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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 reallocation of workers towards manufacturing can lead to industrial development. However, when workers moving to manufacturing are mostly unskilled, this process reinforces a country's comparative advantage in unskilled-labor intensive industries. To the extent that these industries undertake less innovative activities, this change in industrial specialization can lead to lower long run growth. We highlight this mechanism in an endogenous growth model and provide empirical evidence 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 manufacturing productivity in the long-run.

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1 Introduction

Early development economists perceived the reallocation of workers from agriculture to manufacturing as fundamental for development and growth.[1] In particular, scholars argue that high agricultural productivity can induce rural workers to find employment in the industrial sector which can lead to higher growth (Gollin, Parente, and Rogerson 2002). This is because labor productivity is lower in agriculture than in the rest of the economy (Gollin, Lagakos, and Waugh 2014). In addition, the manufacturing sector is characterised 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 growth may not only depend on the size of the industrial sector but also on its composition. Thus, if workers leaving the agricultural sector are mostly unskilled, agricultural productivity growth can reinforce comparative advantage in non-innovating industries, reducing long run growth.

In this paper we study the effects of the adoption of new agricultural technologies on industrial specialization and growth. For this purpose, we exploit the legalization of genetically engineered (GE) soybean seeds in Brazil as a natural experiment. This new technology requires fewer but relatively high-skilled workers to yield the same output, thus can be characterized as unskilled-labor-saving technical change. In addition, the new technology had a differential impact on yields in areas with different soil and weather characteristics. This regional variation permits to assess the causal effects of agricultural technical change on industrial specialization and growth by comparing the evolution of employment and productivity across micro-regions subject to different rates of exogenous agricultural productivity growth.[2]

As a measure of exogenous technical change we use the difference between the potential yield of soy in each micro-region before and after the legalization of GE soy seeds as in Bustos, Caprettini, and Ponticelli (2016). This measure of technical change in soy production is a function of weather and soil characteristics of different areas, and not of actual yields. In addition, we use 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.

[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.

We start by providing evidence that the adoption of GE soy led to a decrease in the employment of unskilled labor in agriculture and a reallocation of unskilled workers towards the manufacturing sector.[3] Our estimates indicate that micro-regions with a one standard deviation higher increase in soy technical change experienced a 2.4 percentage points larger decrease in the share of unskilled workers employed in agriculture, and a corresponding 2.1 percentage points larger increase in the share of unskilled workers employed in manufacturing. Next, 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 unskilled workers amounts to an increase in the relative supply of unskilled labor. We document that this inflow of unskilled workers was completely absorbed by an expansion of the manufacturing industries in the lowest quartile of skill intensity. In addition, these industries are the least innovative as measured by expenditure in research and development (R&D) as a share of sales.

To interpret our findings, we build a three sector model where final goods are traded across regions but production factors are immobile. The agricultural sector produces an homogeneous good using land, skilled and unskilled labor. The manufacturing sector has two industries, H and L, which also produce homogeneous goods combining skilled and unskilled labor. However, the H industry uses a more complex technology which is more skilled-labor intensive and requires differentiated intermediate inputs. These intermediate inputs are non-traded goods produced by monopolistically competitive firms which use their profits to invest in R&D and invent new input varieties. The introduction of new inputs generates knowledge which diffuses locally. In equilibrium, profits from introducing new varieties are proportional to demand, which is given by the size of the H industry. Thus, the growth rate of knowledge and output in the regional economy are proportional to the size of the H industry.

In this setup, we model the introduction of GE soy seeds as a skilled-labor-augmenting technical change in agriculture. We show that when skilled and unskilled workers are imperfect substitutes and land and labor are strong complements in production, this type of technical change leads to an absolute decrease in the marginal product of unskilled labor in agriculture. As a result, given initial production levels in each sector, there is a reduction in labor demand in agriculture and an excess supply of unskilled workers. In equilibrium, these unskilled workers reallocate towards the manufacturing sector as long as the L manufacturing industry is not much more skill intensive than agriculture.[4] The reallocation of unskilled workers towards the L industry from agriculture reinforces its

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

[4]If agriculture is much more intensive in low-skilled labor than all manufacturing industries, then unskilled workers are absorbed again by the agricultural sector. This is because of Heckshер-Ohlin forces: an increase in the relative supply of a factor generates an expansion of the sector using that factor intensively (Rybczinsky Theorem).

comparative advantage. Thus, the L industry absorbs workers from the H industry, as in the Rybczinsky Theorem. Since the H industry is the market for intermediate inputs, a decrease in the size of this sector reduces the incentive to innovate. As a result, in the long run, the regional economy conducts less R&D, exports more unskilled-labor intensive products in exchange for high-skill intensive, high-R&D goods, and its total output grows slower.

We test the predictions of the model by tracing the effects of agricultural technical change on industrial specialization and productivity. For this purpose, we use yearly data from the Annual Industrial Survey (PIA) which allows us to observe the evolution of employment and productivity growth in the manufacturing sector. We find that micro-regions facing faster agricultural technical change experienced faster employment growth in unskilled-labor intensive manufacturing industries, which is consistent with the findings reported above using population census data. In addition, we find that these regions face a slowdown in manufacturing productivity growth. Our estimates imply that micro-regions with a one standard deviation larger increase in potential soy yields experienced a 9.1 percent larger increase in the relative size of the low-skill intensive industry and a 1.2 percent lower yearly growth rate of manufacturing productivity. This decrease in manufacturing productivity is not simply due to a composition effect. As predicted by the model, it is driven by a reduction in productivity growth within high-skill intensive industries.

Overall, our empirical findings indicate that unskilled labor-saving technical change in agriculture can lead to a reallocation of labor towards unskilled-labor-intensive manufacturing industries. This leads to an expansion of the industrial sectors with lower R&D intensity in the economy, decreasing overall manufacturing productivity in the long run. We interpret this result as a cautionary tale on the effects of structural change on aggregate productivity growth. The adoption of new technologies in agriculture may result in static productivity gains in the agricultural sector but 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 unskilled-labor-saving technical change in agriculture – rather than manufacturing productivity growth – 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 highly mechanised agricultural sectors. Our results suggest that positive agriculture productivity shocks coming from technology adoption may be more effective if coupled with 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 both productivity- and welfare-enhancing.[6] Second, there can be dynamic productivity gains when labor reallocates towards manufacturing if this sector is subject to agglom-

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

[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)).

eration 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 build on the work of Grossman and Helpman (1991a) who study open economy endogenous growth models. In their setup, there are two manufacturing industries with different skill intensities but that use differentiated intermediates with the same intensity. As a result, incentives for inventing new goods depend on the opportunity cost of performing R&D, which in their case is driven by the skill premium, and not on the relative size of the two industries. This implies that in Grossman and Helpman (1991a), an expansion of the supply of unskilled workers does not affect the growth rate. This is so because if both industries are active in the trade equilibrium, there is factor price equalization and, hence, an increase in the supply of unskilled workers leads to an expansion of the output of the low industry which is exported at constant prices and wages. In contrast, our model is an open economy version of Romer (1990). Thus, in our setting, the incentive to do R&D depends on the relative size of the two industries. As a result, an increase in the supply of unskilled labor generates an expansion of the unskilled-labor intensive industry and a reduction in the growth rate.

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.

[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.

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). Thus, the use of GE soybean seeds allows farmers to spray their fields with glyphosate without harming soy plants, reducing labor requirements for weed control.[8] The planting of traditional seeds is usually preceded by soil preparation in the form of tillage, the operation of removing the weeds in the seedbed that would otherwise crowd out the crop or compete with it for water and nutrients. In contrast, the planting GE soy seeds requires no tillage, as the application of herbicide selectively eliminates all unwanted weeds without harming the crop. As activities related to weed control are mostly performed by unskilled workers, the introduction of GE soy seeds should displace unskilled labor relatively more than skilled labor.

The first generation of GE soy seeds (Monsanto's Roundup Ready) was commercially released in the U.S. in 1996 and legalized in Brazil in 2003.[9] The 2006 Brazilian Agricultural Census reports that, only three years after their legalization, 46.4% of Brazilian farmers producing soy were using GE seeds with the "objective of reducing production costs" (IBGE 2006, p.144). According to the Foreign Agricultural Service of the USDA, by the 2011-2012 harvesting season, GE soy seeds covered 85% of the area planted with soy in Brazil (USDA 2012).

Panel (a) of Figure 1 documents that the legalization of GE soy seeds was followed by a fast expansion of the area planted with soy, which increased from 11 to 19 million hectares between 2000 and 2010.[10] Panel (b) of Figure 1 documents that, in the same period, the number of workers employed in the soy sector decreased substantially. This is consistent with the adoption of GE seeds reducing the number of agricultural workers per hectare required to cultivate soy. Bustos et al. (2016) document that labor intensity in soy production fell from 28.6 workers per 1000 hectares in 1996 to 17.1 workers per 1000 hectares in 2006. In addition, the production of soy is less labor-intensive than all other major agricultural activities. According to the Agricultural Census, the average labor intensity of cereals in 2006 was 94.9 workers per 1000 hectares, 129.8 for other seasonal crops, and 126.7 for permanent crops.[11] Thus, whenever soy displaced other agricultural

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

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

[10]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).

[11]According to the 2006 Agricultural Census, even cattle ranching uses more workers per unit of land than soy production (30.6 per 1000 hectares).

activities, labor intensity in agriculture likely decreased.

In panel (c) of Figure 1, we decompose the decrease in employment in the soy sector between skilled workers and unskilled workers, where a worker is considered as skilled if she has completed at least the 8^{th} grade. As shown, the decrease in employment in the soy sector is entirely driven by low-skilled workers, while the skilled ones were retained. This is consistent with GE soy seeds being an unskilled labor saving technology. Notice also that soy production is more skill intensive than most other agricultural activities. As shown in panel (d) of Figure 1, the share of skilled workers (those completed at least the 8^{th} grade) employed in soy is above 20 percent, while in most other agricultural activities this share ranges between 5 and 15 percent. Thus, whenever soy displaced other agricultural activities, skill-intensity of agriculture likely increased.

2.2 Data

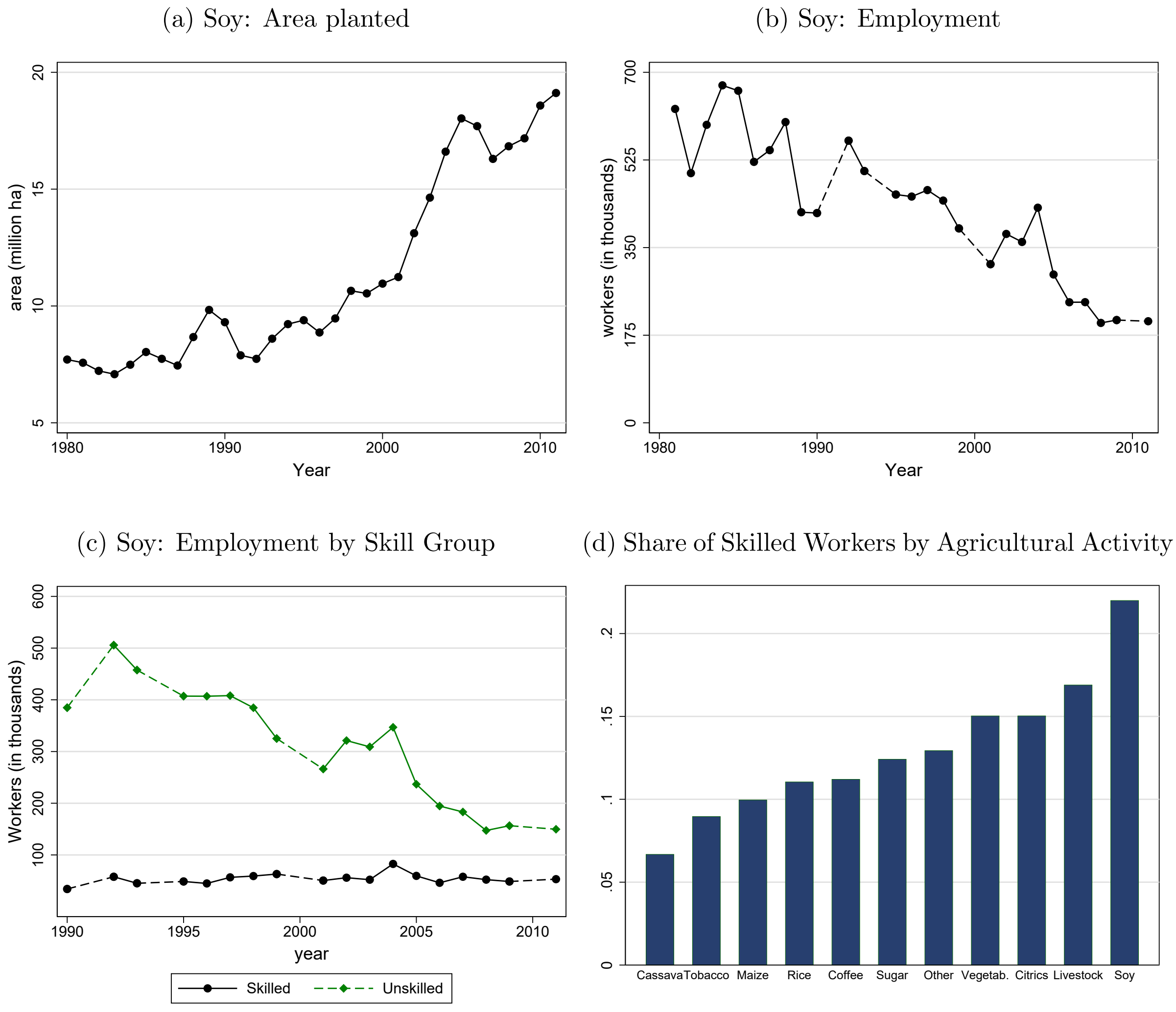
The four main data sources used in this paper are the FAO-GAEZ database, the Brazilian Population Census, the Annual Industrial Survey (*PIA*), and the Industrial Survey of Technological Innovation (*PINTEC*) which we describe in detail in this section. In our analysis, we use microregions as our unit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

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

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

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

Figure 1: Soy Production and Employment

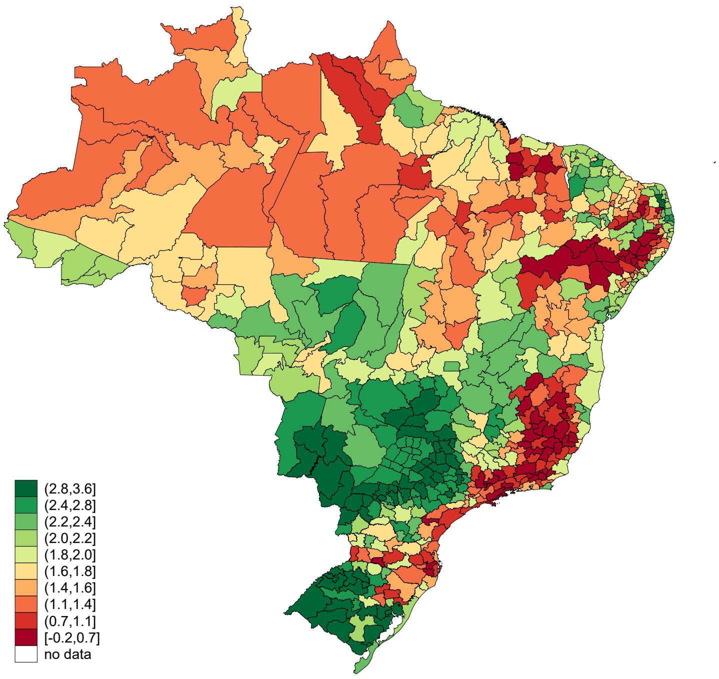


Notes: Figures in Panels (a) and (b) are from Bustos et al. (2016). Data sources are CONAB (Panel A), PNAD (Panel B and C) and 2000 Population Census (Panel D). CONAB is the Companhia Nacional de Abastecimento, an agency within the Brazilian Ministry of Agriculture, which runs surveys of farmers and agronomists to monitor the annual harvests of major crops in Brazil. PNAD is the Brazilian National Household Sample Survey. 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 Panels C and D, an individual is classified as skilled if she has completed at least the 8^{th} grade.

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

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: 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.

We obtain information on employment, wages and other worker characteristics from the Brazilian population census. 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.[13] Moreover, we only consider individuals not enrolled in the education system at the time of the survey. For each individual, we define the sector of occupation as the sector of their main job during the last week. The population census also provides information on the number of hours worked during the last week and the monthly wage.

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

Therefore, we compute hourly wages as the monthly wage divided by 4.33 times the hours worked last week. For each microregion, we compute employment shares as the number of workers in each sector divided by total employment.[14]

We use information on education from the population census to categorize individuals as unskilled or skilled. We define a worker as skilled if they have completed at least the 8^{th} grade, although our results are robust to alternative definitions of this threshold. 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 reports summary statistics of individual level characteristics for workers operating in agriculture, low-skill manufacturing, high-skill manufacturing and services.[15] As shown, there is large heterogeneity in skill intensity of workers across these broad sectors. As much as 93.5% of workers in agriculture had not completed the 8^{th} grade in 2000, 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

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

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

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 source is the Population Census (2000, 2010). Manufacturing industries are classified as low-skill or high-skill intensive depending on whether their skill intensity is below or above the median in 2000 (weighting industries by number of employees so that each group captures around 50 percent of total manufacturing employment). We define skill intensity as the share of skilled workers in a particular industry as per the 2000 Population Census. A worker is classified as skilled if she has completed at least the 8^{th} grade (completed middle school).

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 the microregion level.

Table 2 provides summary statistics for the main variables used in the empirical analysis at the 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.

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 source is the Population Census (2000, 2010). Manufacturing industries are classified as low-skill or high-skill intensive depending on whether their skill intensity is below or above the median in 2000 (weighting industries by number of employees so that each group captures around 50 percent of total manufacturing employment). We define skill intensity as the share of skilled workers in a particular industry as per the 2000 Population Census. A worker is classified as skilled if she has completed at least the 8^{th} grade (completed middle school).

Finally, we use data from the two different manufacturing surveys mentioned above to investigate the dynamic effects of labor reallocation on industrial output. To study the dynamic effect of labor reallocation on employment and value added per worker we use data on number of workers, value added and wage bill from the Annual Industrial Survey (*PIA*).[16] This data comes aggregated at micro-region level and is constructed using

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

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. To construct our measure of R&D intensity 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.

3 Model

3.1 General setting

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

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

The model has three sectors and three factors of production: agriculture, low-skill 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. For simplicity, we assume that land is only used in agriculture. To talk more easily about structural transformation – which we define as the movement of resources away from agriculture – we denote by high- and low-skilled

[17]We simplify Romer (1990) using Chapter 3 of Aghion and Howitt (2008). As explained in the introduction, our model is also related to small open economy models with endogenous growth developed in Grossman and Helpman (1991a).

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

intensive *industries* the two sectors in manufacturing.

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

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

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

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

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

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

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

Where K_t is the total amount of input varieties in the industry at time t. We also refer to K_t as the knowledge in the economy. We interpret knowledge as the necessary local ideas that may be necessary to fully develop complex products or organize production in a given region. We assume that these ideas are developed in the high-skill intensive sector, but that once developed they are common local knowledge. Hence, we assume that knowledge in the economy affects the productivity in agriculture and low-skilled manufacturing. It is worth noting that this assumption on local spillovers guarantees balanced-growth across sectors, but is not essential to our overall argument.[19]

Note that by investing in R&D activities the high-skill intensive industry can expand the set of inputs used in production and hence total production. We assume that each input in the high-skill intensive industry is monopolized by the person who invented it, who decides how much output to produce given the profits. The input for producing the

[19] In the absence of productivity spillovers across sectors the economy would eventually converge to the high-skilled intensive manufacturing industry. If there are shocks that limit the movement of workers to this sector, then the convergence toward it would be slower or slowed down.

intermediates is the final good of the industry.[20] Hence, for each input k we have that profits are given by:

$$\Pi_k = p_k x_k - x_k$$

Intermediate producers take as given the demand for their intermediate given the final good production function and optimally chose how much to produce. This generates some rents that attracts potential inventors of new ideas.[21]

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

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

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

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

3.2 Structural transformation

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

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

Proof. See Appendix B. □

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

[20] This assumption simplifies the algebra. We are inspired by chapter 3 of Aghion and Howitt (2008). This chapter is, in turn, an adaptation of the original Romer (1990). See also Grossman and Helpman (1991b) for a continuous sector version of the endogenous growth 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.

[21] We discuss in more detail all the assumptions of the model in Appendix B.

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

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

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

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

3.3 Industrial specialization and economic growth

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

We start by analyzing how skill-biased factor-augmenting technical change in agriculture affects the return to the three factors in the economy, namely: land, high- and low-skill labor. To do so, we need to analyze the zero profit conditions in each sector of activity. These are given by:

$$p_a = c_a(w_s, w_u, r, A_s, K_t) = c_a(w_s, w_u, r, A_s)/K_t \tag{6}$$

$$1 = c_m^h(w_s, w_u, p, K_t) = (c_m^h(w_s, w_u, 1)^{1-\alpha} p^\alpha)/K_t \propto c_m^h(w_s, w_u, 1)/K_t \tag{7}$$

$$p_m^\ell = c_m^\ell(w_s, w_u, K_t) = c_m^\ell(w_s, w_u)/K_t \tag{8}$$

where $c_a()$, $c_m^h()$, and $c_m^\ell()$ are the unit cost functions in each sector.[22] To obtain these equations we also have used the fact that knowledge enters in a Hicks-neutral way in both agriculture and low-skill manufacturing, and the fact that, given the symmetry and the optimal behavior in the intermediate market, all intermediates are priced at the same level p and produced in the same quantity x, and hence, K_t also enters as a Hick-neutral term in high-skilled manufacturing. Finally, it is also worth mentioning that, given our assumptions, the high-skilled manufacturing sector is also a constant return to scale sector in high- and low-skilled labor once optimal production of intermediates is taken into account.

Lemma 1. *If all three sectors are active, the effect of an increase in skilled-biased-factor-augmenting technology in agriculture (A_s) on wages is mediated by the effect of A_s on local knowledge (K_t). In particular:*

$$\frac{\partial \ln w_s}{\partial A_s} = \frac{\partial \ln w_u}{\partial A_s} = \frac{\partial \ln K_t}{\partial A_s}$$

and the effect of A_s on land prices is given by:

$$\frac{\partial \ln r}{\partial A_s} = \frac{\partial \ln K_t}{\partial A_s} + \frac{\theta_{S_a}}{A_s \theta_{T_a}}$$

where θ_{S_a} is the cost share of high-skilled workers and θ_{T_a} is the cost share of land in agriculture.

Proof. See Appendix B. □

Lemma 1 says that when all sectors of activity are active the economy is in an "efficiency corrected" (labor) price equalization set. This is so, because the price of high- and low-skilled labor is determined exclusively by manufacturing industries and international

[22] We provide the exact definitions of the unit cost functions in Appendix B.

markets. Land prices are, instead, determined by what happens in the agricultural sector given the prevailing prices of labor.

As a result of this setting, it is crucial to understand how an increase in skilled-biased-factor-augmenting technolgy in agriculture leads to particular patterns of industrial specialization. We summarize our results with the following theorem.

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

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

Proof. In Appendix B we provide a proof of this theorem assuming that all sectors are active. □

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

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

Theorem 4. *When the following conditions hold:*

1. *High- and low-skilled workers are imperfect substitutes (i.e. when $\varepsilon > 1$)*

2. *Land and labor are strong complements (i.e. when $\sigma < \varepsilon\Gamma$)*

3. *Agriculture is not much more intensive in low-skilled labor than the low-skill intensive industry.*

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

1. *Static gains from increased productivity in the agricultural sector.*

2. *Dynamic losses shaped by the decrease in the size of the R&D, high-skilled intensive manufacturing industry.*

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

$$g_C = \frac{\chi A_m^h F_m^h(U_m^h, S_m^h) - \rho}{\eta} \tag{9}$$

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

$$\frac{\partial \ln GDP_t}{\partial A_s} = \underbrace{\omega_a \frac{\partial \ln p_a A_a F_a}{\partial A_s} + \omega_m^\ell \frac{\partial \ln p_m^\ell A_m^\ell F_m^\ell}{\partial A_s} + \omega_m^h \frac{\partial \ln A_m^h F_m^h}{\partial A_s}}_{\textit{Static gains/losses}} + \underbrace{\frac{\chi}{\eta} \frac{\partial A_m^h F_m^h}{\partial A_s} t}_{\textit{Dynamic gains/losses}} \tag{10}$$

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

Proof. See Appendix B. □

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

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

In steady state, total output depends on the sectoral composition and the economy grows based on the size of the high-skilled intensive sector. We can then apply theorems 1 to 3 to obtain the result that skill-biased-factor-augment technological change in agriculture leads, under the three conditions stated in theorem 4, to the expansion of the low-skilled intensive industry and a contraction of the high-skill intensive one. This movement of resources into the "wrong" industries lowers the long-run growth rate, something that we labeled as *dynamic loses*. On impact, however, total output increases since there are productivity gains in agriculture and employment gains in low-skill intensive manufacturing. This is what we labeled as *static gains*, which is different from the static gains emphasized in prior literature and that we abstract from in the model.[23]

We provide a qualitative illustration of theorem 4 in Figure 3, where we abstract from transition dynamics. The left-graph of the figure shows the evolution of total output in the economy under two scenarios. Shown in a solid line, total output keeps increasing over time (log) linearly at the steady state growth rate. If A_s increases (permanently) at a point in time (denoted by $t = 0$ in the graph), then total output increases instantaneously, as shown by the dashed line. This instantaneous increase is the result of the higher productivity in agriculture and the increased output in manufacturing due to the entry of low-skilled workers into the sector. However, because the sector that absorbs labor is the low-skilled intensive manufacturing industry and some high-skilled workers leave the high-skilled intensive industry, the new equilibrium growth rate decreases, shown in the graph as a lower trend in the dashed line.[24] The increase in total output in manufacturing is lower than the increase in total output, as shown in the right-graph of Figure 3, because total output in manufacturing only increases on impact because of the reallocation of workers away from agriculture and not because of technological progress. After the initial increase in manufacturing output, industrial specialization lowers the trend in manufacturing output in exactly the same way as it lowers the trend in overall output. In what follows, we explore how these theoretical insights can help us understand the patterns in the data.

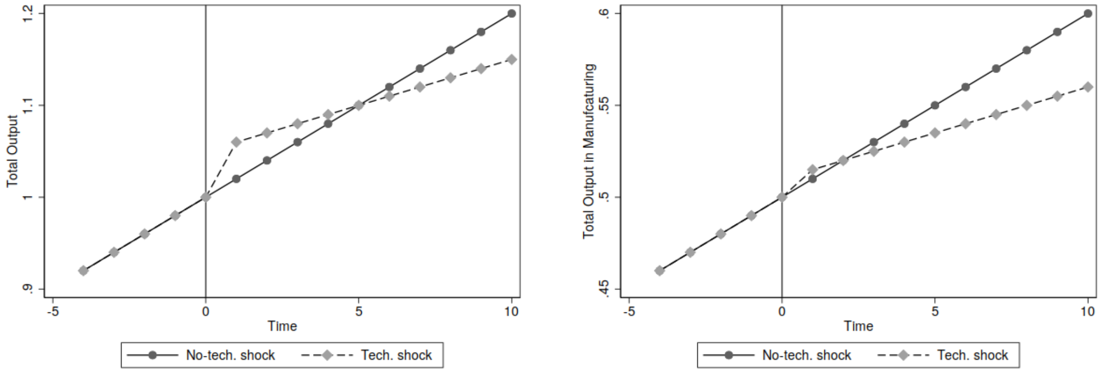
4 Empirics

This section describes our identification strategy and reports the main empirical results of the paper. We start by discussing our identification strategy in section 4.1. In section 4.2 we study the effect of soy technical change on the reallocation of low-skilled and high-skilled workers across sectors, as well as its effect on the wages of these two types of workers. In section 4.3 we study industrial specialization, i.e. we document the effect

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

[24]In Appendix C we provide a variant of the model where an increase in low-skilled labor in the low-skill intensive sector alone generates a slow-down in manufacturing productivity.

Figure 3: Evolution of output given an increase in A_s



Total Output **Total Output in Manufacturing**

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

of soy technical change on labor allocation across industries within the manufacturing sector. Finally, in section 4.4, we focus on the impact of industrial specialization driven by soy technical change on manufacturing productivity in the long-run.

4.1 Identification Strategy

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

$$\Delta Y_k = \alpha + \beta \Delta A_k^{soy} + \varphi X_k + \varepsilon_k \tag{11}$$

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

In our baseline specification, we include as controls the share of rural population in 1991 and a measure of technical change in maize. The lagged share of rural population captures differential trends in the outcome variable between urban and rural microregions, whereas the technical change in maize captures the differential impact across microregions of new maize production methods that were introduced in this period.[25] In our extended

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

specification, we also control for the initial level of income per capita, alphabetization rate, and population density, all observed in 1991 and sourced from the Population Census. These controls are meant to capture differential trends across microregions with different initial levels of income and human capital.

4.2 Effect of Technical Change on Labor Reallocation and Wages

In this section we start by documenting that soy technical change introduced by GE seeds was labor-saving. Microregions that could benefit more from the new technology experienced a reallocation of workers from the agricultural sector to the manufacturing and services sectors. Next, we document that soy technical change was also skill-biased. In particular, with the introduction of this new technology, high-skilled workers had relatively more opportunities in the agricultural sector than low-skilled workers. This led low-skilled workers to leave agriculture. Finally, we document the effect of this increase in low-skill labor supply on local wages.

We start in Table 3 by documenting that soy technical change generated a reallocation of labor from agriculture into manufacturing, i.e. it led to structural transformation. We find that microregions with higher exposure to soy technical change experienced a decrease in the share of workers employed in agriculture and an increase in the share of workers employed in manufacturing and services. Notice that – as shown in column (2) – soy technical change had only small and not significant effects on total employment. Thus, the employment changes that we document in what follows are not driven by migration between microregions or by changes in the total number of workers employed, but by movement of workers across sectors within microregions.[26] The estimate presented in column (4) indicates that microregions with a one standard deviation larger increase in soy technical change experienced a 2.4 percentage points lower change in agricultural employment share. This estimate is stable to the inclusion of controls. These agricultural workers displaced by the new soy technology relocated into manufacturing and services. Manufacturing employment shares increased by 1.7 percentage points – and services employment share by 0.7 percentage points for a standard deviation difference in soy technical change –, hence absorbing the bulk of workers released from agriculture. In sum, the results presented in Table 3 indicate that soy technical change was labor-saving and led to structural transformation, which are the main findings documented in Bustos et al. (2016).[27]

[26] In Table A2 in the Appendix we provide direct evidence on the lack of internal migration responses.

[27] Bustos et al. (2016) find that soy technical change had a positive and significant effect on the employment share in manufacturing but no significant effect on the employment share in the services sector. Table 3 in this paper documents that microregions more exposed to soy technical change experienced an increase in employment share in both manufacturing and services. There are two reasons behind this difference in results when the outcome is the employment share in the services sector. The first is that, in this paper, we focus on remunerated labor – i.e. workers receiving a wage – whereas Bustos et al.

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

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

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

Next, in Table 4, we study the effect of soy technical change on the reallocation across sectors of workers with different skills. More specifically, we characterize whether the reallocation of workers from agriculture to manufacturing documented in Table 3 is mostly driven by unskilled or skilled workers.

In Panel A of Table 4 we focus on unskilled workers. Columns (1) and (2) show that soy technical change had a negative – although not precisely estimated – effect on the total number of low-skilled workers. Then, in columns (3) to (8), we study the effect of soy technical change on the share of low-skilled workers employed in each sector. We find that microregions more exposed to soy technical change experienced a reallocation of unskilled workers from agriculture to manufacturing. The magnitude of the estimated coefficients indicate that microregions with a standard deviation higher increase in soy technical change experienced a 2.4 percentage points larger decrease in the share of low-skilled workers employed in agriculture, and a corresponding 2.1 percentage points larger increase in the share of low-skilled workers employed in manufacturing. These magnitudes correspond to a 7.2 percent decrease in the initial share of low-skilled workers employed in agriculture, and a 15 percent increase of the share of those employed in manufacturing. Combined with the coefficient presented in column (2), these results are consistent with a decline in the absolute demand for low-skilled labor in agriculture in response to skilled labor-augmenting technical change, as predicted by the model. The low-skilled employees released from agriculture moved primarily into manufacturing.

In Panel B we focus instead on skilled workers. We find that microregions more exposed to soy technical change experienced a higher increase in the total number of high-skill workers, as shown in Columns (1) and (2).[28] Columns (3) to (8) report the effect of

(2016) also included workers who helped household members without receiving a payment or worked in subsistence agriculture. The second is the unit of observation, which is a microregion in Table 3, a municipality in Bustos et al. (2016).

[28]As we document in Table A2 in the Appendix, this differential increase in high-skill workers is not

soy technical change on the share of high-skilled workers by sector of employment. We find that microregions more exposed to soy technical change experienced a larger decrease in the share of high-skill workers in agriculture.[29] We also find that microregions more exposed to soy technical change experienced a larger increase in the share of high-skill workers employed in manufacturing, consistently with some complementarity in the use of both types of workers. The magnitude of the estimated coefficients indicate that microregions with one standard deviation higher increase in soy technical change experienced a 1.2 percentage points larger decrease in the share of high-skilled workers employed in agriculture (10 percent of their initial share), and a corresponding 1 percentage points increase in the share of high-skilled workers employed in manufacturing (5.8 percent of their initial share).

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

Panel A: Reallocation of Unskilled Labor

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

Panel B: Reallocation of Skilled Labor

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

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: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Taken together, our estimates show that the agricultural sector experienced a decrease in its employment share of both low-skill and high-skill labor, while the manufacturing

driven by internal migration but rather by an increase in local employment.

[29]Notice that this negative coefficient does not indicate a larger decrease in the total number of high-skilled workers employed in agriculture. This is because microregions more exposed to soy technical change experienced a larger increase in total high-skill employment, as shown in column (2).

sector experienced an increase in its employment share of both low-skill and high-skill labor. The loss in the employment share of agriculture and the increase in the employment share of manufacturing were stronger for low-skilled workers than for high-skilled workers.

If labor supply across sectors or microregions is imperfectly elastic, the documented effects on employment should also be observable in wage changes. Instead, if workers mobility across sectors over the decade is high, we should not observe substantial differences in wage changes across sectors. This is what we investigate in what follows.

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

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

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

Notes: Changes in wages are calculated over the years 2000 to 2010. 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 of hourly wage on microregion fixed effects, and a vector of individual characteristics that includes dummies for sector, skill group, age group, race, and all the interactions between these variables. Robust standard errors reported in brackets. Significance levels: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Given the evidence presented in Table 4 we also study differences in wage response across low-skill and high-skill workers. We investigate this in Table 6. Columns (1) and (2) of Panel A show no significant effects of soy technical change on average wages of low-skilled workers.[30] When splitting workers by sector, we find that low-skilled agricultural workers experienced higher wage growth in microregions more exposed to the soy shock. We interpret this result as evidence that only the "best" low-skilled workers – in

[30]In part it may be that wages did not decline because of the large increase in minimum wages during that period, see for instance Engbom and Moser (2018). To explore whether low-skilled workers in manufacturing were disproportionately pushed into minimum wage levels in soy affected regions we show in Table A4 in the Appendix regressions where the dependent variable is the number of workers in manufacturing at the minimum wage. The evidence shows that the number of workers at the minimum wage level increased more in high relative to low soy shocked microregions.

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

Panel A: Wages of Unskilled Labor

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

Panel B: Wages of Skilled Labor

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

Panel C: Skill Premia

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

Notes: Changes in wages and skill premia are calculated over the years 2000 to 2010. All 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 A we lose one observation because there are no unskilled manufacturing workers in our sample in the microregion Amapá (IBGE ID 16002) in 2010. In columns (5) and (6) of Panel B we lose two observations 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 (5) and (6) of Panel C follow from the above explanation. We recover the estimates of the dependent variable from a first stage Mincerian regression in which we estimate a regression of the log of hourly wage on microregion fixed effects, and a vector of individual characteristics that includes dummies for sector, skill group, age group, race, and all the interactions between these variables. Robust standard errors reported in brackets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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.[31]

In Panel B of Table 6, we focus on wages of high-skilled workers as an outcome. Consistent with the increase in employment of high-skill workers, wages of high-skilled workers increased faster in microregions more exposed to soy technical change. Although

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

this result holds across sectors, the effect is larger in agriculture. This is in line with the idea that agriculture experienced a relative increase in the demand for high-skilled workers, which is partly observable in employment and partly in wages.

Finally, in Panel C, we investigate whether the increase in the relative demand for high-skilled workers in agriculture led to systematic differences in the relative wages across types of workers in the different sectors of the economy. As can be seen in this panel, the estimates in each sector are similar in magnitude, which is consistent with the idea that labor reallocation across sectors is relatively elastic.

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

4.3 Industrial Specialization

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

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

Table 7 reports the main results of this section. We start in panel A by estimating equation (11) when the outcome variable is the share of unskilled labor employed in manufacturing over total unskilled labor in a given microregion. Column (1) shows that microregions more exposed to soy technical change experienced a larger increase in the share of low-skilled workers employed in manufacturing. In columns (2) and (3) we split the manufacturing sector into low-skill-intensive and high-skill-intensive industries. The estimated coefficients indicate that the increase in low-skilled manufacturing employment driven by soy technical change is concentrated exclusively in low-skill-intensive manufacturing industries. In columns (4) and (5) we replicate the same exercise splitting the manufacturing sector into low versus high R&D intensive industries. We find results consistent with low skilled workers released from agriculture being absorbed mostly by low R&D intensive manufacturing industries. In terms of magnitudes, the estimated coefficients in columns (2) and (4) indicate that microregions with a one standard deviation larger increase in soy technical change experienced a 2 percent higher change in low-skilled manufacturing employment share in low-skilled-intensive or low R&D industries.

Table 7: 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

Notes: Changes in dependent variables are calculated over the years 2000 and 2010 (source: Population Censuses). The unit of observation is the microregion. 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 split manufacturing industries at the median of their level of skill intensity and R&D activity in such a way that roughly 50% of the Brazilian manufacturing employment is in each group. We define skill intensity as the share of skilled workers in a particular industry according to 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: $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

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

So far, we have split manufacturing into two industries making sure that half of total manufacturing employment is assigned to each industry. This is, however, an arbitrary split of the manufacturing sector. In fact, the model suggests that low-skill intensive manufacturing expands only if the unskill-intensity of the sector is sufficiently close to that of agriculture. To investigate this further, we split manufacturing into four industries, ranked by their skill intensity, and each employing one fourth of total manufacturing workers. Then, we estimate which of the four groups absorbed low-skilled labor using the following equation:

$$\Delta \frac{L_{m,ik}}{L_k} = \alpha + \beta_i \Delta A_k^{soy} \times \gamma_i + \gamma_i + \varepsilon_{ik} \tag{12}$$

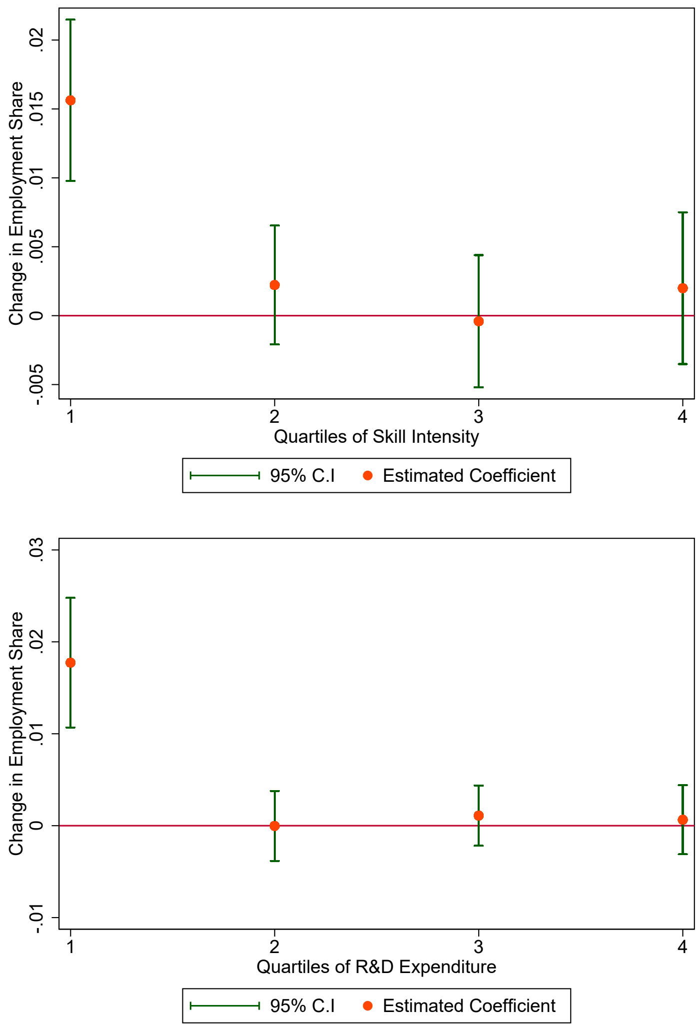
where i indexes quartiles of skill intensity at industry level and k indexes microregions. The outcome variable in this regression is the change in manufacturing employment in each quartile of industry skill-intensity as a share of total employment in a given microregion. For example, $\Delta \frac{L_{m,1k}}{L_k}$ is the change in manufacturing workers employed in industries belonging to the lowest quartile of initial skill-intensity divided by total workers in a given microregion. When estimating equation (12) we include the standard set of controls at microregion level interacted with quartiles of skill intensity at the industry level (γ_i).

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

Overall, the results presented in Figure 4 show that soy-driven increases in manufacturing employment are concentrated in the lowest skill-intensive and R&D intensive industries. This result is consistent with the model introduced in Section 3 when skill intensity in manufacturing is not too far from that of agriculture, and it is in line with the logic of the classical Heckscher-Ohlin theory of international trade.

As argued in Section 3, we view these findings on industrial specialization as a cautionary note on the potential benefits of structural change. When structural change is driven by skill-biased technical change in agriculture, the workers leaving agriculture may be negatively selected, and may, thus, favor the expansion of sectors in manufacturing with lower innovation-intensity. The fact that these effects are concentrated in low R&D manufacturing industries, thus, has implications for manufacturing productivity and long-run growth. We test empirically these implications in what follows.

Figure 4: Employment Share Growth by Quartile of Skill Intensity



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

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

for $i = 1, 2, 3, 4$ where γ_i is a dummy for the different quartiles of skill intensity (upper graph) and R&D intensity (lower graph). We split manufacturing industries in quartiles according to their level of skill and R&D intensity so 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. We define R&D intensity as R&D expenditure as a share of total sales at baseline and we source it from from the 2000 *Pesquisa de Inovação Tecnológica* (PINTEC)

4.4 Dynamic Effects on Manufacturing Productivity

In section 4.3 we showed that technical change in soy production led to a reallocation of low-skilled workers into low-skill intensive and low-R&D intensive manufacturing industries. A key implication of the theoretical framework presented in section 3 is that this type of industrial specialization may push the economy towards a lower GDP growth path in the long run. In this section we provide empirical evidence consistent with this argument.

The empirical analysis presented in this section relies on data from the Annual Industrial Survey (PIA), described in detail in Section 2.2. There are two main advantages of the PIA data relative to the Census data. First, it provides detailed information on both labor and value added for the universe of manufacturing firms above a certain employment threshold operating across Brazilian microregions. Second, because the data is reported annually, it allows us to study the effect of soy technical change on manufacturing employment and productivity at a yearly frequency. The main draw-back of these data is that we cannot distinguish between high- and low-skilled workers as we did with Census data.

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

$$\ln y_{k,t} = \delta_t + \delta_k + \sum_{j=2001}^{j=2009} \beta_j \Delta A_k^{soy} + \gamma X_{k,t} + t \times X'_{k,1991}\omega + \varepsilon_{k,t} \tag{13}$$

where ΔA_k^{soy} is the change in our exogenous measure of technical change in soy in microregion k, and $\ln y_{k,t}$ is an outcome of interest in microregion k at time t. δ_k and δ_t are microregion and year fixed effects, respectively, $X_{k,t}$ are time-varying controls and $X_{k,1991}$ are baseline controls interacted with a time trend.[32] β_j estimates the effect of the change in the productivity of soy in each year between 2000 and 2009, using 2000 as the omitted category.[33] Thus, we flexibly allow β_j to capture the effect of soy ten year technical change on the outcomes of interest in each year. Given that genetically modified soy was introduced in 2003, we expect significant effects of our exogenous measure of technical change on the outcomes of interest starting around 2003. This type of specification is also informative on the persistence of these effects.

We use equation (13) to study the effect of soy technical change on two main outcomes: manufacturing employment and manufacturing productivity. For each of these outcomes we separately study the effects in low-skill intensive industries and high-skill intensive industries. For each outcome we plot the estimated β_j in equation (13) for each year between 2000 and 2009, along with the 95 percent confidence interval around the point estimates.

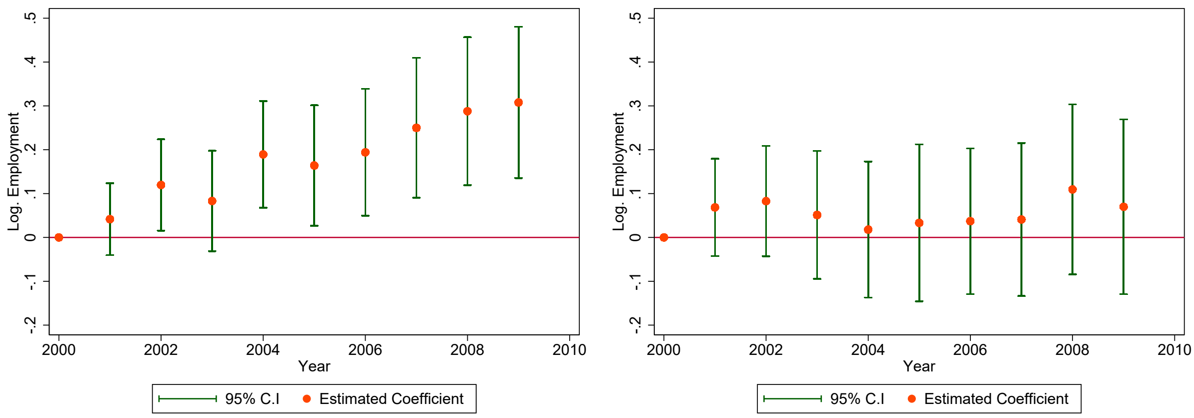
We start by studying the yearly effect of soy technical change on manufacturing employment. Figure 5 reports the results when the outcome variables are log employment in low-skill intensive manufacturing industries (Figure 5a) and log employment in high-skill

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

[33] When estimating equation 13 in the data we additionally control for the change in maize technical change interacted with year fixed effects as well as for the standard set of microregion level controls used in previous tables, interacted with time fixed effects.

Figure 5: Effect of the Soy Shock on Manufacturing Employment by Type of Industry

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



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

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

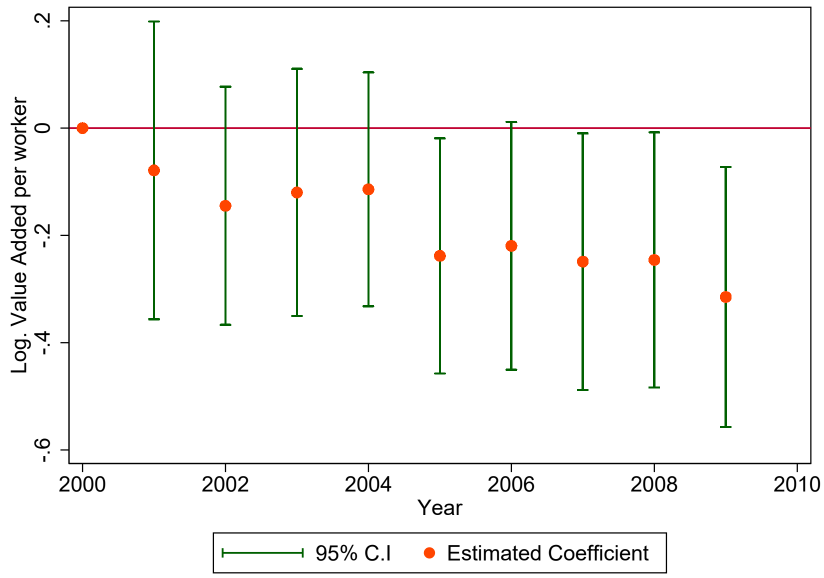
Standard errors are clustered at the microregion level. $\ln y_{k,t}$ corresponds to aggregate log. employment in microregion k at the end of year t for each group of industries (Source: PIA). We split manufacturing industries at the median of their initial level of skill intensity in such a way that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

intensity manufacturing industries (Figure 5b). We find that in regions more affected by soy productivity increases, more labor enters low-skilled manufacturing industries, while there are no differential effects of soy technical change on employment in high-skill intensive industries.[34] In addition, the amount of labor entering low-skill intensive industries starts to increase substantially after 2003, consistent with the timing of introduction of GE soybean seeds. These results are also consistent with those presented in sections 4.2 and 4.3 using Census data, which showed that the workers entering manufacturing following the soy shock were mainly low-skilled, and that they tended to be absorbed by low-skill intensive industries.

Next, we investigate the effect of soy technical change on manufacturing productivity. Ideally, we would like to use total factor productivity in manufacturing as an outcome. However, due to data limitations in the reporting of book value of physical capital in the Annual Industrial Survey, we use value added per worker and relative to total wage bill in a given micro-region as proxies for manufacturing productivity. Figure 6 shows the differential dynamics in labor productivity as a function of the change in soy technical

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

Figure 6: 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:

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

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

change. The graph shows that micro-regions more exposed to the soy shock experienced a relative decline in labor productivity. The effect becomes statistically significant in 2005, two years after the legalization of GE soybean seeds, and increases in magnitude over the decade.

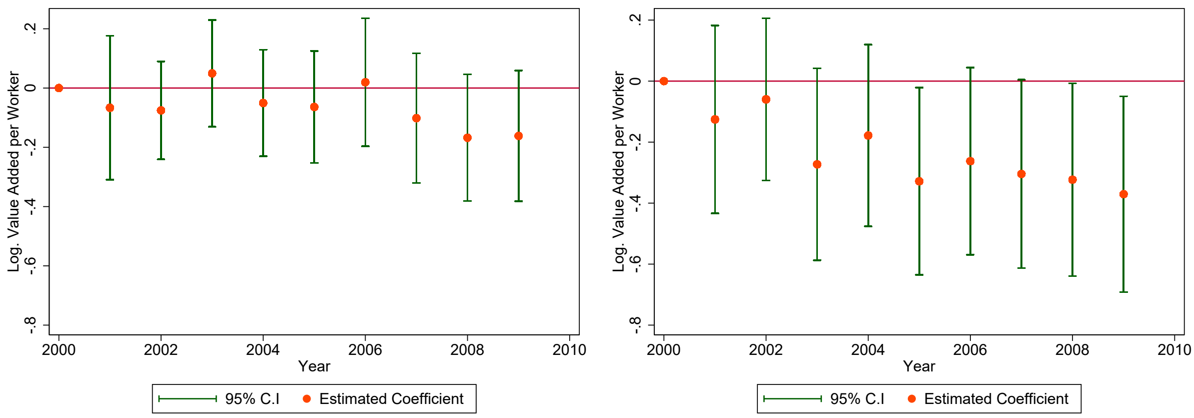
While Figure 6 seems to confirm the predictions of the model, it could also be explained by labor productivity decreasing in manufacturing purely as a result of a composition effect. If labor productivity is lower in low-skill intensive industries, then the movement of workers towards these industries necessarily results in lower aggregate labor productivity in manufacturing. Our model highlights instead that manufacturing productivity decreases because the incentives to innovate in high-skill-intensive sectors decrease. To investigate this, we split manufacturing between high- and low-skill-intensive industries, as we did in Figure 5. The results are reported in Figure 7. As highlighted in our model, the decrease in manufacturing productivity originates in high-skill-intensive industries.

We quantify the estimates shown in Figures 6 and 7 in Table 8. To this end we use the following regression:

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

Figure 7: Effect of the Soy Shock on Manufacturing Productivity by Type of Industry

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



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

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

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

where $A_{k,t}^{soy}$ is defined as potential soy yield under high inputs for the years between 2003 and 2009, and the potential soy yield under low inputs for the years between 2000 and 2002 in microregion k. δ_k and δ_t are microregion and year fixed effects, respectively, and $X_{k,t}$ are time-varying controls and $X_{k,1991}$ are baseline controls interacted with a time trend.[35] Hence, β is the (continuous) difference-in-difference estimate obtained from comparing microregions before and after 2003.[36]

Column (1) of Panel A shows that microregions more exposed to soy technical change experienced a larger increase in aggregate manufacturing employment. In this analysis we use data from the manufacturing survey PIA, which does not allow us to distinguish between low- and high-skilled workers. However, the data allows us to split workers between those employed in low-skill vs high-skill intensive industries. We do that in Panels B and C of Table 8. The results are consistent with those obtained with the Population Census data: the increase in manufacturing employment driven by soy technical change was concentrated in low-skilled intensive industries. Next, we study the effect of soy technical change on manufacturing value added. We find no significant effect on aggregate

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

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

value added. However, microregions more exposed to soy technical change experienced an expansion of value added of low-skill intensive industries and a contraction of value added of high-skill intensive industries. Finally, we study the effect of soy technical change on labor productivity as measured by value added divided by number of workers.[37] We find that microregions more exposed to soy technical change experienced a decline in overall labor productivity. Taken together, the estimates presented in Table 8 imply that microregions with a one standard deviation larger increase in potential soy yields experienced a 9.1 percent larger increase in the relative size of the low-skill intensive industry and a 1.2 percent lower yearly growth rate of manufacturing productivity.[38]

In the model, manufacturing productivity declines because the inflow of low-skilled workers into manufacturing reinforces the comparative advantage in low-skill intensive industry and reduces the size of the high-skill intensive one. Since the high-skill intensive industry is the only user of intermediate inputs, when this industry shrinks, investing in developing new intermediate inputs becomes less profitable. Hence, innovation decreases, and so does overall manufacturing productivity. Moreover, if there is some delay in the knowledge spillover across sectors, the decrease in productivity should be initially driven by the high-skilled intensive industries, which is what we observe in the data.

Notice that, in our model, what drives the decrease in size of the high-skill intensive industry is that labor relocates away from it. In the data, we find a non significant effect of soy technical change on employment in high-skill intensive industries. In an extension of our baseline model explained in detail in Appendix C we show that a small deviation from the assumptions made, based on the work by Jones (1995), is sufficient to generate a slowdown in manufacturing productivity growth even if labor does not leave the high-skill intensive industry but the low-skill intensive industry increases in size relative to the high-skill intensive one.[39]

In sum, Figures 6 and 7, along with Table 8 provide empirical evidence consistent with one of the key implications of the model discussed in Section 3. An increase in agricultural productivity due to the introduction of new technologies can benefit the

[37]Table A1 in the Appendix shows that we obtain similar results by using value added divided by total wage bill as an alternative measure of labor productivity.

[38]We quantify the effect of soy technical change on the relative size of the low-skill intensive manufacturing industry by subtracting the coefficient reported in column (1) of Panel C from the coefficient reported in column (1) of Panel B, and multiplying the difference by a standard deviation in soy technical change. The effect on the yearly growth rate of manufacturing productivity is computed by multiplying the coefficient in column (3) of Panel A by a standard deviation in soy technical change and computing the annualized effect on labor productivity for the post GE soy legalization years.

[39]In Appendix C we show that if the low-skilled intensive sector uses congestionable intermediate input varieties – i.e. what matters in production is the number workers per input variety –, then an expansion of the L-industry drives innovative activities towards this industry, at least for some time. The L-sector, however, does not have endogenous growth type forces – because of the congestionable intermediate input varieties – and hence when resources are diverted to it, overall manufacturing growth slows down. Appendix C follows the discussion in (Aghion and Howitt, 2008, p. 97), adapted to our context. See also Romer (1990) and Jones (1995).

Table 8: Effect of soy technical change on manufacturing employment, value added, and productivity

Panel A: Aggregate

VARIABLES	(1) Log Labor	(2) Log Value Added	(3) L-productivity
A^{soy}	0.118***	0.013	-0.105**
	[0.034]	[0.051]	[0.047]
Observations	3,350	3,350	3,350
R-squared	0.976	0.965	0.864
Baseline Controls	Yes	Yes	Yes
All Controls	Yes	Yes	Yes

Panel B: Low Skill-Intensive

VARIABLES	(1) Log Labor	(2) Log Value Added	(3) L-productivity
A^{soy}	0.156***	0.129**	-0.025
	[0.047]	[0.064]	[0.054]
Observations	3,350	3,350	3,350
R-squared	0.955	0.930	0.777
Baseline Controls	Yes	Yes	Yes
All Controls	Yes	Yes	Yes

Panel C: High Skill-Intensive

VARIABLES	(1) Log Labor	(2) Log Value Added	(3) L-productivity
A^{soy}	0.033	-0.137*	-0.163***
	[0.053]	[0.081]	[0.059]
Observations	3,350	3,350	3,350
R-squared	0.962	0.951	0.841
Baseline Controls	Yes	Yes	Yes
All Controls	Yes	Yes	Yes

Notes: The dependent variables correspond to aggregate log. employment in each microregion at the end of each year, aggregate log. value added, and log. value added per worker. We use aggregate information from PIA at the microregion level for the time period 2000-2009. We include only those microregions that have positive employment in both low-skill intensive and high-skill intensive industries for all the years in the sample. A^{soy} is defined as potential soy yield under high inputs for the years between 2003 and 2009, and the potential soy yield under low inputs for the years between 2000 and 2002. Baseline controls include 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 1991, all interacted with a linear trend. The unit of observation is a microregion. Standard errors clustered at the microregion level reported in parentheses. Significance levels: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

local economy in the short-run. However, when these technologies are skilled biased they tend to displace low-skilled workers into manufacturing, expanding the least productive manufacturing industries. Thus, compared to a counterfactual where workers leaving agriculture enter the most vibrant and R&D intensive sectors, our evidence suggests that structural transformation may not lead the economy from a "subsistence" sector with negligible productivity to a capitalist and high growth potential sector, as argued by Lewis (1954) and Kuznets (1973). Depending on the circumstances, the workers leaving agriculture may expand the "wrong" industries, leading to lower productivity growth in the long-run than what was believed in the previous literature.

5 Conclusions

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

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

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

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

References

Acemoglu, D. (2002, October). Directed Technical Change. *The Review of Economic Studies 69*(4), 781–809.

Acemoglu, D. and V. Guerrieri (2008, June). Capital Deepening and Nonbalanced Economic Growth. *Journal of Political Economy 116*(3), 467–498.

Aghion, P. and P. Howitt (1992). "A Model of Growth through Creative Destruction". *Econometrica 60*(2), 323–351.

Aghion, P. and P. Howitt (2008). *The Economics of Growth*. The MIT Press.

Autor, D., D. Dorn, and D. Hanson (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review 103(6)*, 2121–2168.

Baumol, W. (1967). Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis. *American Economic Review 57(3)*, 415–26.

Bayoumi, T., D. Coe, and E. Helpman (1999). R & D Spillovers and Global Growth. *Journal of International Economics 47*(2), 399–428.

Bragança, A. (2014). *Three Essays on Rural Development in Brazil*. Ph. D. thesis, PUC-Rio.

Buera, F., J. Kaboski, and R. Rogerson (2015). Skill-Biased Structural Change. *Mimeo*.

Bustos, P., B. Caprettini, and J. Ponticelli (2016). Agricultural Productivity and Structural Transformation: Evidence from Brazil. *American Economic Review*.

Caselli, F. (2005). Chapter 9 Accounting for Cross-Country Income Differences. Volume 1, Part A of *Handbook of Economic Growth*, pp. 679 – 741. Elsevier.

Caselli, F. and W. J. Coleman (2001, June). The U.S. Structural Transformation and Regional Convergence: A Reinterpretation. *Journal of Political Economy 109*(3), 584–616.

Costa, F., J. Garred, and J. P. Pessoa (2016, September). Winners and losers from a commodities-for-manufactures trade boom. *Journal of International Economics 102*, 50–69.

Dix-Carneiro, R. and B. K. Kovak (2019, March). Margins of labor market adjustment to trade. *Journal of International Economics 117*, 125–142.

Duffy, M. and D. Smith (2001). "Estimated Costs of Crop Production in Iowa". *Iowa State University Extension Service FM1712*.

Engbom, N. and C. Moser (2018). "Earnings Inequality and the Minimum Wage: Evidence from Brazil". *Federal Reserve Bank of Minneapolis OIGI Working Paper 7*.

Fernandez-Cornejo, J., C. Klotz-Ingram, and S. Jans (2002). "Estimating Farm-Level Effects of Adopting Herbicide-Tolerant Soybeans in the USA". *Journal of Agricultural and Applied Economics 34*, 149–163.

Ferreira, F., S. Firpo, and J. Messina (2017). Ageing Poorly? Accounting for the Decline in Earnings Inequality in Brazil, 1995-2012. *IDB Working Paper Series*.

Foster, A. D. and M. R. Rosenzweig (1996). Technical Change and Human-Capital Returns and Investments: Evidence from the Green Revolution. *The American Economic Review 86*(4), 931–953.

Gollin, D., D. Lagakos, and M. E. Waugh (2014). The Agricultural Productivity Gap. *Quarterly Journal of Economics*.

Gollin, D., S. Parente, and R. Rogerson (2002). The Role of Agriculture in Development. *American Economic Review*, 160–64.

Grossman, G. and E. Helpman (1991a). *Innovation and Growth in the Global Economy.* The MIT Press.

Grossman, G. and E. Helpman (1991b). Quality Ladders in the Theory of Growth. *Review of Economic Studies 58*, 43–61.

Grossman, G. and E. Helpman (1994). Endogenous Innovation in the Theory of Growth. *Journal of Economic Perspectives 8*(1), 23–44.

Helpman, E. (1993). Innovation, Imitation, and Intellectual Property Rights. *Econometrica 61*(6), 1247–1280.

Herrendorf, B. and T. Schoellman (2018). Wages, Human Capital and Structural Transformation. *American Economic Journal: Macroeconomics*.

Huggins, D. R. and J. P. Reganold (2008). "No-Till: the Quiet Revolution". *Scientific American 299*, 70–77.

IBGE (2006). *"Censo Agropecuário 2006"*. Rio de Janeiro, Brazil: Instituto Brasileiro de Geografia e Estatística (IBGE).

Jones, C. I. (1995). R&d-based models of economic growth. *Journal of Political Economy 103*, 759–784.

Kongsamut, P., S. Rebelo, and D. Xie (2001). Beyond Balanced Growth. *The Review of Economic Studies 68*(4), 869–882.

Krugman, P. (1987). The Narrow Moving Band, the Dutch Disease, and the Competitive Consequences of Mrs. Thatcher: Notes on Trade in the Presence of Dynamic Scale Economies. *Journal of Development Economics 27*(1-2), 41–55.

Kuznets, S. (1973). Modern Economic Growth: Findings and Reflections. *American Economic Review*.

Lagakos, D. and M. E. Waugh (2013). Selection, Agriculture, and Cross-Country Productivity Differences. *American Economic Review 103*(2), 948–80.

Lewis, A. W. (1954). Economic Development with Unlimited Supplies of Labor. *The Manchester School*.

Lucas, R. (1988). On the mechanics of economic development. *Journal of Monetary Economics*.

Matsuyama, K. (1992a). A Simple Model of Sectoral Adjustment. *The Review of Economic Studies*, 375–388.

Matsuyama, K. (1992b, December). Agricultural Productivity, Comparative Advantage, and Economic Growth. *Journal of Economic Theory 58*(2), 317–334.

McMillan, M. and D. Rodrik (2011). Globalization, Structural Change and Productivity Growth. In *Making Globalization Socially Sustainable.* ILO/WTO.

McMillan, M., D. Rodrik, and C. Sepulveda (2017). Structural Change, Fundamentals and Growth: A Framework and Case Studies. *National Bureau of Economic Research Working Paper Series No. 23378.*

Monras, J., J. Vazquez-Grenno, and F. Elias (2018). Understanding the Effects of Legalizing Undocumented Immigrants. *CEPR DP 12726*.

Murphy, K. M., A. Shleifer, and R. Vishny (1989). Income Distribution, Market Size, and Industrialization. *The Quarterly Journal of Economics 104*(3), 537–564.

Ngai, L. R. and C. A. Pissarides (2007). Structural change in a multisector model of growth. *American Economic Review 97*(1), 429–443.

Nurkse, R. (1953). *Problems of Capital Formation in Underdeveloped Countries.* Oxford: Basil Blackwell.

Restuccia, D., D. T. Yang, and X. Zhu (2008). Agriculture and Aggregate Productivity: A Quantitative Cross-Country Analysis. *Journal of Monetary Economics 55*(2), 234 – 250.

Romer, P. (1990). Endogenous Technological Change. *Journal of Political Economy 98*(5).

Rostow, W. (1960). *The Stages of Economic Growth: A Non Communist Manifesto.* Cambridge University Press.

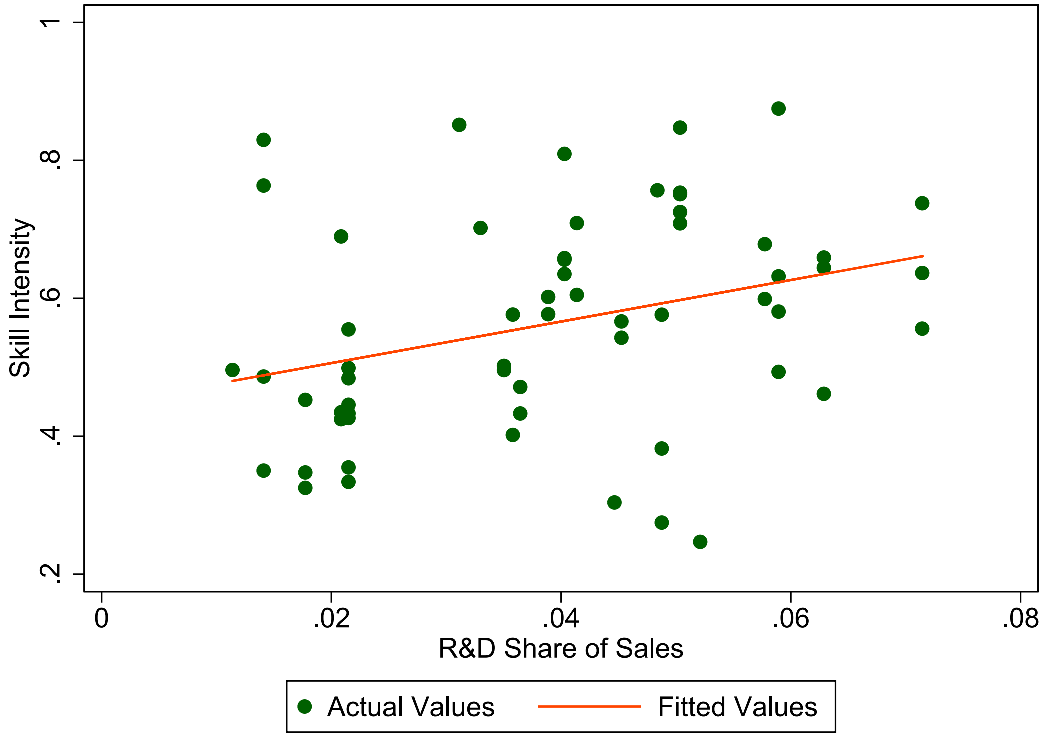
Schultz, T. (1953). *The Economic Organization of Agriculture.* New York: McGraw-Hill.

USDA (2012). "Agricultural Biotechnology Annual". United States Department of Agriculture, Economic Research Service.

A Appendix: Empirics

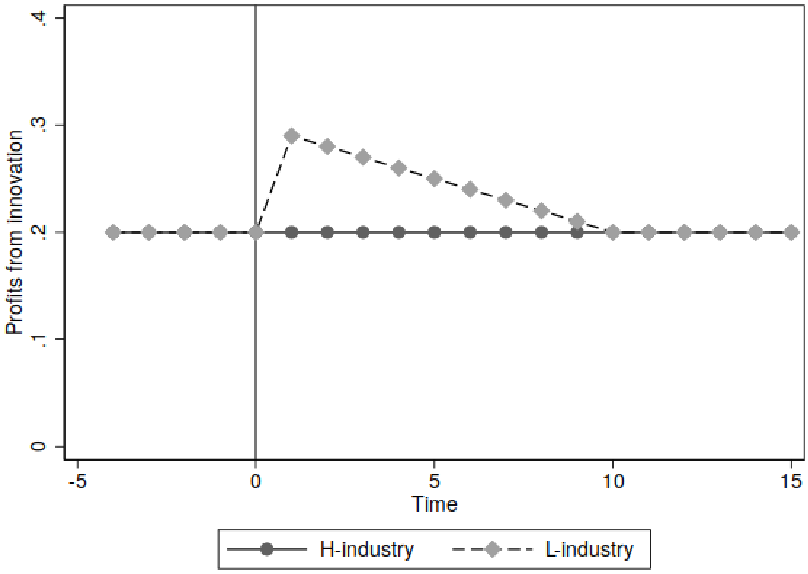
A.1 Figures and Tables

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



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

Figure A.2: Evolution of profits from innovation given an increase in A_s



Notes: This figure shows the qualitative theoretical evolution of profits from innovating in the L- and H-industries implied by the extension of our model discussed in Appendix C when at time $t = 0$ skilled-biased-factor-augmenting technology (A_s) in agriculture increases.

Table A1: Effect of soy technical change on manufacturing value added, wage bill and productivity

Panel A: Aggregate

VARIABLES	(1) Log WL	(2) Log VA/WL
A^{soy}	0.113***	-0.104**
	[0.037]	[0.043]
Observations	3,350	3,350
R-squared	0.979	0.708
Baseline Controls	Yes	Yes
All Controls	Yes	Yes

Panel B: Low Skill-Intensive

VARIABLES	(1) Log WL	(2) Log VA/WL
A^{soy}	0.151***	-0.025
	[0.053]	[0.052]
Observations	3,350	3,350
R-squared	0.958	0.603
Baseline Controls	Yes	Yes
All Controls	Yes	Yes

Panel C: High Skill-Intensive

VARIABLES	(1) Log WL	(2) Log VA/WL
A^{soy}	0.044	-0.180***
	[0.060]	[0.055]
Observations	3,350	3,350
R-squared	0.967	0.699
Baseline Controls	Yes	Yes
All Controls	Yes	Yes

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

Table A2: Internal migration

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

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

Table A3: Classification of Manufacturing Industries by Skill Intensity

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

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

Table A4: Effect of technical change in soy on the number of workers at the minimum wage

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Log. L at the Minimum Wage					
VARIABLES	Manufacturing	Manufacturing	Manufacturing Low	Manufacturing Low	Manufacturing High	Manufacturing High
ΔA_{soy}	0.185***	0.196***	0.215***	0.234***	0.194**	0.179**
	[0.041]	[0.043]	[0.044]	[0.047]	[0.083]	[0.087]
Observations	556	556	555	555	508	508
R-squared	0.120	0.178	0.104	0.185	0.012	0.018
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	No	Yes	No	Yes	No	Yes

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

B Appendix: Theory

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

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:

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

$$U_a(w_s, w_u, L_a) = \frac{\left(\frac{w_u}{A_u}\right)^{-\varepsilon} L_a}{A_u \left[w_s^{1-\varepsilon} A_s^{\varepsilon-1} + w_u^{1-\varepsilon} A_u^{\varepsilon-1}\right]^{\frac{\varepsilon}{\varepsilon-1}}} \tag{15}$$

$$C(w_s, w_u, L_a) = L_a \left[\left(\frac{w_s}{A_s}\right)^{1-\varepsilon} + \left(\frac{w_u}{A_u}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \tag{16}$$

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

$$\frac{S_a}{U_a} = \left(\frac{w_u}{w_s}\right)^{\varepsilon} \left(\frac{A_s}{A_u}\right)^{\varepsilon-1} \tag{17}$$

□

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:

$$MPU_a = A_n K \gamma \Theta^{\frac{1}{\sigma-1}} A_L^{\frac{\sigma-1}{\sigma}} L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}} A_u^{\frac{\varepsilon-1}{\varepsilon}} U_a^{\frac{-1}{\varepsilon}} \tag{18}$$

$$MPS_a = A_n K \gamma \Theta^{\frac{1}{\sigma-1}} A_L^{\frac{\sigma-1}{\sigma}} L_a^{\frac{-(\varepsilon-\sigma)}{\varepsilon\sigma}} A_s^{\frac{\varepsilon-1}{\varepsilon}} S_a^{\frac{-1}{\varepsilon}} \tag{19}$$

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

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

Moreover,

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

Therefore,

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

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

Notice that $\kappa > 0$. Thus,

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

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

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

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

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

$$\frac{\partial MPU_a}{\partial A_s} < 0 \iff \sigma < \varepsilon \left(\frac{(1-\gamma)(A_T T_a)^{\frac{\sigma-1}{\sigma}}}{\Theta} \right) \tag{20}$$

□

Lemma 1. *If all three sectors are active, the effect of an increase in skilled-biased-factor-augmenting technology in agriculture (A_s) on wages is mediated by the effect of A_s on local knowledge (K_t). In particular:*

$$\frac{\partial \ln w_s}{\partial A_s} = \frac{\partial \ln w_u}{\partial A_s} = \frac{\partial \ln K_t}{\partial A_s}$$

and the effect of A_s on land prices is given by:

$$\frac{\partial \ln r}{\partial A_s} = \frac{\partial \ln K_t}{\partial A_s} + \frac{\theta_{S_a}}{A_s \theta_{T_a}}$$

where θ_{S_a} is the cost share of high-skilled workers and θ_{T_a} is the cost share of land in agriculture.

Proof. The unit cost functions are defined as:

$$c_a(w_s, w_u, r, A_s, K_t) = \min\{w_s S_a + w_u U_a + rT_a \mid F_a(S_a, U_a, T_a, A_s, K_t) \geq 1\}$$

$$c_m^h(w_s, w_u, r, p, K_t) = \min\{w_s S_m^h + w_u U_m^h + pK_t x \mid A_m^h F_m^h(S_m^h, U_m^h, x, K_t) \geq 1\}$$

$$c_m^\ell(w_s, w_u, r, K_t) = \min\{w_s S_m^\ell + w_u U_m^\ell \mid A_m^\ell F_m^\ell(S_m^\ell, U_m^\ell, K_t) \geq 1\}$$

Where A_s denotes skilled-biased factor-augmenting technologies in agriculture, K_t is the local knowledge which is an endogenous hicks neutral technology, and p is the price of inputs and x is the quantity of inputs. Note that we already use the symmetry of the input market to simplify notation.

From the unit cost functions we can define the unit factor demands:

$$a_{U_i}(w_s, w_u, r, A_i, K_t) = \frac{\partial c_i(w_s, w_u, r, A_i, K_t)}{\partial w_u}$$
$$a_{S_i}(w_s, w_u, r, A_i, K_t) = \frac{\partial c_i(w_s, w_u, r, A_i, K_t)}{\partial w_s}$$
$$a_{T_i}(w_s, w_u, r, A_i, K_t) = \frac{\partial c_i(w_s, w_u, r, A_i, K_t)}{\partial r}$$

In this economy, when all sectors are active, zero profit conditions are given by:

$$p_a = c_a(w_s, w_u, r, A_s, K_t) = c_a(w_s, w_u, r, A_s)/K_t$$

$$1 = c_m^h(w_s, w_u, p, K_t) = c_m^h(w_s, w_u, p)/K_t$$

$$p_m^\ell = c_m^\ell(w_s, w_u, K_t) = c_m^\ell(w_s, w_u)/K_t$$

These equations can be re-written as:

$$p_a = c_a(\frac{w_s}{A_s}, w_u, r)/K_t$$

$$1 = c_m^h(w_s, w_u, p)/K_t$$

$$p_m^\ell = c_m^\ell(w_s, w_u)/K_t$$

Where we made clear that the unit cost function in agriculture depends on the skilled biased factor-augmenting technology A_s that we study, and that the productivity in all sectors also depends on K_t. Taking log derivatives of these equations with respect to A_s we obtain that:

$$\frac{\partial \ln p_a}{\partial A_s} = \theta_{T_a}\frac{\partial \ln r}{\partial A_s} + \theta_{S_a}\frac{\partial \ln w_s}{\partial A_s} - \theta_{S_a}\frac{\partial \ln A_s}{\partial A_s} + \theta_{U_a}\frac{\partial \ln w_u}{\partial A_s} - \frac{\partial \ln K_t}{\partial A_s}$$

$$\frac{\partial \ln 1}{\partial A_s} = \theta_{S_m^h}\frac{\partial \ln w_s}{\partial A_s} + \theta_{U_m^h}\frac{\partial \ln w_u}{\partial A_s} + \theta_{x_m^h}\frac{\partial \ln p}{\partial A_s} - \frac{\partial \ln K_t}{\partial A_s}$$

$$\frac{\partial \ln p_m^\ell}{\partial A_s} = \theta_{S_m^\ell}\frac{\partial \ln w_s}{\partial A_s} + \theta_{U_m^\ell}\frac{\partial \ln w_u}{\partial A_s} - \frac{\partial \ln K_t}{\partial A_s}$$

But, we will later see that the price of inputs is proportional to the cost of producing them. And the cost of producing one input is the same as the final good.[40] Defining:

$$\tilde{\theta}_{S_m^h} = (\theta_{S_m^h} + \theta_{x_m^h}\frac{\theta_{S_m^h}}{\theta_{S_m^h} + \theta_{U_m^h}})$$

We then have:

$$\frac{\partial \ln K_t}{\partial A_s} = \tilde{\theta}_{S_m^h}\frac{\partial \ln w_s}{\partial A_s} + \tilde{\theta}_{U_m^h}\frac{\partial \ln w_u}{\partial A_s}$$

$$\frac{\partial \ln K_t}{\partial A_s} = \theta_{S_m^\ell}\frac{\partial \ln w_s}{\partial A_s} + \theta_{U_m^\ell}\frac{\partial \ln w_u}{\partial A_s}$$

Hence:

$$\frac{\partial \ln K_t}{\partial A_s} = \tilde{\theta}_{S_m^h}\frac{\partial \ln w_s}{\partial A_s} + (1 - \tilde{\theta}_{S_m^h})\frac{\partial \ln w_u}{\partial A_s}$$

$$\frac{\partial \ln K_t}{\partial A_s} = \theta_{S_m^\ell}\frac{\partial \ln w_s}{\partial A_s} + (1 - \theta_{S_m^\ell})\frac{\partial \ln w_u}{\partial A_s}$$

In matrix form:

$$\begin{bmatrix} \frac{\partial \ln K_t}{\partial A_s} \\ \frac{\partial \ln K_t}{\partial A_s} \end{bmatrix} = \begin{bmatrix} \tilde{\theta}_{S_m^h} & (1 - \tilde{\theta}_{S_m^h}) \\ \theta_{S_m^\ell} & (1 - \theta_{S_m^\ell}) \end{bmatrix} \begin{bmatrix} \frac{\partial \ln w_s}{\partial A_s} \\ \frac{\partial \ln w_u}{\partial A_s} \end{bmatrix}$$

[40]Note that an alternative is to use the fact that the cost function is Cobb-Douglas as we have in the main text.

Using Cramer's rule:

$$\begin{bmatrix} \frac{\partial \ln w_s}{\partial A_s} \\ \frac{\partial \ln w_u}{\partial A_s} \end{bmatrix} = \frac{1}{\tilde{\theta}_{S_m^h} - \theta_{S_m^\ell}} \begin{bmatrix} (\tilde{\theta}_{S_m^h} - \theta_{S_m^\ell})\frac{\partial \ln K_t}{\partial A_s} + (1 - \tilde{\theta}_{S_m^h})(\frac{\partial \ln K_t}{\partial A_s} - \frac{\partial \ln K_t}{\partial A_s}) \\ (\tilde{\theta}_{S_m^h} - \theta_{S_m^\ell})\frac{\partial \ln K_t}{\partial A_s} - \theta_{S_m^\ell}(\frac{\partial \ln K_t}{\partial A_s} - \frac{\partial \ln K_t}{\partial A_s}) \end{bmatrix}$$

Hence:

$$\begin{bmatrix} \frac{\partial \ln w_s}{\partial A_s} \\ \frac{\partial \ln w_u}{\partial A_s} \end{bmatrix} = \begin{bmatrix} \frac{\partial \ln K_t}{\partial A_s} \\ \frac{\partial \ln K_t}{\partial A_s} \end{bmatrix}$$

This equation means that skilled-biased factor-augmenting technical change in agriculture will result in wage increases for high and low skilled workers of the exact same magnitude. Note that this result is a consequence of the small open economy assumption. If increased exports of low-skill intensive goods decreased prices of low-skilled intensive goods, then Stolper-Samuelson type forces would appear, which would tend to decreased low-skilled workers' wages.

We now turn to land prices.From,

$$0 = \theta_{T_a}\frac{\partial \ln r}{\partial A_s} + \theta_{S_a}\frac{\partial \ln w_s}{\partial A_s} - \theta_{S_a}\frac{\partial \ln A_s}{\partial A_s} + \theta_{U_a}\frac{\partial \ln w_u}{\partial A_s} - \frac{\partial \ln K_t}{\partial A_s}$$

we have that:

$$\frac{\partial \ln r}{\partial A_s} = \frac{(1 - \theta_{S_a} - \theta_{U_a})}{\theta_{T_a}}\frac{\partial \ln K_t}{\partial A_s} + \frac{\theta_{S_a}}{A_s\theta_{T_a}} = \frac{\partial \ln K_t}{\partial A_s} + \frac{\theta_{S_a}}{A_s\theta_{T_a}}$$

□

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

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

Proof. Consider the factor market clearing equilibrium conditions,

$$a_{Ta}Q_a = T \tag{21}$$
$$a_{Sa}Q_a + a_{S_m^\ell}Q_m^\ell + a_{S_m^h}Q_m^h = S \tag{22}$$
$$a_{Ua}Q_a + a_{U_m^\ell}Q_m^\ell + a_{U_m^h}Q_m^h = U \tag{23}$$

Log-differentiating Equations 21, 22 and 23 we get that:

$$\begin{aligned} a_{Ta}dQ_a + da_{Ta}Q_a &= dT \\ a_{Sa}dQ_a + da_{Sa}Q_a + a_{S_m^\ell}dQ_m^\ell + a_{S_m^h}dQ_m^h &= dS \\ da_{Ua}Q_a + a_{Ua}dQ_a + a_{U_m^\ell}dQ_m^\ell + a_{U_m^h}dQ_m^h &= dU \end{aligned}$$

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

$$\lambda_{Ta}\widehat{Q}_a + \lambda_{Ta}\widehat{a}_{Ta} = \widehat{T} \tag{24}$$

$$\lambda_{Sa}\widehat{Q_a} + da_{Sa}\frac{Q_a}{S} + \lambda_{S_m^\ell}\widehat{Q_m^\ell} + \lambda_{S_m^h}\widehat{Q_m^h} = \widehat{S} \tag{25}$$

$$\lambda_{Ua}\widehat{Q_a} + da_{Ua}\frac{Q_a}{U} + \lambda_{U_m^\ell}\widehat{Q_m^\ell} + \lambda_{U_m^h}\widehat{Q_m^h} = \widehat{U} \tag{26}$$

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

$$\widehat{Q_a} = -\widehat{a_{Ta}} \tag{27}$$

$$\lambda_{Sa}\widehat{Q_a} + \lambda_{S_m^\ell}\widehat{Q_m^\ell} + \lambda_{S_m^h}\widehat{Q_m^h} = -da_{Sa}\frac{Q_a}{S} \tag{28}$$

$$\lambda_{Ua}\widehat{Q_a} + \lambda_{U_m^\ell}\widehat{Q_m^\ell} + \lambda_{U_m^h}\widehat{Q_m^h} = -da_{Ua}\frac{Q_a}{U} \tag{29}$$

Combining these expressions, we arrive to:

$$\lambda_{S_m^\ell}\widehat{Q_m^\ell} + \lambda_{S_m^h}\widehat{Q_m^h} = -\widehat{a_{Sa}}\lambda_{Sa} + \lambda_{Sa}\widehat{a_{Ta}} = \underbrace{\lambda_{Sa}(\widehat{a_{Ta}} - \widehat{a_{Sa}})}_{\gamma_s} \tag{30}$$

$$\lambda_{U_m^\ell}\widehat{Q_m^\ell} + \lambda_{U_m^h}\widehat{Q_m^h} = -\widehat{a_{Ua}}\lambda_{Ua} + \lambda_{Ua}\widehat{a_{Ta}} = \underbrace{\lambda_{Ua}(\widehat{a_{Ta}} - \widehat{a_{Ua}})}_{\gamma_u} \tag{31}$$

$$\widehat{Q_m^h} = \frac{\lambda_{U_m^\ell}\gamma_s - \lambda_{S_m^\ell}\gamma_u}{\Delta} \tag{32}$$

$$\widehat{Q_m^\ell} = \frac{\lambda_{S_m^h}\gamma_u - \lambda_{U_m^h}\gamma_s}{\Delta} \tag{33}$$

where $\Delta \equiv \lambda_{U_m^\ell}\lambda_{S_m^h} - \lambda_{U_m^h}\lambda_{S_m^\ell}$ and $\Delta > 0$ since the share of unskilled in the low-skilled intensive industry times the share of skilled in the skill-intensive industry is greater than the share of high-skilled in the low-skilled intensive industry times the share of unskilled in the high-skilled intensive industry. Then, $\widehat{Q^h_m} < 0$ iff $\lambda_{U^\ell_m}\gamma_s - \lambda_{S^\ell_m}\gamma_u < 0$. Which holds iff:

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

This can be re-written as:

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

This can be further simplified to:

$$\lambda_{U^\ell_m}\lambda_{Sa}(\widehat{a_{Sa}} + \widehat{Q_a}) > \lambda_{S^\ell_m}\lambda_{Ua}(\widehat{a_{Ua}} + \widehat{Q_a})$$

And so, $\widehat{Q^h_m} < 0$ iff:

$$\frac{\lambda_{U^\ell_m}}{\lambda_{S^\ell_m}}\frac{(\widehat{a_{Sa}} + \widehat{Q_a})}{(\widehat{a_{Ua}} + \widehat{Q_a})} > \frac{\lambda_{Ua}}{\lambda_{Sa}}$$

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

Finally we are going to prove that $\widehat{a_{Sa}} > \widehat{a_{Ua}}$. This condition basically says that the elasticity of the agricultural unit factor demand with respect to A_s is larger for the skilled factor than for the unskilled factor, i.e $\frac{\partial ln a_{Sa}}{\partial ln A_s} > \frac{\partial ln a_{Ua}}{\partial ln A_s}$. Now, take the marginal productivities for skilled and unskilled labor in agriculture (Equations 18 and 19) 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,

$$\widehat{a_{Sa}} > \widehat{a_{Ua}} \iff \frac{\partial lna_{Sa}}{\partial lnA_s} > \frac{\partial lna_{Ua}}{\partial lnA_s} \iff \frac{\partial lnS_a}{\partial lnA_s} > \frac{\partial lnU_a}{\partial lnA_s} \iff \varepsilon - 1 > 0 \tag{34}$$

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

□

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

Theorem 4. *When the following conditions hold:*

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

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

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

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

$$g_C = \frac{\chi A^h_m F^h_m(U^h_m, S^h_m) - \rho}{\eta} \tag{35}$$

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

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

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

Proof. First, we assume that each input in the high-skill intensive industry is monopolized by the person who invented it, who decides how much output to produce given the profits. The input for producing the final good is the same final good.[41] Hence,

$$\Pi_k = p_k x_k - x_k$$

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

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

We can use this price to find the optimal quantity of intermediate produced and then use this to obtain output in the final good industry. This is given by:[42] $x_k = (1-\alpha)^{2/\alpha} A_m^h F_m^h (U_m^h, S_m^h)$. From this, it is straightforward to show that total production in the high-skilled industry is given by:[43]

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

where $\kappa = (1-\alpha)^{2*(1-\alpha)/\alpha}$. We also obtain that that profits in the sector are given by:[44]

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

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

[41] This assumption simplifies the algebra. We are inspired by chapter 3 of Aghion and Howitt (2008). This chapter is, in turn, an adaptation of the original Romer (1990). See also Grossman and Helpman (1991b) for a continuous sector version of the endogenous growth model, Helpman (1993) and Bayoumi et al. (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.

[42] Note that profits are:

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

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

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

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

in this we can plug in the amount of input.

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

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

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

We also need to obtain net output in the sector, i.e. total output minus what is used for intermediate production. Hence:[45]

$$Q^h_m - K_t x = \varsigma A^h_m F^h_m(U^h_m, S^h_m) K_t \tag{36}$$

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

Note that this model has the simplifying feature that both total output in the sector, profits, and net output are all proportional to $A^h_m F^h_m(U^h_m, S^h_m)$.

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

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

The rate of return in the economy is given by the (flow) profits that can be made in investing in new ideas. To invent new ideas, entrepreneurs use final H-industry good. Hence,

$$(\frac{\Pi}{r}) I_t - I_t$$

are the flow profits from inventing new varieties. Free entry implies that in equilibrium:

$$r = \Pi$$

We can now use the standard CRRA Euler equation from the consumer maximization problem, which implies that the growth rate in consumption is given by:

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

And hence:

$$g^C = \frac{\chi A^h_m F^h_m(U^h_m, S^h_m) - \rho}{\eta}$$

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

[45] From:

$$Q^h_m - K_t x = \kappa A^h_m F^h_m(U^h_m, S^h_m) K_t - K_t (1-\alpha)^{2/\alpha} A^h_m F^h_m(U^h_m, S^h_m)$$

we have that:

$$Q^h_m - K_t x = [(1-\alpha)^{2*(1-\alpha)/\alpha} - (1-\alpha)^{2/\alpha}] A^h_m F^h_m(U^h_m, S^h_m) K_t$$

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

consumption.

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

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

to obtain that:

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

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

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

And hence:

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

And hence

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

And hence:

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

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

Which is equal to:

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

Or:

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

□

C Appendix: Scale Economies

A divergence between the empirical exercise and the model shown in the main text is that, in the model, innovation depends on the size of the high-skill intensive industry, which in turn only depends on the workers working in that sector. In the data we do not find a decrease in employment of the high-skilled sector, although we do observe a decrease in valued added in the sector as reported in Table 8. Hence, from the view point of the model and given that in the model the only factors of production in manufacturing are workers, we should not see a decline in manufacturing productivity in soy shocked regions relative to others. However, it could be that just the fact that the *relative* size of the high-skilled intensive sector declines in shocked relative to non-shocked regions is sufficient to divert resources devoted to innovative activities.

In this section we introduce a variant of our model where an increase in the size of the low-skilled intensive sector, without a (necessarily) contraction of the high-skilled intensive one, leads to the predictions on productivity and GDP growth that we observe in the data. We do not make the model in this Appendix the main model of our paper because the one in the main text is slightly more tractable and allows the main intuitions of our general argument to be more transparent.

To do so, we build on the critique of the original Romer (1990) model by Jones (1995), which we adapt to our context. The result of this exercise is a model that predicts that, in the short-run, the growth rate of the economy depends on the composition of the manufacturing industries and not just on the size of the high-skilled intensive sector.

We keep all the assumptions we made in Section 3 except that we assume that the production function in the low-skilled intensive industry takes the following form:

$$Q_m^\ell = (\frac{A_m^\ell F_m^\ell(U_m^\ell, S_m^\ell)}{K_t^\ell})^\alpha (\int^{K_t^\ell} x_j^{1-\alpha} dj)$$

This production function captures the idea that in the L-industry what matters is workers per input variety, rather than the total amount of workers (Aghion and Howitt, 2008, p. 97). This is important since, unlike in the H-industry, it is more costly (in terms of employment) to have a larger set of input varieties. The second difference between this industry and the H-industry is that it does not generate spillovers towards the other sectors, i.e. K_t^ℓ does not multiply the production function of agriculture or high-skilled manufacturing. The third difference is that entrepreneurs need to decide whether they want to invent new input varieties for the H-industry or for the L-industry, something that depends on profits made on the new inputs invented.

A part from these differences, the L-industry operates like the H-industry. We will see, though, that in equilibrium $K_t^\ell = K^\ell$ is a constant, i.e. the set of input varieties does not grow over time in the L-industry.

Demand for the intermediate varieties is given by:

$$p_j = \frac{\partial Q^\ell_m}{\partial x_j} = (1-\alpha)(\frac{A^\ell_m F^\ell_m(U^\ell_m, S^\ell_m)}{K^\ell_t})^\alpha x_j^{-\alpha}$$

Profits for the intermediate varieties are given by:

$$\Pi_j = (1-\alpha)(\frac{A^\ell_m F^\ell_m(U^\ell_m, S^\ell_m)}{K^\ell_t})^\alpha x_j^{1-\alpha} - x_j$$

Profit maximization then leads to:[46]

$$x_j = (1-\alpha)^{2/\alpha}(\frac{A^\ell_m F^\ell_m(U^\ell_m, S^\ell_m)}{K^\ell_t})$$

Hence, in equilibrium, operating profits are given by:

$$\Pi^\ell = \Pi_j = \chi\frac{A^\ell_m F^\ell_m(U^\ell_m, S^\ell_m)}{K^\ell_t}$$

Where χ is defined as before.

Free entry in the invention of new varieties means that the net present value flow profit from inventing new input varieties for the L-industry cannot be larger than in the H-industry. Hence:

$$\frac{\Pi^\ell}{r} = \frac{\Pi}{r}$$

And hence:

$$K^\ell = \chi A^\ell_m F^\ell_m(U^\ell_m, S^\ell_m)\Pi$$

This is the equilibrium mass of varieties in the L-industry. It is worth noting that this is a constant (in contrast to the H-sector where the mass K_t grows indefinitely).

In this model, when there is an increase in A_s, i.e. the factor-augmenting productivity of high-skilled workers in agriculture, low-skilled workers leave agriculture and enter low-skilled manufacturing (provided that conditions (1) to (3) in theorem 3 are satisfied).

With an inflow of workers into the L-industry, profits for inventing new input varieties increase above equilibrium. This is, $\Pi^\ell > \Pi$ (at least for some time). This drives entrepreneurs towards developing new input varieties for the L-industry instead of the H-industry. If K^ℓ can adjust instantaneously, then the invention of new input varieties created for the L-industry and hence not invented for the H-industry is short-lived. If

[46]We only need to use:

$$\frac{\partial \Pi_j}{\partial x_j} = (1-\alpha)^2(\frac{A^\ell_m F^\ell_m(U^\ell_m, S^\ell_m)}{K^\ell_t})^\alpha x_j^{-\alpha} - 1 = 0$$

and re-arrange.

instead there is an adjustment cost, this diversion towards inventing input varieties for the L-industry may last for longer. In either case, when entrepreneurs stop inventing input varieties for the H-industry, K_t stops growing and so does the economy since the across-sector spillovers generated from the H-industry are not present in the L-industry.

Figure A.2 illustrates the evolution of profits from innovation. Before the increase in A_s there are positive profits in inventing input varieties for the H-industry which are a fraction of the output in the industry (set a 20 percent for illustrative purposes). The profits of innovating in the L-industry are at the exact same level, except that if any positive mass of new input varieties is invented then profits drop below this level. This keeps entrepreneurs from inventing new varieties for the L-industry. With the inflow of low-skilled workers into low-skilled manufacturing, the profits from innovating in this sector increase. Hence all innovating activity is geared towards this sector. As more varieties are invented, profits decline until they reach the profits that entrepreneurs can make when inventing varieties for the H-industry.

For some time, which in the figure is 10 periods, there are no new input varieties invented for the H-industry. Hence, for some time K_t does not expand. Given that growth is primarily driven by this sector since it's a source of positive externalities towards all other sectors, for some time growth slows down following the increase in A_s. This slowdown in growth comes from the fact that entrepreneurs stop to innovate for the H-industry. Hence, the slowdown comes from the H-industry (as in the data).