Structural Transformation, Industrial Specialization, and Endogenous Growth

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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.

Keywords: Agricultural Productivity, Skill-Biased Technical Change, Labor Mobility, Genetically Engineered Soy, Brazil.

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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 a micro-region with average increase in soy technical change experienced a decrease in unskilled employment in agriculture of around 20%, and no 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 reductions in the skill intensity of production technologies in low-skilled intensive manufacturing industries, consistent with technological downgrade. 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 two sectors: agriculture and 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, low-skilled workers reallocate towards the manufacturing sector.

Next, we analyze the implications of this increase in the relative supply of low-skilled workers in light of the Grossman and Helpman (1991a) model. In this model, the man-

[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.

ufacturing sector has two industries. In one industry, firms perform R&D to produce differentiated products using a skill-intensive production technology. In the other industry, firms produce homogeneous goods using unskilled labor more intensively. Their findings are reminiscent of the Heckscher-Ohlin model: an increase in the relative supply of unskilled labor reduces comparative advantage in the creation of knowledge and in producing differentiated products. As a result, in the long run, the economy conducts less R&D, exports more homogeneous products in exchange for the differentiated good, and its manufacturing 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 Brazilian Manufacturing 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 micro-regions more exposed to technical change in soy production experienced faster employment growth in low-skill intensive manufacturing industries in the short-run and lower average value added per worker in manufacturing in the long-run.

Finally, we quantify the aggregate effects of labor reallocation driven by skill-biased technical change in agriculture on the innovation-intensity of the Brazilian manufacturing sector. To this end, we use data from the Technological Innovation Survey (PINTEC), which monitors the innovative activities of Brazilian manufacturing firms. The data indicates that aggregate R&D expenditure per worker in manufacturing increased by 40 percent in the decade between 2000 and 2010. Reallocation of labor *between* industries can explain around one quarter of this change, the other three-quarter being explained by increases in R&D expenditure *within* industries. Our estimates suggest that if the average change in soy potential yields across Brazilian micro-regions had been one standard deviation smaller, the increase in R&D expenditure per worker in manufacturing during this period would have been 3.47 percentage points larger.

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 manufacturing. 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).[5] 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

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

both productivity- and welfare-enhancing.[6] 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.[7] 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

[6]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)).

[7]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. First, the use of GE seeds allows farmers to spray their fields with glyphosate without harming soy plants. Thus, the adoption of GE soybean seeds reduces labor requirements – and therefore costs – for weed control.[8] In addition, GE soy seeds increase agricultural profitability because they require fewer herbicide applications, allow a higher density of the crop on the field and reduce the time between cultivation and harvest.[9]

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). The legalization of GE soy seeds was followed by a fast expansion of the area planted with soy. 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).

The adoption of GE soy affected labor demand in the agricultural sector through two different channels: the within-crop effect and the across-crop effect. Within soy production, GE soybeans decreased 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. In addition, the expansion of area cultivated with soy came at the expense of the production of other crops. This across-crop effect reduced the labor intensity of production in the agricultural sector because soy production is one of the least labor-intensive agricultural activities, requiring 17 workers per 1000 hectares in 2006, while seasonal crops and permanent crops require 84 and 127, respectively.[11]

Figure 1 panels (a) and (b) document that while the area planted with soy in Brazil increased from 11 to 19 million hectares between 2000 and 2010, the number of workers employed in the soy sector decreased substantially. In panel (c) of Figure 1 we decompose the decrease in employment in the soy sector between skilled workers and unskilled workers (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 the fast adoption of GE soy seeds

[8] The planting of traditional seeds is 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, planting GE soy seeds requires no tillage, as the application of herbicide selectively eliminates all unwanted weeds without harming the crop. As a result, GE soy seeds can be applied directly onto last season's crop residue.

[9] Fields cultivated with GE soybeans require an average of 1.55 sprayer trips against 2.45 for conventional soybeans (Duffy and Smith 2001; Fernandez-Cornejo, Klotz-Ingram, and Jans 2002). No tilling allows for greater density of the crop on the field (Huggins and Reganold 2008).

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

[11] See Table 1 in Bustos et al. (2016).

across Brazilian farmers observed in this period, as this new technology requires fewer but relatively high-skilled workers.

Figure 1 goes around here

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.

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 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.[12] 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.[13]

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.[14] As

[12] 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.

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

[14] 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

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, 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

control: public administration, education, health, international organizations, extraction, and public utilities.

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*).[15] 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 Theoretical Framework

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 production using Acemoglu (2002) – and the endogenous growth model developed in Grossman and Helpman (1991a). 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 three sectors and three factors of production: agriculture, low-skill 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 we denote as high- and low-skilled intensive *industries* the two sectors in manufacturing. Structural transformation in this context is the movement of workers from agriculture to manufacturing. Growth in the model is determined by sectoral composition.

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:

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

[15] 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.

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 technical change, respectively, and σ is the elasticity of substitution between labor (L_a) and land (T_a). K is the knowledge in the local economy which is driven by high-skilled intensive manufacturing output as we discuss below. The main difference to 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 one industry, profit-seeking entrepreneurs invest human capital and labor to invent new input varieties of a differentiated product. Total output in this heterogeneous, monopolistically competitive input industry takes the form:

$$Q_m^h = \sum_{j=1}^{K} A_m^h F_m^h(U_{jm}^h, S_{jm}^h) = K A_m^h F_m^h(U_m^h, S_m^h) \tag{4}$$

Where K is the total amount of varieties in the industry, which we call knowledge. Grossman and Helpman (1991a) provide two alternative interpretations of K. In one interpretation K is the total amount of varieties in the sector. An alternative interpretation is that K represents the quality of varieties. The fact that K affects productivity in each sector is important for the balanced growth path. If knowledge did not affect the productivity in one of the sectors, the sector would shrink until disappearing.

In the other homogeneous-good manufacturing industry, firms produce a homogeneous good under conditions of perfect competition according to:

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

Both sectors combine low- and high-skilled labor (or human capital as is labeled in Grossman and Helpman (1991a)). The only difference across industries is that the monopolistically competitive industry h is relatively more intensive in high-skilled labor than the homogeneous good industry ℓ.

The growth rate of the economy (g) is determined by the composition of the local economy and the production resources of the high-skilled intensive industry devoted to expanding K:[16]

[16] Define total output by $Q = Q_a + Q_m^\ell + Q_m^h$, this is equal to $Q = K(F_a + F_m^\ell + F_m^h)$, if we log-differentiate this expression we are going to obtain: $\dot{Q}/Q \equiv g = \frac{\dot{K}}{K} + \omega_a \widehat{F_a} + \omega_m^\ell \widehat{F_m^\ell} + \omega_m^h \widehat{F_m^h}$.

$$g = \frac{\dot{K}}{K} + \omega_a g_a + \omega_m^\ell g_m^\ell + \omega_m^h g_m^h \tag{6}$$

where the ω_j's determine the weight of each sector in total output and g_j is the growth rate of each sector. When total output in the manufacturing high-skilled industry ω_m^h is larger then the growth rate of the economy g depends to a larger extent on this sector's growth rate.

We further assume that the only sector with endogenous growth forces is high-skilled manufacturing. In particular, we assume that the size of industry h determines the speed at which new varieties are invented which, in turn, determines long-run growth in the sector. Accordingly we assume that:

$$\dot{K} = \alpha Q_m^h$$

This assumption is micro-founded in Chapter 3 of Grossman and Helpman (1991a), where α is the share of resources spent in innovation or R&D activities. As emphasized in Romer (1986) and Romer (1990), the presence of increasing returns to scale and monopolistic competition generates some rents in the production of inputs that can be invested in expanding the set of inputs used in final production. We would obtain similar results if instead of using knowledge spillovers across sectors, we assumed that inventing new varieties is increasingly expensive, as is done in Aghion and Howitt (1992).

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 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 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 looks like an exogenous increase in the relative supply of labor. To be able to think about the effects that this has both for the sector and for the long-run growth we rely on the model presented in Chapter 6 of Grossman and Helpman (1991a).[17]

Theorem 3. *An increase in low-skilled workers into manufacturing, which occurs when land and labor are strong complements (i.e. when $\sigma < \varepsilon\Gamma$) and when high-and low-skilled*

[17] 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.

workers are imperfect substitutes (i.e. when $\varepsilon > 1$), is absorbed through an expansion of low-skill intensive manufacturing industries.

Proof. In Appendix B we provide a proof of this theorem assuming that the economy is inside the factor price equalization set. For a full discussion of what happens outside the factor price equalization set we refer the reader to chapter 6 in Grossman and Helpman (1991a), and especially to Grossman and Helpman (1990). □

The intuition for this results follows from standard Hecksher-Ohlin international trade theory. When low-skilled workers released from agriculture enter manufacturing, they expand the low-skilled intensive industry more than proportionately and shrink the high-intensive industry. The reason for that is that if all resources are put in the low-skilled intensive sector 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. Hence, some high-skilled labor would leave the high-skilled intensive industry towards the low-skilled intensive one. As a result, the high-skill intensive industry shrinks and all the labor that entered manufacturing plus some high-skilled labor enter the low-skilled intensive industry expanding its size.

The final result in this section, relates industrial composition and economic growth. The growth rate of the economy depends on the growth rate in each sector weighted by its size. Hence, technical change in agriculture affects the (instantaneous) growth rate in the economy, and given that sectors change size, the overall longer-run growth rate.

Theorem 4. *When land and labor are strong complements (i.e. when $\sigma < \varepsilon\Gamma$) and when high-and low-skilled workers are imperfect substitutes (i.e. when $\varepsilon > 1$), an exogenous change in skill-biased-factor-augmenting technologies 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 manufacturing industry.*

In equations we have that:[18]

$$\frac{\partial g}{\partial A_s} = \alpha \frac{\partial Q_m^h}{\partial A_s} + \omega_a \frac{\partial g_a}{\partial A_s} + \frac{\partial \omega_a}{\partial A_s} g_a + \frac{\partial \omega_m^l}{\partial A_s} g_m^l + \frac{\partial \omega_m^h}{\partial A_s} g_m^h$$

In the long-run, the growth rate in every sector is exclusively driven by exogenous changes to productivity, and hence $g_j = 0$. Only the high-skilled intensive manufacturing industry contributes to growth by expanding knowledge (K), using a fraction α of its

[18]From equation 7 we have that: $g = \alpha Q_m^h + \omega_a g_a + \omega_m^\ell g_m^\ell + \omega_m^h g_m^h$

resources to that. Thus, how much knowledge expands depends exclusively on the size of the high-skilled intensive sector:

$$\frac{\partial g}{\partial A_s} = \omega_a \frac{\partial g_a}{\partial A_s} + \alpha \frac{\partial Q_m^h}{\partial A_s} \tag{7}$$

The first term of equation 7 is positive since, on impact, increases in A_s increase total output in agriculture. The second term in this equation is negative, because output in high-skilled manufacturing decreases with an increase in A_s. Hence, improvements in skill-biased-factor-augmenting agricultural technologies, like the introduction of genetically modified crops, possibly result in static gains and dynamic losses.

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

4 Empirics

This section reports the main estimates of the paper. We start the section by discussing our identification strategy in more detail in sections 4.1. We then turn, in sections 4.2 and 4.3, to documenting how low-skilled labor relocated away from agriculture towards manufacturing and services in micro-regions more exposed to technical change in soy, while high-skilled agricultural employment was not affected. Thus, we first establish that the soy shock was both *labor-saving* and *skill-biased.* We then consider the wages of high- and low-skilled workers. The estimates show that wages (especially of high-skilled workers) in agriculture increased, which we interpret as evidence that the soy shock was skill-biased and that favored the "best" among both high- and low-skilled workers in the agricultural sector. The workers that were "freed" from agriculture moved into both services and (especially) manufacturing.

In section 4.4 we show that workers that moved to manufacturing were mostly absorbed into low-skilled-intensive industries, which led to an expansion of the less innovation-intensive industrial sectors in the economy, as measured by R&D expenditure as a share of sales. This pattern is in line with an extended version of the theoretical insights in Bustos et al. (2016) and Grossman and Helpman (1991a), as discussed in Section 3. There, we argue that, if land and labor are strong complements, an increase in high-skilled-labor agricultural productivity leads low-skilled workers to relocate towards manufacturing. Given that manufacturing has high- and low-skilled-intensive industries, this "freed" labor is absorbed mainly into low-skill-intensive industries, which, in turn, has implications for manufacturing productivity and long-term growth. We test empirically these implications in Subsections 4.5 and 4.6.

4.1 Identification Strategy

To estimate the causal effect of the change in the potential soy yields on different outcomes, we use regressions of the following form:

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

where ΔY_k is the change in the variable of interest in microregion k between 2000 and 2010, ΔA_k^{soy} corresponds to our exogenous measure of technical change in soy, and X_k is a vector of controls of microregion k. In our baseline specification, we include the share of rural population in 1991 and a measure of technical change in maize as controls. The lagged share of rural population controls for microregion specific trends in the outcome variable relates to starting conditions that differ across regions, whereas the technical change in maize at the microregion level is included because it might have affected some of the outcomes and is partially correlated with the soy shock. In our extended specification, we also control for the initial level of income per capita, alphabetization rate, and population density in 1991 in each microregion. Again, these should control for potentially different trends related to these baseline observables. This specification captures the reduced-form causal effect of technical change on a number of outcomes.

4.2 Effect of Technical Change on Labor Reallocation and Skill Intensity

As argued in Bustos et al. (2016), the soy shock in Brazil was labor-saving. Microregions that could benefit more from the new technology saw a number of agricultural workers move to the manufacturing sector. In this paper we argue that this technological change was not only labor-saving, but also high-skill biased, which has consequences for the economy that were unexplored in Bustos et al. (2016), as argued in Section 3. That is, with this technical change the higher-skilled workers had relatively more opportunities in the agricultural sector than the low-skilled, something that led low-skill workers to enter manufacturing. Tables 3 and 4 document this process. We start in Table 3 by documenting that the soy shock moved labor from agriculture into manufacturing (i.e., it led to structural transformation). This reproduces the main finding in Bustos et al. (2016). The first two columns investigate whether there was a significant change in total employment across microregions related to technical change. If anything, microregions that became more productive in agriculture lost a little bit of population, but the magnitude is relatively small, and when controlling for the starting conditions in Column 2, the estimates are not distinguishable from 0. Thus, the employment changes that we document in what follows are not driven by migration between microregions or by changes in the number of workers working across regions. All the changes are, instead, driven by changes across sectors within microregions.

Table 3 goes around here

In Columns (3) to (8), we investigate within-region labor relocation. As shown in Bustos et al. (2016), the positive technological shock in soy production led to a *decrease* in the total number of workers in agriculture. The estimates suggest that agriculture lost around 6% of its employment share for the mean change in potential soy yields.[19] This estimate is remarkably stable to the inclusion of various types of controls, as can be observed when comparing Columns (3) and (4). These low-skilled workers moved into manufacturing and services. Manufacturing employment shares increased by around 4 percentage points at the mean change in soy-yield potential, which can be seen in Columns (5) to (8), hence absorbing the bulk of these low-skilled workers released from agriculture. This adjustment shows that the soy shock was *labor-saving* and "freed" many workers, who moved into manufacturing.

In Table 4, we investigate whether the soy shock 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. We first look at whether, for each skill type, regions most favorably affected by the shock gained or lost employment in this factor type. We then consider whether there are significant differences across sectors within microregions. In Panel A of Table 4, we show that the soy shock had small but, if anything, negative effects on the employment of low-skilled workers at the microregional level, as recorded in Columns (1) and (2). Columns (3) to (8) investigate whether there was some relocation across sectors within regions by looking at the change in the share of workers employed in each sector, relative to the overall low-skilled employment. It is clear from Columns (3) and (4) in Panel A of Table 4 that agriculture lost low-skilled employment, both relative to total employment and in absolute terms.[20] These low-skill employees moved primarily into manufacturing, as observed in Columns (5) to (8).

Table 4 goes around here

Panel B of Table 4 repeats the exercise of Panel A, but instead focuses on high-skilled employment. Contrary to what happened with low-skill employment, microregions positively affected by the soy shock *gained* high-skilled employment, as shown in Columns (1) and (2). Columns (3) to (8) explore whether there is some heterogeneity across sectors

[19]The mean increase in potential soy yields is almost 2, as shown in Table 2. Thus, to obtain the employment effects of the mean change in potential soy yields, we only need to multiply the coefficient in the employment regressions by a factor of 2.

[20]Absolute numbers are easier to read in Table A2 in the Appendix.

in terms of how much high-skilled employment each sector gained. Our estimates suggest that, on the one hand, in microregions more exposed to the shock, agriculture lost high-skilled employment in *relative* terms, but not in absolute terms (i.e., the size of high-skilled employment in agriculture stayed constant despite experiencing a labor-saving technical change).[21] 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. Altogether, 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, we estimate in Panel C the effect of the soy shock on skill intensity, measured as the (log) ratio of high-skilled workers over low-skilled workers. As could have been expected from Panels A and B, microregions positively affected by the soy shock became more skill-intensive, a consequence of the increase in high-skill employment. However, not all sectors in these microregions became more skill-intensive. Only services and *especially* agriculture became more skill-intensive as a result of the soy shock.

In sum, Table 4 shows that soy-shock regions gained high-skilled employment. At the same time, low-skilled workers left agriculture and moved mainly into manufacturing. In this sense, Table 4 shows that the soy shock was both labor-saving and skill-biased. It also shows that manufacturing absorbed a large fraction of this excess supply of low-skilled workers. It is crucial, thus, to understand how these workers that moved into manufacturing were absorbed across manufacturing industries. Before showing these results, however, we investigate wage changes.

4.3 Effect of Technical Change on Wages and Skill Premia

So far, we have seen evidence consistent with 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. We investigate whether that is the case 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, then we distinguish between factor types. Table 5 shows that (composition-adjusted) wages increased in microregions with positive soy shocks. These modest wage gains come entirely from agriculture, the sector that became more productive. This change can be seen in Columns (3) and (4) of Table 5. It is important to remember that we use composition-adjusted wages, as explained in Section 2.2, because we are interested in distinguishing changes in the unit price of labor from factor composition. This means that we always net out all the observable characteristics of the workers in

[21] Also see Table A2 in the Appendix.

Mincerian regression, to obtain a measure of how much each factor type is paid.

Table 5 goes around here

Given the evidence presented in Subsection 4.2, it is very likely that Table 5 hides important differences across factor types. We investigate this in Table 6. As before, we first look at each factor type separately, then we look at relative (composition-adjusted) wages. Panel A of Table 6 indicates that average (composition-adjusted) wages of low-skilled workers in microregions positively affected by the soy shock did not increase substantially, as shown in Columns (1) and (2). Only low-skilled workers in agriculture (the sector that became more productive) gained somewhat, despite the fact that many low-skilled workers left the sector. We interpret this pattern 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.[22]

Table 6 goes around here

In Panel B of Table 6, we look at the labor-market price of high-skilled workers. Consistent with the increase in employment of high-skill workers, wages in microregions positively affected by the soy shock increased. This trend is true in every sector, but the increase is disproportionate in agriculture, as shown in Columns (3) and (4). 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.

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 rewards across factors in the different sectors of the economy. As can be seen in this panel, the estimates in each sector are similar in magnitude, which is consistent with the idea that factor relocation across sectors is relatively elastic.

In sum, the evidence from wage regressions is consistent with what we learn from the employment responses, which gives further support to the idea that the soy shock – affecting the agricultural sector directly – was 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 investigate labor relocation within sectors more deeply. We turn to this point in the following subsection.

[22]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.

4.4 Reallocation 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 long-term consequences for industrial specialization and, possibly, welfare. In this section, we document which industries absorbed the low-skilled workers who relocated away from agriculture.

To investigate this point, we distinguish between industries in manufacturing that are low-skill-intensive and industries that are high-skill-intensive. We make a split of the various industries by employment, which means that we rank industries by skill intensity and we nominate as high-skill-intensive industries the sectors that are at the top of this rank, which also host 50% (or other percentiles of the employment distribution) of total employment. The rest of the manufacturing industries are labeled as low-skill-intensive. We also show results where the split follows R&D intensity.

To show these results, we start by plotting the change in employment between 2000 and 2010 as a function of the skill and R&D intensity in the sector across microregions and the intensity of the soy shock change. More concretely, in Figure 3 we split industrial-skill intensities into quartiles and plot the estimate for each of these quartiles. This figure shows, non-parametrically, the effect of the soy shock on employment relocation.

Figures 3 and 4 go around here

Figure 3 shows very clearly that employment gains are concentrated in the most low-skill-intensive industries. In a small, open economy, these are the industries that can absorb the excess supply of low-skilled labor "freed" from agriculture more easily. These is in line with the logic of classical Heckscher-Ohlin theory, which is what drives the results of Grossman and Helpman (1991a) discussed above. Furthermore, in Figure 4 we show how these relocations concentrated more explicitly in low R&D sectors, which – through the lens of Grossman and Helpman (1991a) – has implications for long-run growth potential. Thus, the exogenous increase (from the viewpoint of manufacturing) of low-skilled labor is absorbed through increases in low-skilled, low-R&D-intensive industries, as predicted in the Grossman and Helpman (1991a) model.

We quantify these results using regressions in Table 7. Column (1) of Panel A in Table 7 shows that manufacturing gained low-skilled workers, which is something that we already documented when discussing Table 4 above. Interestingly, this increase in low-skilled employment in manufacturing concentrated *exclusively* in the low-skill-intensive industries within manufacturing. As can be seen in Column (3), high-skill-intensive industries did not increase low-skilled employment. In terms of magnitudes, the share of low-skilled workers moving into low-skilled-intensive industries or low R&D industries increased by around 5 percentage points for the mean change in soy productivity.

Table 7 goes around here

Panel B of Table 7 investigates whether similar patterns emerge when looking at high-skilled employment, as documented before. First, Column 1 shows that manufacturing gained high-skilled employment, in line with the fact that microregion positively affected by the shock gained high-skilled employment. Columns (2) and (3) in Panel B show, however, that there are not large differences in the increase of high-skilled workers in high- vs low-skilled-intensive sectors. These relatively small numbers are also obtained when splitting industrial sectors between high and low R&D expenditures. Using this R&D split, 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. As previously argued, this same logic underlies Grossman and Helpman 1991a's model.

The combination of Panels A and B seems to suggest that skill intensities within manufacturing changed as a result of the soy shock.[23] We show this explicitly in Panel C of Table 7. The first column shows that manufacturing became more low-skill-intensive. However, there are important differences across industries within manufacturing. As we can see in Columns (2) and (3) of Panel C, low-skill-intensive industries became *more* low-skill-intensive with the soy shock. In Columns (4) and (5), we show the split of industries using R&D expenditures.[24] In line with what is shown in Columns (2) and (3), we see that the industries that could expand to accommodate the excess supply of low-skilled labor that left agriculture were industries with low R&D expenditures and presumably low growth potential.

We view this finding, as argued in the introduction and in Section 3, 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

Through the lens of the theoretical framework we argued that one of the threats of the reallocation of low-skilled workers from agriculture towards manufacturing is that this may lead to specialization in low R&D, low-skilled intensive sectors. This in turn, may push the economy towards a lower path in the evolution of GDP given that the manufacturing sector becomes less productive. We provide in this section evidence consistent with this theoretical framework.

[23]In classical H-O theory, factor intensities may change only when the economy is outside of the factor-price equalization set.

[24]Table A3 shows the full list of industries considered.

To guide this discussion we use data from PIA, previously described. This allows to track the local economies at a much higher frequency. Instead of using ten year differences, we can see the evolution of soy-shocked regions every year. To provide evidence in this context we use the following event-type estimation equation:

$$\ln y_{k,t} = \delta_t + \delta_k + \sum_{j=2001}^{j=2009} \beta_j \Delta A_k^{soy} + \sum_{j=2001}^{j=2009} \gamma_j \Delta A_k^{mze} + t X'_{k,1991} \omega + \varepsilon_{k,t} \tag{9}$$

where ΔA_k^{soy} is the change in our exogenous measure of technical change in soy in microregion k between 2000 and 2009, and $\ln y_{k,t}$ is our outcome of interest in microregion k at time t. δ_k and δ_t are microregion and year fixed effects, respectively. β_j estimates the effect of the change in the productivity of soy in each of the years of the decade. 2000 is the omitted category. Thus, we flexibly allow β_j to capture the effect of the decadal change in productivity, in each year. Given that the change in productivity of soy was spread across years, and genetically modified soy was only introduced in 2003, we would expect significant changes starting at around 2004 and increased intensity over the years, to conclude that the changes in the outcome can be attributed to the change in productivity induced by the genetically modified soy.

Figure 6 goes around here

Using this estimating equation we investigate three different outcomes. First, we show that the movement of labor towards low-skill intensive manufacturing tracks well the evolution of soy production, shown in Figure 1. In regions positively affected by soy productivity increases, more labor – mainly low-skilled labor as documented using census data – enters low-skilled manufacturing.[25] This can be seen in the left graph of Figure 6. Especially after 2003, the amount of labor entering low-skill intensive sectors starts to increase substantially. Second, we show that high skilled intensive manufacturing did not expand disproportionately in high soy shock regions. We show this in the graph on the right of Figure 6. This corroborates the main results shown using Census data.

Figure 7 goes around here

The third result investigates the effect of soy technical change on manufacturing productivity. Ideally, we would like to use total factor productivity in manufacturing as an outcome. However, the Brazilian Manufacturing Survey does not report information on

[25]With PIA data we cannot separate high and low-skilled workers accurately, which is why we have used Census data in the previous sections.

the book value of physical capital. Thus, we use value added per worker in a given micro-region as a proxy for manufacturing productivity. We define value added per worker 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 value added per worker as a function of the change in soy productivity. The graph shows that micro-regions more exposed to the soy shock experienced a relative decline in value added per worker. The effect becomes apparent in 2005 and increases in magnitude over the decade.

Figure 7 provides further empirical evidence for one of the key aspects of the model discussed in Section 3. While an increase in productivity in the agricultural sector is good for the microregion, the fact that the new technology is skilled biased means that low-skilled workers are the ones moving towards manufacturing. This expands the sectors within manufacturing that are least productive. Thus, compared to a counterfactual where workers leaving agriculture enter the most vibrant and R&D intensive sectors, this evidence suggests that it is not necessarily the case that structural transformation necessarily leads 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). 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 this early literature.

4.6 Within-Between Decomposition

In this section 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$.[26] 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.[27]

Change in R&D expenditure per worker in Brazilian manufacturing can be driven by

[26]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).

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

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 (10), which shows a decomposition of the decadal change in R&D expenditure per worker:

$$\Delta \frac{RD}{L_M} \approx \underbrace{\frac{RD^h_{2000}}{L^h_{M,2000}} \Delta \frac{L^h_M}{L_M} + \frac{RD^\ell_{2000}}{L^\ell_{M,2000}} \Delta \frac{L^\ell_M}{L_M}}_{\text{Between}} + \underbrace{\Delta \frac{RD^h}{L^h_M} \frac{L^h_{M,2000}}{L_{M,2000}} + \Delta \frac{RD^\ell}{L^\ell_M} \frac{L^\ell_{M,2000}}{L_{M,2000}}}_{\text{Within}} \quad (10)$$

The superscripts h and l in equation (10) 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 (11) – and study the effect of labor reallocation driven by skill-biased technical change in agriculture on $\Delta \frac{RD}{L_M}_{Between}$.

$$\Delta \frac{RD}{L_M}_{Between} \approx \frac{RD^h_{2000}}{L^h_{M,2000}} \Delta \frac{L^h_M}{L_M} + \frac{RD^\ell_{2000}}{L^\ell_{M,2000}} \Delta \frac{L^\ell_M}{L_M} \quad (11)$$

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 (11).[28]

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 Appendix A.2 and compute the implied change in $\Delta \frac{L^k_M}{L_M}$ 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

[28]Data on R&D expenditure per worker in 2000 for both high-skill and low-skill intensive industries in equation (11) 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 $\frac{RD^H_{2000}}{L^H_{M,2000}} \approx 1.707$ and $\frac{RD^L_{2000}}{L^L_{M,2000}} \approx 0.175$.

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. Section A.2 in the Appendix of the paper describes in detail this quantification.

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. In addition, we find that, following an increase in low-skilled labor supply from the agricultural sector, industries using low-skilled labor more intensively become even more low-skilled-intensive, which is consistent with technological downgrade. We show that this translates into lower valued added per worker in manufacturing at the microregion level. Taken together, our findings indicate that structural transformation obtained through labor-saving and skill-biased technical change in agriculture can attenuate the standard gains from reallocation into manufacturing emphasized by the existing literature.

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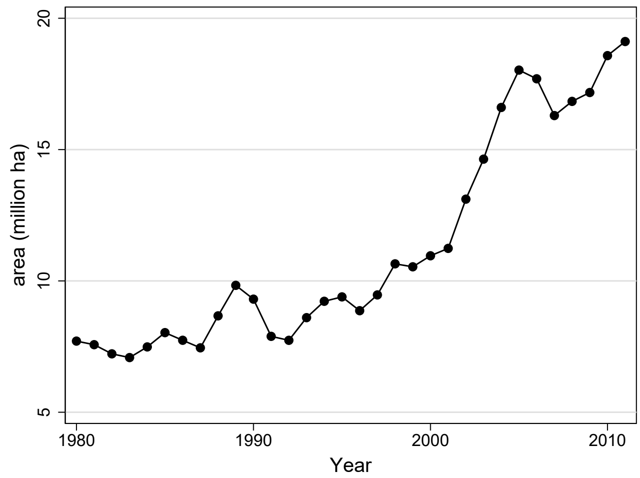
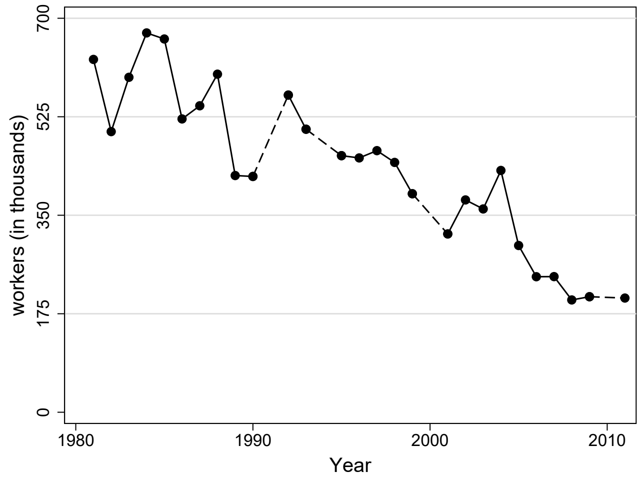
6 Figures and Tables

Figure 1: Soy Production and Employment

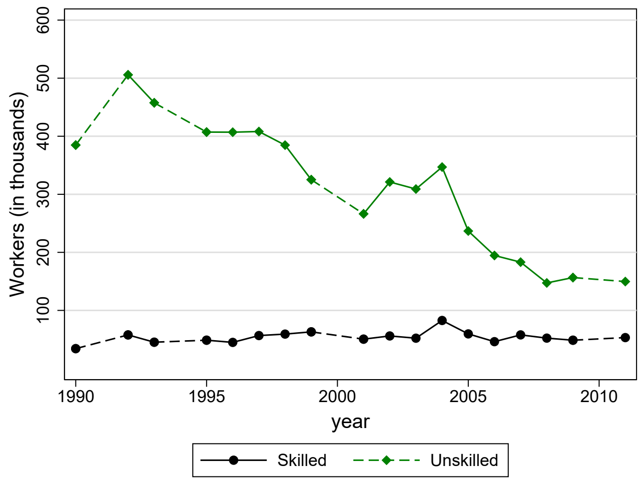
(a) Soy: Area planted



(b) Soy: Employment

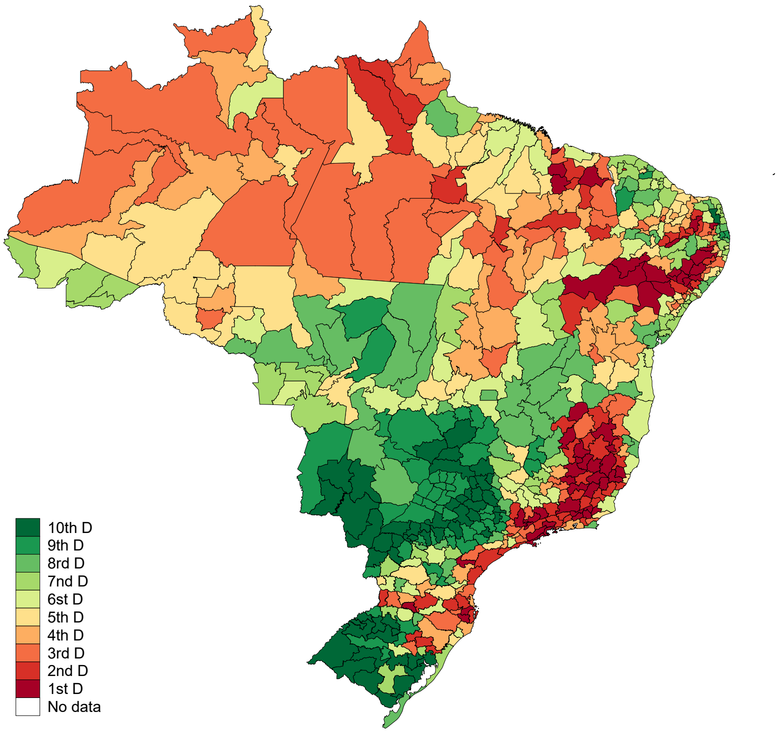


(c) Soy: Employment by Skill Group



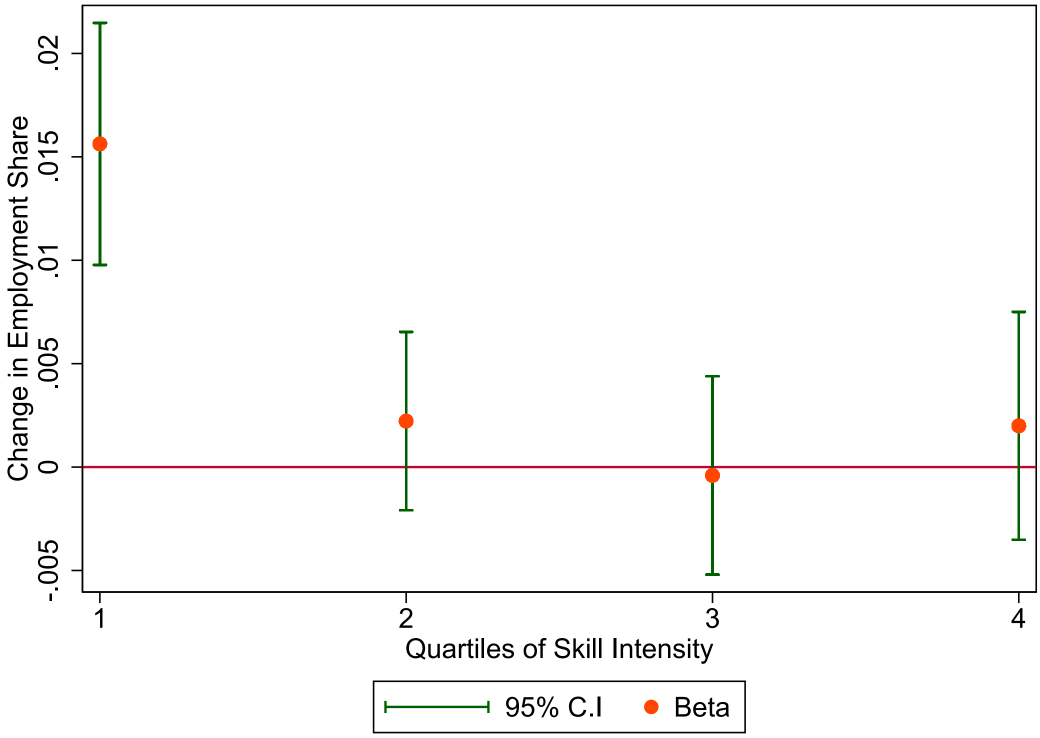
Notes: First two figures taken from Bustos et al. (2016). Data sources of Panel A is CONAB and of Panel B and C is PNAD. The states of Rondonia, Acre, Amazonas, Roraima, Pará, Amapá, Tocantins, Mato Grosso do Sul, Goias, and Distrito Federal are excluded due to incomplete coverage by PNAD in the early 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: Employment Share Growth by Quartile of Skill Intensity

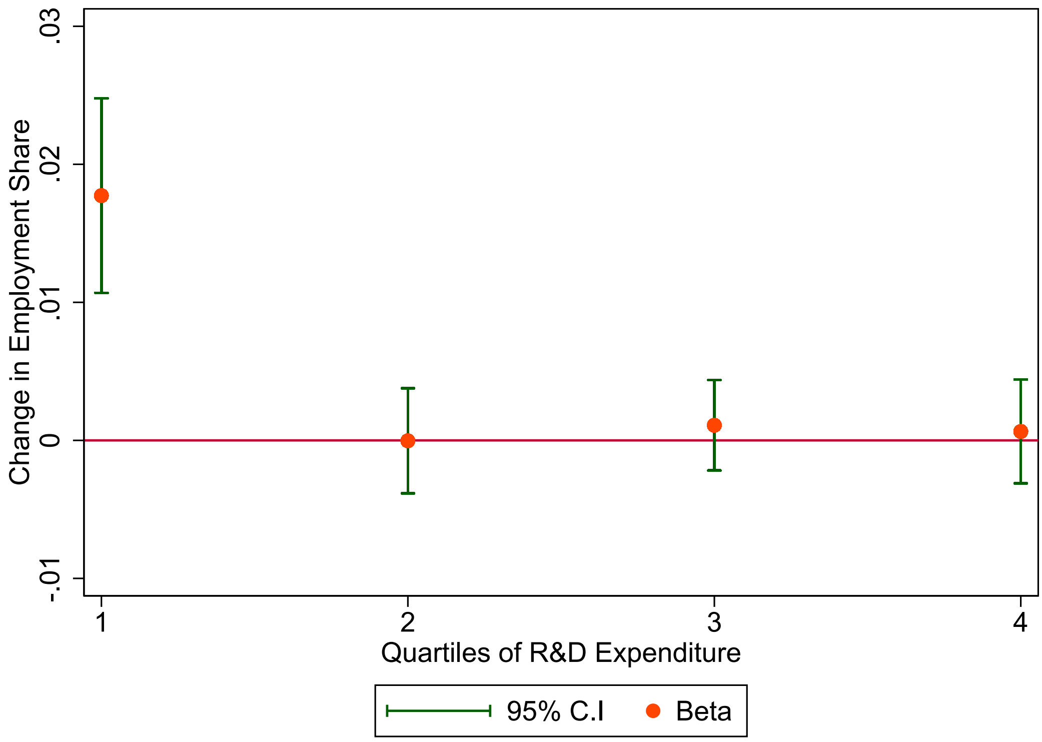


Notes: The plot shows the β_i coefficients of the following regression:

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

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 4: Employment Share Growth by Quartile of R & D Expenditure

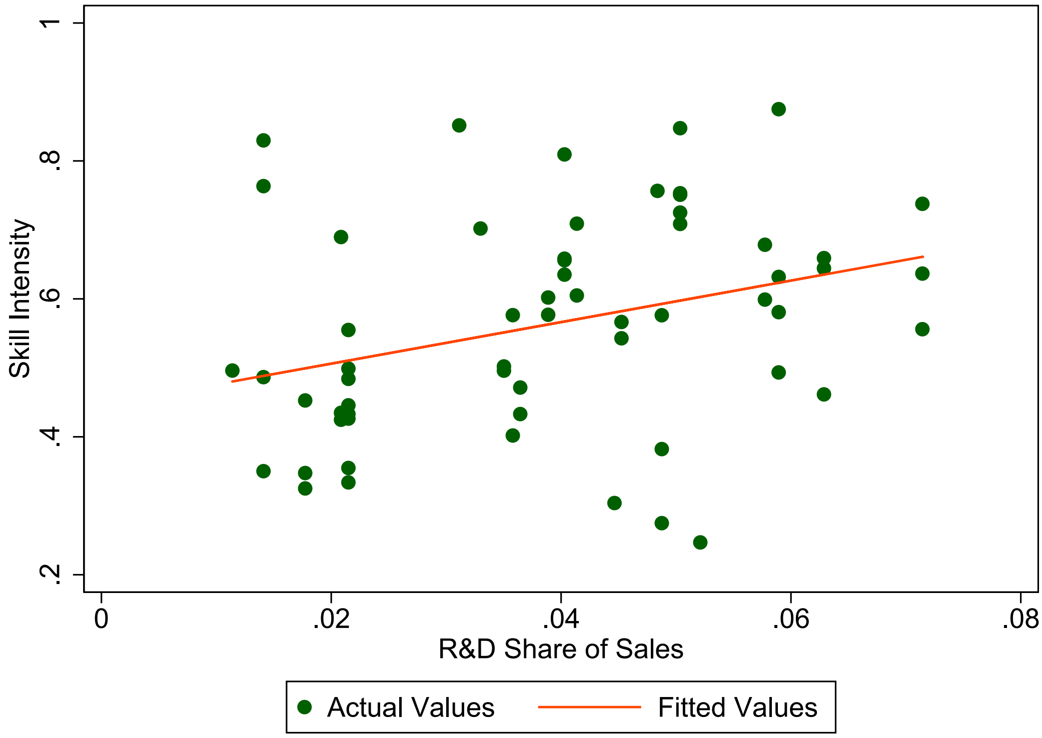


Notes: The plot shows the β_i coefficients of the following regression:

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

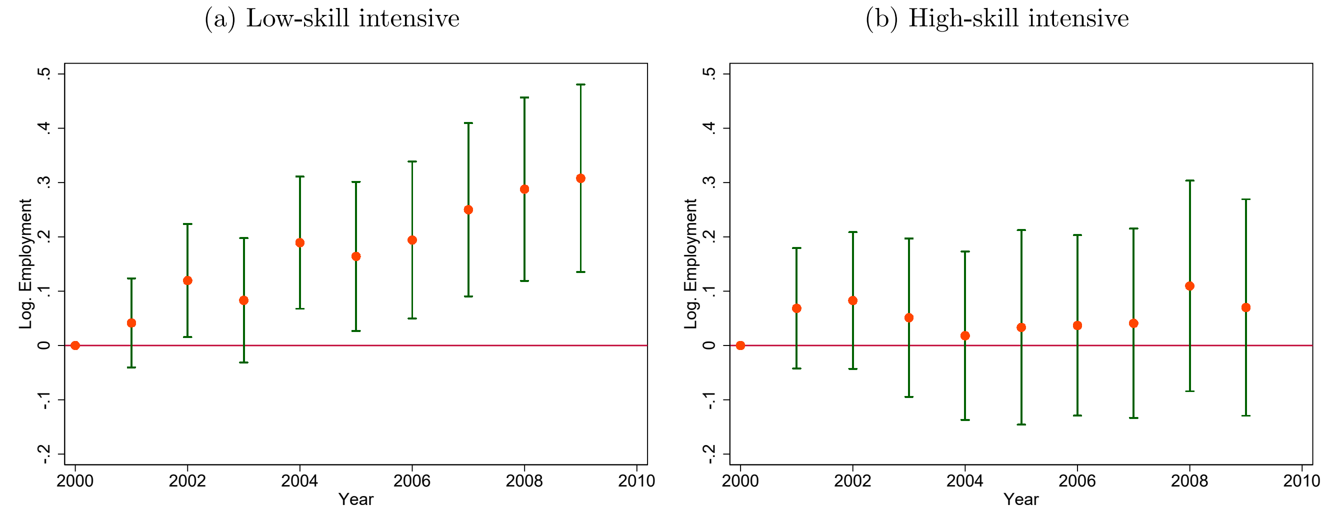
for $i = 1, 2, 3, 4$ where γ_i is a dummy for the different quartiles of R&D activity. We are splitting splitting manufacturing industries in quartiles according to their level of R&D activity in such a way that roughly 25% of the Brazilian manufacturing employment is in each group. Changes in dependent 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 5: 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.

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

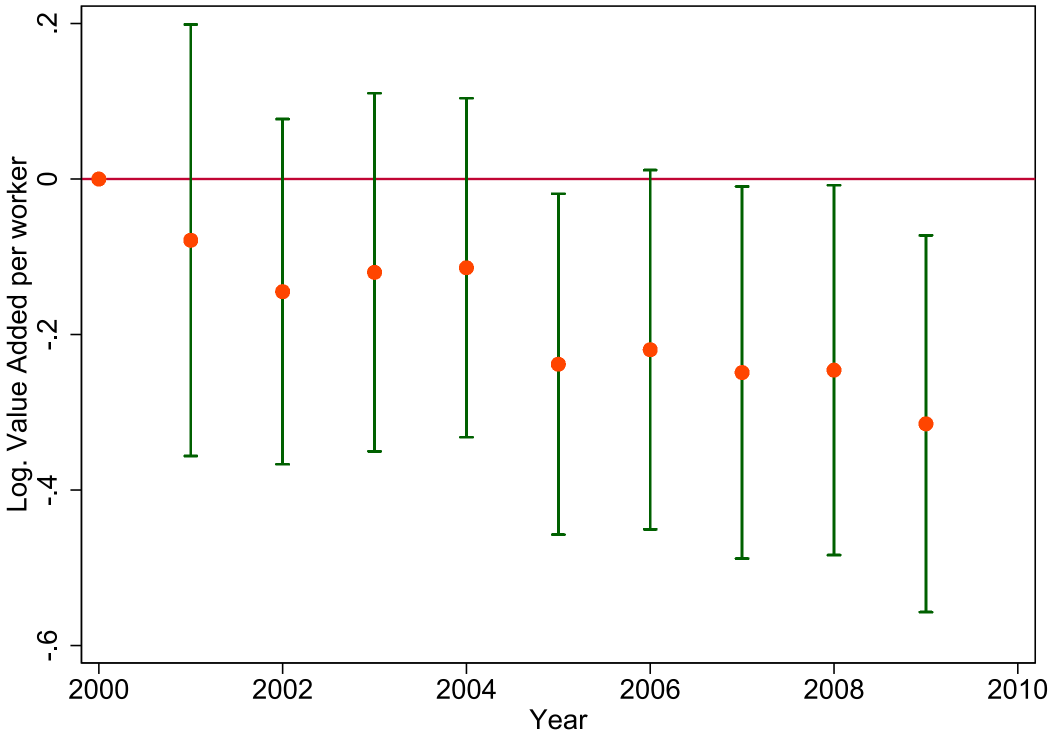


Notes: The plot shows the point estimates and the 95% confidence intervals for the estimates of the β_j coefficients of the following regression:

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

$\ln y_{k,t}$ 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:

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

$\ln y_{k,t}$ 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]
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	0.023	0.154	0.218	0.242	0.086	0.107	0.251	0.311

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]
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	0.136	0.301	0.106	0.120	0.092	0.100	0.117	0.142

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]
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	0.301	0.446	0.030	0.043	0.057	0.076	0.032	0.069

Panel C: Log. of Skill Intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$\Delta \log \frac{S}{U}$		$\Delta \log \frac{S_a}{U_a} - \Delta \log \frac{S}{U}$		$\Delta \log \frac{S_m}{U_m} - \Delta \log \frac{S}{U}$		$\Delta \log \frac{S_s}{U_s} - \Delta \log \frac{S}{U}$	
ΔA_{soy}	0.094***	0.075***	0.010	0.007	-0.086***	-0.100***	-0.025***	-0.012
	[0.017]	[0.016]	[0.028]	[0.030]	[0.027]	[0.026]	[0.009]	[0.008]
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	556	556	557	557
R-squared	0.174	0.213	0.065	0.074	0.021	0.041	0.131	0.150

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 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]
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	0.035	0.177	0.121	0.179	0.039	0.087	0.023	0.195

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]
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	556	556	557	557
R-squared	0.181	0.262	0.118	0.170	0.027	0.068	0.018	0.169

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]
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	555	555	557	557
R-squared	0.063	0.164	0.058	0.164	0.034	0.070	0.030	0.157

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]
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	554	554	557	557
R-squared	0.081	0.121	0.028	0.098	0.012	0.014	0.018	0.025

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) $\Delta\frac{S_m}{U_m}$	(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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A Appendix: Empirics

A.1 Figures and Tables

Table A1: Reallocation of Labor to Manufacturing

	(1)	(2)	(3)	(4)	(5)
VARIABLES	$\Delta\frac{L_m}{L}$	$\Delta\frac{L_M}{L}$ Skill Intensity=Low	$\Delta\frac{L_M}{L}$ Skill Intensity=High	$\Delta\frac{L_M}{L}$ R&D Expenditure=Low	$\Delta\frac{L_M}{L}$ R&D Expenditure=High
ΔA_{soy}	0.023***	0.019***	0.004*	0.019***	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	0.107	0.079	0.046	0.092	0.044

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 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 A2: Effect of technical change in soy on Log. Employment by Sector

Panel A: Employment of Unskilled Labor

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Δ Log. U	Δ Log. U	Δ Log. U_a	Δ Log. U_a	Δ Log. U_m	Δ Log. U_m	Δ Log. U_s	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]
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	556	556	557	557
R-squared	0.136	0.301	0.077	0.129	0.033	0.095	0.276	0.431

Panel B: Employment of Skilled Labor

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Δ Log. S	Δ Log. S	Δ Log. S_a	Δ Log. S_a	Δ Log. S_m	Δ Log. S_m	Δ Log. S_s	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]
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	0.301	0.446	0.178	0.217	0.086	0.100	0.298	0.481

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 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.

A.2 Within-Between Decomposition

This appendix describes the quantitative exercise that analyzes the effect of labor reallocation driven by skill-biased technical change in agriculture on the aggregate innovation-intensity of the manufacturing sector in Brazil in subsection 4.6 of the paper. We can approximate the decadal change in R&D expenditure per worker as follows:

$$\Delta\frac{RD}{L_M} \approx \underbrace{\frac{RD^h_{2000}}{L^h_{M,2000}}\Delta\frac{L^h_M}{L_M} + \frac{RD^\ell_{2000}}{L^\ell_{M,2000}}\Delta\frac{L^\ell_M}{L_M}}_{\text{Between}} + \underbrace{\Delta\frac{RD^h}{L^h_M}\frac{L^h_{M,2000}}{L_{M,2000}} + \Delta\frac{RD^\ell}{L^\ell_M}\frac{L^\ell_{M,2000}}{L_{M,2000}}}_{\text{Within}} \tag{12}$$

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:

$$\Delta\frac{RD}{L_M}_{Between} \approx \frac{RD^h_{2000}}{L^h_{M,2000}}\Delta\frac{L^h_M}{L_M} + \frac{RD^\ell_{2000}}{L^\ell_{M,2000}}\Delta\frac{L^\ell_M}{L_M} \tag{13}$$

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-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 10. 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

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

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

$$\Delta\left(\frac{L_M^k}{L_M}\right) = \Delta\left(\frac{L_M^k}{L}\right)\frac{L}{L_M} + \frac{L_M^k}{L}\Delta\left(\frac{L}{L_M}\right) \tag{14}$$

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

$$\Delta\left(\frac{L}{L_M}\right) = \Delta\left(\frac{1}{\frac{L_M}{L}}\right) \approx -\left(\frac{L_M}{L}\right)^{-2} \times \Delta\left(\frac{L_M}{L}\right) \tag{15}$$

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):

   - $\frac{L_M}{L} = 0.227$
   - $\frac{L}{L_M} = \frac{1}{0.227} = 4.412$

- $\frac{L^{\ell}_M}{L} = 0.110$
- $\frac{L^{h}_M}{L} = 0.117$

5. Finally, we plug these estimates into equations 13, 14 and 15 to get:

$$\Delta \frac{RD}{L_M}_{Between} \approx 0.1754 \times 0.0228 + 1.7066 \times -0.0227 \approx -0.0347 \tag{16}$$

Table A4: Weighted Summary Statistics of the Sample of Microregions

	Source:	2000 Mean	2000 SD	2000-2010 Mean	2000-2010 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: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

B Appendix: Theory

In this appendix we provide the proofs of Theorems 1 to 3.

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, monopolistically-competitive input industry. 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. 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:[29]

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

For the following statements 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:

$$S_a(w_s, w_u, L_a) = \frac{\left(\frac{w_s}{A_s}\right)^{-\varepsilon} L_a}{A_s \left[w_s^{1-\varepsilon} A_s^{\varepsilon-1} + w_u^{1-\varepsilon} A_u^{\varepsilon-1}\right]^{\frac{\varepsilon}{\varepsilon-1}}} \tag{18}$$

$$U_a(w_s, w_u, L_a) = \frac{\left(\frac{w_u}{A_u}\right)^{-\varepsilon} L_a}{A_u \left[w_s^{1-\varepsilon} A_s^{\varepsilon-1} + w_u^{1-\varepsilon} A_u^{\varepsilon-1}\right]^{\frac{\varepsilon}{\varepsilon-1}}} \tag{19}$$

$$C(w_s, w_u, L_a) = L_a \left[\left(\frac{w_s}{A_s}\right)^{1-\varepsilon} + \left(\frac{w_u}{A_u}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \tag{20}$$

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

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

$$\det \begin{pmatrix} a_{U_m^\ell}(\omega) & a_{U_m^h}(\omega) \\ a_{S_m^\ell}(\omega) & a_{S_m^h}(\omega) \end{pmatrix} > 0 \tag{17}$$

$$\frac{S_a}{U_a} = \left(\frac{w_u}{w_s}\right)^{\varepsilon} \left(\frac{A_s}{A_u}\right)^{\varepsilon-1} \tag{21}$$

$\square$

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:

$$MPU_a = A_n K \gamma \Theta^{\frac{1}{\sigma-1}} A_L^{\frac{\sigma-1}{\sigma}} L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}} A_u^{\frac{\varepsilon-1}{\varepsilon}} U_a^{\frac{-1}{\varepsilon}} \tag{22}$$

$$MPS_a = A_n K \gamma \Theta^{\frac{1}{\sigma-1}} A_L^{\frac{\sigma-1}{\sigma}} L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}} A_s^{\frac{\varepsilon-1}{\varepsilon}} S_a^{\frac{-1}{\varepsilon}} \tag{23}$$

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,

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

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

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

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

$$\frac{\partial MPU_a}{\partial A_s} < 0 \iff \sigma < \varepsilon\left(\frac{(1-\gamma)(A_T T_a)^{\frac{\sigma-1}{\sigma}}}{\Theta}\right) \tag{24}$$

□

Theorem 3. *An increase in low-skilled workers into manufacturing, which occurs when land and labor are strong complements (i.e. when $\sigma < \varepsilon\Gamma$) and when high-and low-skilled workers are imperfect substitutes (i.e. when $\varepsilon > 1$), is absorbed through an expansion of low-skill intensive manufacturing industries.*

Proof. Consider the factor market clearing equilibrium conditions,

$$a_{Ta}Q_a = T \tag{25}$$

$$a_{Sa}Q_a + a_{S_m^\ell}Q_m^\ell + a_{S_m^h}Q_m^h = S \tag{26}$$

$$a_{Ua}Q_a + a_{U_m^\ell}Q_m^\ell + a_{U_m^h}Q_m^h = U \tag{27}$$

Log-differentiating Equations 25, 26 and 27 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:

$$a_{Ta}dQ_a + da_{Ta}Q_a = \widehat{T} \tag{28}$$

$$\lambda_{Sa}\widehat{Q_a} + da_{Sa}\frac{Q_a}{S} + \lambda_{S_m^\ell}\widehat{Q_m^\ell} + \lambda_{S_m^h}\widehat{Q_m^h} = \widehat{S} \tag{29}$$

$$\lambda_{Ua}\widehat{Q_a} + da_{Ua}\frac{Q_a}{U} + \lambda_{U_m^\ell}\widehat{Q_m^\ell} + \lambda_{U_m^h}\widehat{Q_m^h} = \widehat{U} \tag{30}$$

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

$$\widehat{Q_a} = -\widehat{a_{Ta}} \tag{31}$$

$$\lambda_{Sa}\widehat{Q_a} + \lambda_{S_m^\ell}\widehat{Q_m^\ell} + \lambda_{S_m^h}\widehat{Q_m^h} = -da_{Sa}\frac{Q_a}{S} \tag{32}$$

$$\lambda_{Ua}\widehat{Q_a} + \lambda_{U_m^\ell}\widehat{Q_m^\ell} + \lambda_{U_m^h}\widehat{Q_m^h} = -da_{Ua}\frac{Q_a}{U} \tag{33}$$

Combining these expressions, we arrive to:

$$\lambda_{S_m^\ell}\widehat{Q_m^\ell} + \lambda_{S_m^h}\widehat{Q_m^h} = -\widehat{a_{Sa}}\lambda_{Sa} + \lambda_{Sa}\widehat{a_{Ta}} = \underbrace{\lambda_{Sa}(\widehat{a_{Ta}} - \widehat{a_{Sa}})}_{\gamma_s} \tag{34}$$

$$\lambda_{U_m^\ell}\widehat{Q_m^\ell} + \lambda_{U_m^h}\widehat{Q_m^h} = -\widehat{a_{Ua}}\lambda_{Ua} + \lambda_{Ua}\widehat{a_{Ta}} = \underbrace{\lambda_{Ua}(\widehat{a_{Ta}} - \widehat{a_{Ua}})}_{\gamma_u} \tag{35}$$

Thus, using Cramer rule, the change in $\widehat{Q_m^\ell}$ and $\widehat{Q_m^h}$ is given by:

$$\widehat{Q_m^h} = \frac{\lambda_{U_m^\ell}\gamma_s - \lambda_{S_m^\ell}\gamma_u}{\Delta} \tag{36}$$

$$\widehat{Q_m^\ell} = \frac{\lambda_{S_m^h}\gamma_u - \lambda_{U_m^h}\gamma_s}{\Delta} \tag{37}$$

$$\widehat{Q_m^\ell} - \widehat{Q_m^h} = \frac{\gamma_u\left[1 - \lambda_{Sa}\right] - \gamma_s\left[1 - \lambda_{Ua}\right]}{\Delta} \tag{38}$$

where $\Delta \equiv \lambda_{U_m^\ell}\lambda_{S_m^h} - \lambda_{U_m^h}\lambda_{S_m^\ell}$ and $\Delta > 0$ by Condition 17. $\widehat{Q_m^h} < 0$ iff

$$\frac{\lambda_{U_m^\ell}}{\lambda_{S_m^\ell}} < \frac{\gamma_u}{\gamma_s} = \frac{\lambda_{Ua}(\widehat{a_{Ta}} - \widehat{a_{Ua}})}{\lambda_{Sa}(\widehat{a_{Ta}} - \widehat{a_{Sa}})}$$

A sufficient condition for this inequality is that $\frac{(\widehat{a_{Ta}} - \widehat{a_{Ua}})}{(\widehat{a_{Ta}} - \widehat{a_{Sa}})} > 1$ which only requires that $\widehat{a_{Sa}} > \widehat{a_{Ua}}$[30].
Likewise, $\widehat{Q_m^\ell} > 0$ iff

$$\frac{\lambda_{U_m^h}}{\lambda_{S_m^h}} < \frac{\gamma_u}{\gamma_s} = \frac{\lambda_{Ua}(\widehat{a_{Ta}} - \widehat{a_{Ua}})}{\lambda_{Sa}(\widehat{a_{Ta}} - \widehat{a_{Sa}})}$$

To prove this the same condition as above is sufficient.

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

[30] Since by assumption $\frac{\lambda_{Ua}}{\gamma_{Sa}} > 1$.

productivities for skilled and unskilled labor in agriculture (Equations 22 and 23) and equate them to their factor price:

$$w_u = MPU_a$$
$$w_s = MPS_a$$

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

$$U_a^{\frac{1}{\varepsilon}} = \frac{1}{w_u} A_n K \gamma \Theta^{\frac{1}{\sigma-1}} A_L^{\frac{\sigma-1}{\sigma}} L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}} A_u^{\frac{\varepsilon-1}{\varepsilon}}$$
$$S_a^{\frac{1}{\varepsilon}} = \frac{1}{w_u} A_n K \gamma \Theta^{\frac{1}{\sigma-1}} A_L^{\frac{\sigma-1}{\sigma}} L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}} A_s^{\frac{\varepsilon-1}{\varepsilon}}$$

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,

$$\widehat{a_{Sa}} > \widehat{a_{Ua}} \iff \frac{\partial lna_{Sa}}{\partial lnA_s} > \frac{\partial lna_{Ua}}{\partial lnA_s} \iff \frac{\partial lnS_a}{\partial lnA_s} > \frac{\partial lnU_a}{\partial lnA_s} \iff \varepsilon - 1 > 0 \tag{39}$$

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

□