. *Whether an increase in A_s in agriculture leads to an absolute decrease in the demand for low skilled workers in agriculture depends on whether labor and land are strong complements ($\sigma < \varepsilon\Gamma$).*

Proof. From the production function we can can compute the marginal productivity for each raw labor type:

$$MPU_a = A_n K\gamma\Theta^{\frac{1}{\sigma-1}} A_L^{\frac{\sigma-1}{\sigma}} L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}} A_u^{\frac{\varepsilon-1}{\varepsilon}} U_a^{\frac{-1}{\varepsilon}} \tag{16}$$

$$MPS_a = A_n K\gamma\Theta^{\frac{1}{\sigma-1}} A_L^{\frac{\sigma-1}{\sigma}} L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}} A_s^{\frac{\varepsilon-1}{\varepsilon}} S_a^{\frac{-1}{\varepsilon}} \tag{17}$$

where $\Theta = \gamma(A_L L_a)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_T T_a)^{\frac{\sigma-1}{\sigma}}$. Clearly, can see that

$$\frac{\partial\Theta}{\partial A_s} = \gamma\frac{\sigma-1}{\sigma} A_L^{\frac{\sigma-1}{\sigma}} L_a^{\frac{\sigma-\varepsilon}{\sigma\varepsilon}} S_a^{\frac{\varepsilon-1}{\varepsilon}} A_s^{\frac{-1}{\varepsilon}}$$

Moreover,

$$\frac{\partial L_a^m}{\partial A_s} = mL_a^{m-1+\frac{1}{\varepsilon}} S_a^{\frac{\varepsilon-1}{\varepsilon}} A_s^{\frac{-1}{\varepsilon}}$$

Therefore,

$$\frac{\partial MPU_a}{\partial A_s} = A_n K\gamma A_L^{\frac{\sigma-1}{\sigma}} A_u^{\frac{\varepsilon-1}{\varepsilon}} U_a^{\frac{-1}{\varepsilon}} \left(\frac{1}{\sigma-1}\Theta^{\frac{2-\sigma}{\sigma-1}}\frac{\partial\Theta}{\partial A_s} L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}} + \Theta^{\frac{1}{\sigma-1}}\frac{\partial L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}}}{\partial A_s}\right)$$

$$\frac{\partial MPU_a}{\partial A_s} = \underbrace{A_n K\gamma A_L^{\frac{\sigma-1}{\sigma}} A_u^{\frac{\varepsilon-1}{\varepsilon}} U_a^{\frac{-1}{\varepsilon}} \Theta^{\frac{1}{\sigma-1}} L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}}}_{\kappa} \left(\frac{1}{\sigma-1}\Theta^{-1}\frac{\partial\Theta}{\partial A_s} - \frac{(\varepsilon-\sigma)}{\varepsilon\sigma} L_a^{-1}\frac{\partial L_a}{\partial A_s}\right)$$

Notice that $\kappa > 0$. Thus,

$$\frac{\partial MPU_a}{\partial A_s} = \kappa\left(\frac{\gamma}{\sigma}\Theta^{-1} A_L^{\frac{\sigma-1}{\sigma}} L_a^{\frac{\sigma-\varepsilon}{\sigma\varepsilon}} S_a^{\frac{\varepsilon-1}{\varepsilon}} A_s^{\frac{-1}{\varepsilon}} - \frac{(\varepsilon-\sigma)}{\varepsilon\sigma} L_a^{\frac{1-\varepsilon}{\varepsilon}} S_a^{\frac{\varepsilon-1}{\varepsilon}} A_s^{\frac{-1}{\varepsilon}}\right)$$

$$\frac{\partial MPU_a}{\partial A_s} = \frac{\kappa}{\sigma} L_a^{\frac{1}{\varepsilon-1}} S_a^{\frac{\varepsilon-1}{\varepsilon}} A_s^{\frac{-1}{\varepsilon}} \left(\gamma\Theta^{-1} A_L^{\frac{\sigma-1}{\sigma}} L_a^{\frac{\sigma-\varepsilon}{\sigma\varepsilon}} - \frac{(\varepsilon-\sigma)}{\varepsilon} L_a^{\frac{1-\varepsilon}{\varepsilon}}\right)$$

Since $\frac{\kappa}{\sigma} L_a^{\frac{1}{\varepsilon-1}} S_a^{\frac{\varepsilon-1}{\varepsilon}} A_s^{\frac{-1}{\varepsilon}} > 0$

$$\frac{\partial MPU_a}{\partial A_s} < 0 \iff \gamma \Theta^{-1} A_L^{\frac{\sigma-1}{\sigma}} L_a^{\frac{\sigma-\varepsilon}{\sigma\varepsilon}} - \frac{(\varepsilon-\sigma)}{\varepsilon} L_a^{\frac{1-\varepsilon}{\varepsilon}} < 0$$

$$\frac{\partial MPU_a}{\partial A_s} < 0 \iff \sigma < \varepsilon \left(\frac{\gamma (A_L L_a)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_T T_a)^{\frac{\sigma-1}{\sigma}} - \gamma (A_L L_a)^{\frac{\sigma-1}{\sigma}}}{\Theta} \right)$$

$$\frac{\partial MPU_a}{\partial A_s} < 0 \iff \sigma < \varepsilon \left(\frac{(1-\gamma)(A_T T_a)^{\frac{\sigma-1}{\sigma}}}{\Theta} \right) \tag{18}$$

□

Theorem 3. *An increase in skilled-biased-factor-augmenting technology in agriculture (A_s), leads to an expansion of low-skill intensive manufacturing industries, provided that:*

1. *High- and low-skilled workers are imperfect substitutes (i.e. when $\varepsilon > 1$)*
2. *Land and labor are strong complements (i.e. when $\sigma < \varepsilon\Gamma$)*
3. *Agriculture is not much more intensive in low-skilled labor than the low-skill intensive industry.*

Proof. Consider the factor market clearing equilibrium conditions,

$$a_{Ta} Q_a = T \tag{19}$$

$$a_{Sa} Q_a + a_{S_m^\ell} Q_m^\ell + a_{S_m^h} Q_m^h = S \tag{20}$$

$$a_{Ua} Q_a + a_{U_m^\ell} Q_m^\ell + a_{U_m^h} Q_m^h = U \tag{21}$$

Log-differentiating Equations 19, 20 and 21 we get that:

$$a_{Ta} dQ_a + da_{Ta} Q_a = dT$$

$$a_{Sa} dQ_a + da_{Sa} Q_a + a_{S_m^\ell} dQ_m^\ell + a_{S_m^h} dQ_m^h = dS$$

$$da_{Ua} Q_a + a_{Ua} dQ_a + a_{U_m^\ell} dQ_m^\ell + a_{U_m^h} dQ_m^h = dU$$

Now, define a hat-variable as $\widehat{X} = \frac{dX}{X}$ and $\lambda_{ij} = \frac{a_{Ij} Q_j}{I}$, i.e the share of factor I in industry j. Therefore, dividing at both sides of the equalities by the respective factor endowment, we can write the previous expressions as follows:

$$\lambda_{Ta}\widehat{Q}_a + \lambda_{Ta}\widehat{a}_{Ta} = \widehat{T} \tag{22}$$

$$\lambda_{Sa}\widehat{Q_a} + da_{Sa}\frac{Q_a}{S} + \lambda_{S^\ell_m}\widehat{Q^\ell_m} + \lambda_{S^h_m}\widehat{Q^h_m} = \widehat{S} \tag{23}$$

$$\lambda_{Ua}\widehat{Q_a} + da_{Ua}\frac{Q_a}{U} + \lambda_{U^\ell_m}\widehat{Q^\ell_m} + \lambda_{U^h_m}\widehat{Q^h_m} = \widehat{U} \tag{24}$$

Since in our economy the factor endowments are unchanged, $dT = dS = dU = 0$. This simplifies the expressions above in the following way:

$$\widehat{Q_a} = -\widehat{a_{Ta}} \tag{25}$$

$$\lambda_{Sa}\widehat{Q_a} + \lambda_{S^\ell_m}\widehat{Q^\ell_m} + \lambda_{S^h_m}\widehat{Q^h_m} = -da_{Sa}\frac{Q_a}{S} \tag{26}$$

$$\lambda_{Ua}\widehat{Q_a} + \lambda_{U^\ell_m}\widehat{Q^\ell_m} + \lambda_{U^h_m}\widehat{Q^h_m} = -da_{Ua}\frac{Q_a}{U} \tag{27}$$

Combining these expressions, we arrive to:

$$\lambda_{S^\ell_m}\widehat{Q^\ell_m} + \lambda_{S^h_m}\widehat{Q^h_m} = -\widehat{a_{Sa}}\lambda_{Sa} + \lambda_{Sa}\widehat{a_{Ta}} = \underbrace{\lambda_{Sa}(\widehat{a_{Ta}} - \widehat{a_{Sa}})}_{\gamma_s} \tag{28}$$

$$\lambda_{U^\ell_m}\widehat{Q^\ell_m} + \lambda_{U^h_m}\widehat{Q^h_m} = -\widehat{a_{Ua}}\lambda_{Ua} + \lambda_{Ua}\widehat{a_{Ta}} = \underbrace{\lambda_{Ua}(\widehat{a_{Ta}} - \widehat{a_{Ua}})}_{\gamma_u} \tag{29}$$

$$\widehat{Q^h_m} = \frac{\lambda_{U^\ell_m}\gamma_s - \lambda_{S^\ell_m}\gamma_u}{\Delta} \tag{30}$$

$$\widehat{Q^\ell_m} = \frac{\lambda_{S^h_m}\gamma_u - \lambda_{U^h_m}\gamma_s}{\Delta} \tag{31}$$

where $\Delta \equiv \lambda_{U^\ell_m}\lambda_{S^h_m} - \lambda_{U^h_m}\lambda_{S^\ell_m}$ and $\Delta > 0$ by Condition 11 (Note that this condition is saying that the share of unskilled in the low-skilled intensive industry times the share of skilled in the skill-intensive industry is greater than the share of high-skilled in the low-skilled intensive industry times the share of unskilled in the high-skilled intensive industry). Then, $\widehat{Q^h_m} < 0$ iff $\lambda_{U^\ell_m}\gamma_s - \lambda_{S^\ell_m}\gamma_u < 0$. Which holds iff:

$$\lambda_{U^\ell_m}\gamma_s < \lambda_{S^\ell_m}\gamma_u$$

This can be re-written as:

$$\lambda_{U^\ell_m}\lambda_{Sa}(\widehat{a_{Ta}} - \widehat{a_{Sa}}) < \lambda_{S^\ell_m}\lambda_{Ua}(\widehat{a_{Ta}} - \widehat{a_{Ua}})$$

This can be further simplified to:

$$\lambda_{U_m^\ell}\lambda_{Sa}(\widehat{a_{Sa}}+\widehat{Q_a}) > \lambda_{S_m^\ell}\lambda_{Ua}(\widehat{a_{Ua}}+\widehat{Q_a})$$

And so, $\widehat{Q_m^h} < 0$ iff:

$$\frac{\lambda_{U_m^\ell}}{\lambda_{S_m^\ell}}\frac{(\widehat{a_{Sa}}+\widehat{Q_a})}{(\widehat{a_{Ua}}+\widehat{Q_a})} > \frac{\lambda_{Ua}}{\lambda_{Sa}}$$

Now, note that $\widehat{a_{Sa}} > \widehat{a_{Ua}}$, which we show that it holds in more detail below (note, however, that this is simply saying that the demand for high-skilled labor increases relative to unskilled labor with increases in A_s). From this, we have that, $a^* \equiv \frac{(\widehat{a_{Sa}}+\widehat{Q_a})}{(\widehat{a_{Ua}}+\widehat{Q_a})} > 1$. Hence, we have that $\widehat{Q_m^h} < 0$ iff $\frac{\lambda_{U_m^\ell}}{\lambda_{S_m^\ell}}a^* > \frac{\lambda_{Ua}}{\lambda_{Sa}}$. This condition holds as long as agriculture is not much more intensive in low-skilled labor than the low-skilled intensive industry.

Finally we are going to prove that $\widehat{a_{Sa}} > \widehat{a_{Ua}}$. This condition basically says that the elasticity of the agricultural unit factor demand with respect to A_s is larger for the skilled factor than for the unskilled factor, i.e $\frac{\partial ln a_{Sa}}{\partial ln A_s} > \frac{\partial ln a_{Ua}}{\partial ln A_s}$. Now, take the marginal productivities for skilled and unskilled labor in agriculture (Equations 16 and 17) and equate them to their factor price:

$$\begin{aligned} w_u &= MPU_a \\ w_s &= MPS_a \end{aligned}$$

and notice that we can write the following conditional labor demand equations:

$$\begin{aligned} U_a^{\frac{1}{\varepsilon}} &= \frac{1}{w_u}A_nK\gamma\Theta^{\frac{1}{\sigma-1}}A_L^{\frac{\sigma-1}{\sigma}}L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}}A_u^{\frac{\varepsilon-1}{\varepsilon}} \\ S_a^{\frac{1}{\varepsilon}} &= \frac{1}{w_u}A_nK\gamma\Theta^{\frac{1}{\sigma-1}}A_L^{\frac{\sigma-1}{\sigma}}L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}}A_s^{\frac{\varepsilon-1}{\varepsilon}} \end{aligned}$$

Log-differentiating both expressions with respect to A_s :

$$\frac{\partial lnU_a}{\partial lnA_s} = \varepsilon\left[\frac{1}{\sigma-1}\frac{\partial ln\Theta}{\partial lnA_s} - \frac{(\varepsilon-\sigma)}{\varepsilon\sigma}\frac{\partial lnL_a}{\partial lnA_s}\right]$$
$$\frac{\partial lnS_a}{\partial lnA_s} = \varepsilon\left[\frac{1}{\sigma-1}\frac{\partial ln\Theta}{\partial lnA_s} - \frac{(\varepsilon-\sigma)}{\varepsilon\sigma}\frac{\partial lnL_a}{\partial lnA_s} + \frac{\varepsilon-1}{\varepsilon}\right]$$

Therefore,

$$\widehat{a_{Sa}} > \widehat{a_{Ua}} \iff \frac{\partial ln a_{Sa}}{\partial ln A_s} > \frac{\partial ln a_{Ua}}{\partial ln A_s} \iff \frac{\partial ln S_a}{\partial ln A_s} > \frac{\partial ln U_a}{\partial ln A_s} \iff \varepsilon - 1 > 0 \tag{32}$$

Therefore, $\widehat{Q^h_m} < 0$ and $\widehat{Q^\ell_m} > 0$. Upon the technical change in agriculture, the low-skill intensive industry expands and the high-skill intensive industry contracts.

□

For the last theorem we assume a number of small technical details that are explained in the proof of the theorem.

Theorem 4. *When the following conditions hold:*

1. *High- and low-skilled workers are imperfect substitutes (i.e. when $\varepsilon > 1$)*
2. *Land and labor are strong complements (i.e. when $\sigma < \varepsilon\Gamma$)*
3. *Agriculture is not much more intensive in low-skilled labor than the low-skill intensive industry.*

An exogenous change in skill-biased-factor-augmenting technology (A_s), results in:

1. *Static gains from increased productivity in the agricultural sector.*
2. *Dynamic losses shaped by the decrease in the size of the R&D, high-skilled intensive manufacturing industry.*

In particular, the growth rate of consumption is given by:

$$g_C = \frac{\chi A^h_m F^h_m(U^h_m, S^h_m) - \rho}{\eta} \tag{33}$$

where $\chi > 0$ is a constant defined in Appendix B. And the change in gross domestic output is given by:

$$\frac{\partial \ln GDP_t}{\partial A_s} = \underbrace{\omega_a \frac{\partial \ln p_a A_a F_a}{\partial A_s} + \omega^\ell_m \frac{\partial \ln p^\ell_m A^\ell_m F^\ell_m}{\partial A_s} + \omega^h_m \frac{\partial \ln A^h_m F^h_m}{\partial A_s}}_{\text{Static gains/losses}} + \underbrace{\frac{\chi}{\eta} \frac{\partial A^h_m F^h_m}{\partial A_s} t}_{\text{Dynamic gains/losses}}$$

where $\omega_j = \frac{p_j A_j F_j}{p_a A_a F_a + p^\ell_m A^\ell_m F^\ell_m + \varsigma A^h_m F^h_m}$.

Proof. First, we assume that each input in the high-skill intensive industry is monopolized by the person who invented it, who decides how much output to produce given the profits. The input for producing the final good is the same final good.[32] Hence,

$$\Pi_k = p_k x_k - x_k$$

This equation simply says that the cost of producing an input is equal to the output and the revenues are the price multiplied by the total output. The price of the input is given by the marginal product in the final good production:

$$p_k = \frac{\partial Q_m^h}{\partial x_k} = (1-\alpha) A_m^h F_m^h (U_m^h, S_m^h)^\alpha x_k^{-\alpha}$$

We can use this price to find the optimal quantity of intermediate produced. This is given by:[33] $x_k = (1-\alpha)^{2/\alpha} A_m^h F_m^h (U_m^h, S_m^h)$. From this, it is straightforward to show that total production in the high-skilled industry is given by:[34]

$$Q_m^h = \kappa A_m^h F_m^h (U_m^h, S_m^h) K_t$$

where $\kappa = (1-\alpha)^{2*(1-\alpha)/\alpha}$. We also obtain that that profits in the sector are given by:[35]

$$\Pi_k = \Pi = \chi A_m^h F_m^h (U_m^h, S_m^h)$$

where $\chi = [(1-\alpha)^{(2-\alpha)/\alpha} - (1-\alpha)^{2/\alpha}]$.

We also need to obtain net output in the sector, i.e. total output minus what is used for intermediate production. Hence:[36]

[32]This assumption simplifies the algebra. We are inspired by the chapter 3 of Aghion and Howitt (2008) and chapter 6 of Grossman and Helpman (1991a). These chapters, in turn, are an adaptation of the original Romer (1990). See also Grossman and Helpman (1991b) for a continuous sector version of the model, Helpman (1993) and Bayoumi, Coe, and Helpman (1999) – where knowledge transfers across countries are analyzed –, Aghion and Howitt (1992), and Grossman and Helpman (1994) for a review of (some fundamental aspects of) this literature.

[33]Note that profits are:

$$\Pi_k = (1-\alpha) A_m^h F_m^h (U_m^h, S_m^h)^\alpha x_k^{1-\alpha} - x_k$$

We can take the derivative with respect to x_k to obtain the optimal level of intermediate output.

[34]From the symmetry of the model, we then have that:

$$Q_m^h = K_t A_m^h F_m^h (U_m^h, S_m^h)^\alpha x^{1-\alpha}$$

in this we can plug in the amount of input.

[35]Note that $\Pi_k = (1-\alpha) A_m^h F_m^h (U_m^h, S_m^h)^\alpha ((1-\alpha)^{2/\alpha} A_m^h F_m^h (U_m^h, S_m^h))^{1-\alpha} - ((1-\alpha)^{2/\alpha} A_m^h F_m^h (U_m^h, S_m^h))$, and hence, $\Pi_k = [(1-\alpha)^{1+2(1-\alpha)/\alpha} - (1-\alpha)^{2/\alpha}] A_m^h F_m^h (U_m^h, S_m^h) = [(1-\alpha)^{(\alpha+2(1-\alpha))/\alpha} - (1-\alpha)^{2/\alpha}] A_m^h F_m^h (U_m^h, S_m^h)$, which can be simplified to:

$$\Pi_k = [(1-\alpha)^{(2-\alpha)/\alpha} - (1-\alpha)^{2/\alpha}] A_m^h F_m^h (U_m^h, S_m^h)$$

which is the expression that we were looking for. Note, also, that $[(1-\alpha)^{(2-\alpha)/\alpha} - (1-\alpha)^{2/\alpha}] > 0$.

[36] From:

$$Q_m^h - K_t x = \varsigma A_m^h F_m^h(U_m^h, S_m^h) K_t \tag{34}$$

with $\varsigma = [(1-\alpha)^{2*(1-\alpha)/\alpha} - (1-\alpha)^{2/\alpha}]$

Note that this model has the simplifying feature that both total output in the sector, profits, and net output are all proportional to $A_m^h F_m^h(U_m^h, S_m^h)$.

Finally, we need to know how much K_t grows. K_t grows at a rate that is equal to the resources used in research, which are the ones not consumed, and hence given by I_t:

$$\dot{K}_t = I_t$$

The rate of return in the economy is given by the profits that can be made in investing in new ideas. We can now use the standard CRRA Euler equation from the consumer maximization problem, which implies that the growth rate in consumption is given by:

$$g^C = \frac{\Pi - \rho}{\eta}$$

And hence:

$$g^C = \frac{\chi A_m^h F_m^h(U_m^h, S_m^h) - \rho}{\eta}$$

This equation shows that consumption is growing as a function of the size of the high-skilled sector. More over, knowledge grows at the level of investment, which is given by what is not consumed. The growth rate in each sector is given by the growth rate in K_t which is given by investment. This means that everything is growing at the same rate as consumption.

Finally we need to see how skilled-biased-factor-augmenting productivity increases affect the growth rate of the economy. For this, we obtain the evolution of GDP:

$$GDP_t = p_a K_t A_a F_a + p_m^\ell K_t A_m^\ell F_m^\ell + \varsigma K_t A_m^h F_m^h$$

to obtain that:

$$\ln GDP_t = \ln K_t + \ln(p_a A_a F_a + p_m^\ell A_m^\ell F_m^\ell + \varsigma A_m^h F_m^h)$$

In equilibrium, we have that $\ln K_t = \ln K_0 + g_c t$. And, hence:

$$Q_m^h - K_t x = \kappa A_m^h F_m^h(U_m^h, S_m^h) K_t - K_t (1-\alpha)^{2/\alpha} A_m^h F_m^h(U_m^h, S_m^h)$$

we have that:

$$Q_m^h - K_t x = [(1-\alpha)^{2*(1-\alpha)/\alpha} - (1-\alpha)^{2/\alpha}] A_m^h F_m^h(U_m^h, S_m^h) K_t$$

Note that $[(1-\alpha)^{2*(1-\alpha)/\alpha} - (1-\alpha)^{2/\alpha}] > 0$.

$$\ln GDP_t = \ln K_0 + g_c t + \ln(p_a A_a F_a + p_m^\ell A_m^\ell F_m^\ell + \varsigma A_m^h F_m^h)$$

And hence:

$$\frac{\partial \ln GDP_t}{\partial A_s} = \frac{\partial g_c}{\partial A_s} t + \frac{\partial \ln(p_a A_a F_a + p_m^\ell A_m^\ell F_m^\ell + \varsigma A_m^h F_m^h)}{\partial A_s}$$

And hence

$$\frac{\partial \ln GDP_t}{\partial A_s} = \frac{\partial g_c}{\partial A_s} t + \frac{1}{p_a A_a F_a + p_m^\ell A_m^\ell F_m^\ell + \varsigma A_m^h F_m^h} \left(\frac{\partial p_a A_a F_a}{\partial A_s} + \frac{\partial p_m^\ell A_m^\ell F_m^\ell}{\partial A_s} + \frac{\partial \varsigma A_m^h F_m^h}{\partial A_s} \right)$$

And hence:

$$\frac{\partial \ln GDP_t}{\partial A_s} = \frac{\partial g_c}{\partial A_s} t + \omega_a \frac{\partial \ln p_a A_a F_a}{\partial A_s} + \omega_m^\ell \frac{\partial \ln p_m^\ell A_m^\ell F_m^\ell}{\partial A_s} + \omega_m^h \frac{\partial \ln \varsigma A_m^h F_m^h}{\partial A_s}$$

with $\omega_j = \frac{p_j A_j F_j}{p_a A_a F_a + p_m^\ell A_m^\ell F_m^\ell + \varsigma A_m^h F_m^h}$

Which is equal to:

$$\frac{\partial \ln GDP_t}{\partial A_s} = \frac{\partial g_c}{\partial A_s} t + \omega_a \frac{\partial \ln p_a A_a F_a}{\partial A_s} + \omega_m^\ell \frac{\partial \ln p_m^\ell A_m^\ell F_m^\ell}{\partial A_s} + \omega_m^h \frac{\partial \ln A_m^h F_m^h}{\partial A_s}$$

Or:

$$\frac{\partial \ln GDP_t}{\partial A_s} = \frac{\chi}{\eta} \frac{\partial A_m^h F_m^h}{\partial A_s} t + \omega_a \frac{\partial \ln p_a A_a F_a}{\partial A_s} + \omega_m^\ell \frac{\partial \ln p_m^\ell A_m^\ell F_m^\ell}{\partial A_s} + \omega_m^h \frac{\partial \ln A_m^h F_m^h}{\partial A_s}$$

□

C Appendix: Within-Between Decomposition

C.1 Estimation Results

In this appendix, we attempt to quantify the effect of labor reallocation driven by skill-biased technical change in agriculture on the innovation-intensity of the manufacturing sector in Brazil. As a measure of innovation-intensity of the manufacturing sector we use R&D expenditure per worker. We source data on R&D expenditure from the Industrial Survey of Technological Innovation (*PINTEC*) – which is designed to capture innovation activities of Brazilian firms – and data on number of workers in manufacturing from the Population Census. In particular, we use the 2000 and 2008 waves of the PINTEC survey and the 2000 and 2010 Population Censuses. We compute R&D expenditure as the sum of expenditure in internal R&D and expenditure in external R&D, both expressed in thousands of R$.[37] Combining data from PINTEC and Population Census, we find that R&D expenditure per worker in the Brazilian manufacturing sector increased by 40 percent in the decade between 2000 and 2010.[38]

Change in R&D expenditure per worker in Brazilian manufacturing can be driven by two forces. First, the increase in R&D expenditure per worker *within* each manufacturing sector. Second, a reallocation of workers *across* manufacturing sectors that have different initial R&D intensities. These two forces correspond to the two terms in equation (35), which shows a decomposition of the decadal change in R&D expenditure per worker:

$$\Delta \frac{RD}{L_M} \approx \underbrace{\frac{RD^h_{2000}}{L^h_{M,2000}} \Delta \frac{L^h_M}{L_M} + \frac{RD^\ell_{2000}}{L^\ell_{M,2000}} \Delta \frac{L^\ell_M}{L_M}}_{\text{Between}} + \underbrace{\Delta \frac{RD^h}{L^h_M} \frac{L^h_{M,2000}}{L_{M,2000}} + \Delta \frac{RD^\ell}{L^\ell_M} \frac{L^\ell_{M,2000}}{L_{M,2000}}}_{\text{Within}} \tag{35}$$

The superscripts h and l in equation (35) capture high-skill and low-skill intensive manufacturing industries – defined as described in section 2.2 –, Δ indicates decadal changes between 2000 and 2010, RD indicates value of expenditure in research and development, and L captures employment in number of workers. Using data from the PINTEC survey for RD^h and RD^l, and from the Population Census for L^h_M and L^l_M, we find that approximately three-quarters of the change in R&D expenditure per worker in Brazilian manufacturing between 2000 and 2010 was driven by increases in expenditure *within* industries, one-quarter by reallocation of labor *between* industries.

Next, we focus on the *between* part of the decomposition – reported in equation (36) – and study the effect of labor reallocation driven by skill-biased technical change in agriculture on $\Delta \frac{RD}{L_M}_{Between}$.

$$\Delta \frac{RD}{L_M}_{Between} \approx \frac{RD^h_{2000}}{L^h_{M,2000}} \Delta \frac{L^h_M}{L_M} + \frac{RD^\ell_{2000}}{L^\ell_{M,2000}} \Delta \frac{L^\ell_M}{L_M} \tag{36}$$

In section 4.4 we document that technical change in soy affected labor reallocation across manufacturing industries. In particular, the increase of low-skilled labor supply due to technological upgrade in agriculture was mostly absorbed by low-skill intensive manufacturing industries. Thus, we are interested in studying the effect of the soy shock on the *between* part of the decomposition through labor reallocation across manufacturing industries as captured by $\Delta \frac{L^h_M}{L_M}$ and $\Delta \frac{L^\ell_M}{L_M}$ in equation (36).[39]

[37]Internal R&D consists on systematic creative work with the objective of increasing the knowledge pool and the use of this knowledge to develop new products or processes, and the development of software or scientific advancements. External R&D encompasses the same activities as internal R&D with the difference that they are carried out by another organization (either other companies or technological institutions) and acquired by the firm (IBGE 2010).

[38]We use data from the 2008 wave of the PINTEC survey as a proxy for R&D expenditure in 2010.

[39]Data on R&D expenditure per worker in 2000 for both high-skill and low-skill intensive industries in

To estimate the effect of the soy shock on the *between* component, we decompose the change in employment share of a given industry $k = h, l$ as described in detail in the next section and compute the implied change in $\Delta \frac{L_M^k}{L_M}$ for a given change in ΔA_{soy}. Our estimates suggest that if the average change in soy potential yields across micro-regions had been one standard deviation smaller, the aggregate increase in R&D expenditure per worker in Brazil between 2000 and 2010 would have been 3.47 percentage points larger. The intuition is that, other things being equal, lower skill-biased technical change in agriculture would have generated lower labor reallocation towards low skill-intensive industries within manufacturing. The next section outlines the details of this quantification.

C.2 Estimation Procedure

We start by approximating the total decadal change in R&D expenditure per worker in a between component and a within component following Equation 35:

$$\Delta \frac{RD}{L_M} \approx \underbrace{\frac{RD_{2000}^h}{L_{M,2000}^h}\Delta\frac{L_M^h}{L_M} + \frac{RD_{2000}^\ell}{L_{M,2000}^\ell}\Delta\frac{L_M^\ell}{L_M}}_{\text{Between}} + \underbrace{\Delta\frac{RD^h}{L_M^h}\frac{L_{M,2000}^h}{L_{M,2000}} + \Delta\frac{RD^\ell}{L_M^\ell}\frac{L_{M,2000}^\ell}{L_{M,2000}}}_{\text{Within}}$$

We compute R&D expenditure as the sum of expenditure in internal R&D and expenditure in external R&D, both expressed in thousands of R$. Internal R&D consists on systematic creative work with the objective of increasing the knowledge pool and the use of this knowledge to develop new products or processes, and the development of software or scientific advancements. External R&D encompasses the same activities as internal R&D with the difference that they are carried out by another organization (either other companies or technological institutions) and acquired by the firm (IBGE 2010). We deflate the nominal values to 2000 reais.

In particular, we are interested in the contribution of the labor reallocation to this change so we are interested in the between component:

$$\Delta \frac{RD}{L_M}_{Between} \approx \frac{RD_{2000}^h}{L_{M,2000}^h}\Delta\frac{L_M^h}{L_M} + \frac{RD_{2000}^\ell}{L_{M,2000}^\ell}\Delta\frac{L_M^\ell}{L_M} \quad (37)$$

To compute the effect of the introduction of GE soy in $\Delta \frac{RD}{L_M}_{Between}$ we proceed in the following steps:

1. We start by using the aggregate information on internal and external R&D for each 3-digit CNAE manufacturing industry, which we map to the 5-digit CNAE-

equation (36) are computed combining the R&D expenditure values from PINTEC and the employment from the Population Census data. Specifically in 1000$ reais per worker, the R&D intensities are $\frac{RD_{2000}^H}{L_{M,2000}^H} \approx 1.707$ and $\frac{RD_{2000}^L}{L_{M,2000}^L} \approx 0.175$.

Domiciliar industry. For most of the industries, there is a one-to-one mapping between both classifications. However, in the cases there are one to many or many to many correspondences, we assign industries a proportional weight according to the employment shares within the class at baseline.

2. Once we have made this mapping, we can compute the expenditure in R&D per worker at baseline in low-skill-intensive industries and in high-skill-intensive industries, $\frac{RD^{\ell}_{2000}}{L^{\ell}_{M,2000}}$ and $\frac{RD^{h}_{2000}}{L^{h}_{M,2000}}$, directly from the data. Specifically in 1000$ reais per worker, $\frac{RD^{H}_{2000}}{L^{H}_{M,2000}} \approx 1.707$ and $\frac{RD^{L}_{2000}}{L^{L}_{M,2000}} \approx 0.175$.

   Moreover, with the R&D expenditure data from waves 2000 and 2008 from PINTEC and the employment data from the Census, we can compute the decomposition in Equation 35. Our estimates suggest that R$D expenditure per worker in Brazil increased in 400 reais per worker, of which 22.3% comes from the between component and 71.3% from the within component. The remaining term corresponds to a covariance term.

3. To make this accounting exercise consistent with our estimates we need to further decompose the changes in employment as

$$\frac{L^k_M}{L_M} = \frac{L^k_M}{L}\frac{L}{L_M}$$

   which implies that for any industry k in manufacturing we can decompose the change in its employment share as

$$\Delta\left(\frac{L^k_M}{L_M}\right) = \Delta\left(\frac{L^k_M}{L}\right)\frac{L}{L_M} + \frac{L^k_M}{L}\Delta\left(\frac{L}{L_M}\right) \tag{38}$$

   Finally, we need an expression for $\Delta\left(\frac{L}{L_M}\right)$. Notice, that this is only:

$$\Delta\left(\frac{L}{L_M}\right) = \Delta\left(\frac{1}{\frac{L_M}{L}}\right) \approx -\left(\frac{L_M}{L}\right)^{-2} \times \Delta\left(\frac{L_M}{L}\right) \tag{39}$$

4. Since we are interested in making a claim about the change in the aggregate R&D intensity of Brazil caused by the labor relocation due to the increase in agricultural productivity, we need to use estimates coming from weighted regressions. For this exercise, we weight each observation by the percentage of manufacturing workers located in the microregion at baseline.

   Using the regression estimates in Tables A5 and A6, and the magnitude of one (weighted) standard deviation of the soy shock (St.Dev. in $\Delta A_{soy} = 0.712$ as shown in Table A4) we know that the effect of the soy shock on the changes in the previous formula are:

- $\Delta\left(\frac{L_M}{L}\right) = 0.014 \times 0.712 = 0.010$
- $\Delta\left(\frac{L_M^\ell}{L}\right) = 0.014 \times 0.712 = 0.010$
- $\Delta\left(\frac{L_M^h}{L}\right) = 0.000 \times 0.712 = 0.000$

Moreover, at baseline we know that the mean employment shares are (see Table A4):

- $\frac{L_M}{L} = 0.227$
- $\frac{L}{L_M} = \frac{1}{0.227} = 4.412$
- $\frac{L_M^\ell}{L} = 0.110$
- $\frac{L_M^h}{L} = 0.117$

5. Finally, we plug these estimates into equations 37, 38 and 39 to get:

$$\Delta \frac{RD}{L_M}_{Between} \approx 0.1754 \times 0.0228 + 1.7066 \times -0.0227 \approx -0.0347 \tag{40}$$

Table A4: Weighted Summary Statistics of the Sample of Microregions

		2000		2000-2010		
	Source:	**Mean**	**SD**	**Mean**	**SD**	**Observations**
Potential Yields	*FAO-GAEZ*					
Soy		0.277	0.107	1.913	0.712	557
Maize		1.614	0.828	2.799	1.621	557
Employment Shares	*Population Census*					
Manufacturing		0.227	0.088	-.009	0.036	557
Low-Skill Manufacturing		0.110	0.067	-0.017	0.027	557
High-Skill Manufacturing		0.117	0.068	0.008	0.025	557
Skill Intensity $\frac{S}{S+U}$	*Population Census*					
Local Economy		0.461	0.111	0.166	0.031	557
Low-Skill Manufacturing		0.400	0.079	0.187	0.048	557
High-Skill Manufacturing		0.568	0.108	0.151	0.060	557

Notes: Observations weighted by their share of manufacturing employment at baseline. We are defining Low- and High-Skill manufacturing in the same way we defined it on the paper, based on whether is above or below the median industry in terms of skill intensity..

Table A5: Effect of technical change in soy on employment shares

VARIABLES	(1) Δ Log. L	(2) Δ Log. L	(3) $\Delta\frac{L_a}{L}$	(4) $\Delta\frac{L_a}{L}$	(5) $\Delta\frac{L_m}{L}$	(6) $\Delta\frac{L_m}{L}$	(7) $\Delta\frac{L_s}{L}$	(8) $\Delta\frac{L_s}{L}$
ΔA_{soy}	-0.023	-0.021	-0.017***	-0.017***	0.014**	0.015***	0.003	0.002
	[0.028]	[0.016]	[0.003]	[0.003]	[0.006]	[0.004]	[0.005]	[0.004]
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	557	557	557	557	557	557	557	557
R-squared	0.153	0.419	0.404	0.445	0.196	0.324	0.083	0.161

Notes: Changes in dependent variables are calculated over the years 2000 and 2010 (source: Population Censuses). The unit of observation is the micro-region. All the regressions include the baseline specification controls which are the share of rural population in 1991 and a measure of technical change in maize. The regressions with all controls also include income per capita (in logs), population density (in logs), literacy rate, all observed in the 1991 Population Census. Observations weighted by their share of manufacturing employment at baseline. Robust standard errors reported in brackets. Significance levels: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A6: Reallocation of Labor to Manufacturing

VARIABLES	(1) $\Delta\frac{L_M^k}{L_M}$ Skill Intensity=Low	(2) $\Delta\frac{L_M^k}{L_M}$ Skill Intensity=High	(3) $\Delta\frac{L_M^k}{L_M}$ R&D Expenditure=Low	(4) $\Delta\frac{L_M^k}{L_M}$ R&D Expenditure=High
ΔA_{soy}	0.014***	0.000	0.014***	0.000
	[0.005]	[0.005]	[0.004]	[0.004]
Baseline Controls	Yes	Yes	Yes	Yes
All Controls	Yes	Yes	Yes	Yes
Observations	557	557	557	557
R-squared	0.087	0.343	0.213	0.193

Notes: Changes in dependent variables are calculated over the years 2000 and 2010 (source: Population Censuses). The unit of observation is the micro-region. All the regressions include the baseline specification controls which are the share of rural population in 1991 and a measure of technical change in maize. The regressions with all controls also include income per capita (in logs), population density (in logs), literacy rate, all observed in the 1991 Population Census. In these regressions, we are splitting manufacturing industries across the median according to their level of skill intensity and R&D activity in such a way that roughly 50% of the Brazilian manufacturing employment is at both sides of the median. We define skill intensity as the share of skilled individuals in a particular industry in Brazil at baseline and we source it from the 2000 Population Census. Our measure of R&D activity is R&D expenditure as a share of total sales at baseline and we source it from from the 2000 *Pesquisa de Inovação Tecnológica* (PINTEC). Observations weighted by their share of manufacturing employment at baseline. Robust standard errors reported in brackets. Significance levels: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.