Agricultural Productivity and Structural Transformation. Evidence from Brazil*

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Abstract

We study the effects of the adoption of new agricultural technologies on structural transformation. To guide empirical work, we present a simple model where the effect of agricultural productivity on industrial development depends on the factor bias of technical change. We test the predictions of the model by studying the introduction of genetically engineered soybean seeds in Brazil, which had heterogeneous effects on agricultural productivity across areas with different soil and weather characteristics. We find that technical change in soy production was strongly labor saving and lead to industrial growth, as predicted by the model.

Keywords: Agricultural Productivity, Structural Transformation, Industrial Development, Labor Saving Technical Change, Genetically Engineered Soy.

JEL Classification: F16, F43, 014, Q16.

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1 Introduction

The early development literature documented that the growth path of most advanced economies was accompanied by a process of structural transformation. As economies develop, the share of agriculture in employment falls and workers migrate to cities to find employment in the industrial and service sectors [Clark (1940), Kuznets (1957)]. These findings suggest that isolating the forces that can give rise to structural transformation is key to our understanding of the development process. In particular, scholars have argued that increases in agricultural productivity are an essential condition for economic development, based on the experience of England during the industrial revolution.[1] Classical models of structural transformation formalize their ideas by showing how productivity growth in agriculture can release labor or generate demand for manufacturing goods.[2] However, Matsuyama (1992) notes that the positive effects of agricultural productivity on industrialization occur only in closed economies, while in open economies a comparative advantage in agriculture can slow down industrial growth. This is because labor reallocates towards the agricultural sector, reducing the size of the industrial sector and its scope to benefit from external scale economies. Despite the richness of the theoretical literature, there is scarce direct empirical evidence testing the mechanisms proposed by these models.[3]

In this paper we provide direct empirical evidence on the effects of technical change in agriculture on the industrial sector by studying the recent widespread adoption of new agricultural technologies in Brazil. First, we analyze the effects of the adoption of genetically engineered soybean seeds (GE soy). This new technology requires less labor per unit of land to yield the same output, thus can be characterized as land-biased technical change. In addition, we study the effects of the adoption of second-harvest maize (*milho safrinha*). This type of maize permits to grow two crops a year, effectively increasing the land endowment. Thus, it can be characterized as labor-biased technical change.[4] The simultaneous expansion of these two crops permits to assess the effect of agricultural productivity on structural transformation in open economies.

To guide empirical work, we build a simple model describing a two-sector small open economy where technical change in agriculture can be factor-biased. The model predicts that a Hicks-neutral increase in agricultural productivity induces a reduction in the size of the industrial sector

[1] See, for example, Rosenstein-Rodan (1943), Nurkse (1953), Lewis (1954), Rostow (1960).

[2] See Baumol (1967), Murphy, Shleifer, Vishny (1989), Kongsamut, Rebelo and Xie (2001), Gollin, Parente and Rogerson (2002), Ngai and Pissarides (2007).

[3] Empirical studies of structural transformation include Foster and Rosenszweig (2004, 2008), Nunn and Qian (2011), Michaels, Rauch and Redding (2012), Hornbeck and Keskin (2012). We discuss this literature in more detail below.

[4] Land augmenting technical change is labor-biased when the production displays an elasticity of substitution between land and labor smaller than one.

as labor reallocates towards agriculture, as in Matsuyama (1992). Similar results are obtained when technical change is labor-biased. However, if technical change is strongly labor-saving, labor demand in agriculture falls and workers reallocate towards manufacturing. In sum, the model predicts that the effects of agricultural productivity on structural transformation in open economies depend on the factor-bias of technical change.

In a first analysis of the data we find that regions where the area cultivated with soy expanded experienced an increase in agricultural output per worker, a reduction in labor intensity in agriculture and an expansion in industrial employment. These correlations are consistent with the theoretical prediction that the adoption of strongly labor saving agricultural technologies reduces labor demand in the agricultural sector and induces the reallocation of workers towards the industrial sector. However, causality could run in the opposite direction. For example: an increase in labor demand in the industrial sector could increase wages, inducing agricultural firms to switch to less labor intensive crops, like soy.

We propose to establish the direction of causality by using two sources of exogenous variation in the profitability of technology adoption. First, in the case of GE soy, as the technology was invented in the U.S. in 1996, and legalized in Brazil in 2003, we use this last date as our source of variation across time. Second, as the new technology had a differential impact on yields depending on geographical and weather characteristics, we use differences in soil suitability across regions as our source of cross-sectional variation. Similarly, in the case of maize, we exploit the timing of expansion of second-harvest maize and cross-regional differences in soil suitability.

We obtain an exogenous measure of technological change in agriculture by using estimates of potential soil yields across geographical areas of Brazil from the FAO-GAEZ database. These yields are calculated by incorporating local soil and weather characteristics into a model that predicts the maximum attainable yields for each crop in a given area. Potential yields are a source of exogenous variation in agricultural productivity because they are a function of weather and soil characteristics, not of actual yields in Brazil. In addition, the database reports potential yields under traditional and new agricultural technologies. Thus, we exploit the predicted differential impact of the new technology on yields across geographical areas in Brazil as our source of cross-sectional variation in agricultural productivity. Note that this empirical strategy relies on the assumption that although goods can move across geographical areas of Brazil, labor markets are local due to limited labor mobility. This research design allows us to investigate whether exogenous shocks to local agricultural productivity lead to changes in the size of the local industrial sector. We use municipalities as our geographical unit of observation, that are assumed to behave as the small open economy described in the model.[5]

We find that municipalities where the new technology is predicted to have a higher effect on potential yields of soy did experience a higher increase in the area planted with GE soy. In addition, these regions experienced increases in the value of agricultural output per worker and reductions in labor intensity measured as employment per hectare. Finally, these regions experienced faster employment growth and wage reductions in the industrial sector. Interestingly, the effects of technology adoption are different for maize. Regions where the FAO potential maize yields are predicted to increase the most when switching from the traditional to the new technology did indeed experience a higher increase in the area planted with maize and in the value of agricultural output. However, they also experienced increases in labor intensity, reductions in industrial employment and increases in wages.

The differential effects of technological change in agriculture documented for GE soy and maize indicate that the factor-bias of technical change is a key factor in the relationship between agricultural productivity and structural transformation in open economies. If technical change is labor-biased, as in the case of maize, agricultural productivity growth leads to a reduction in industrial employment, as predicted by Matsuyama (1992). However, if technical change is strongly labor saving, as in the case of GE soy, agricultural productivity growth leads to employment growth in the industrial sector.

Related Literature

There is a long tradition in economics of studying the links between agricultural productivity and industrial development. Nurkse (1953) and Rostow (1960) argued that agricultural productivity growth was an essential precondition for the industrial revolution. Schultz (1953) held the view that an agricultural surplus is a necessary condition for a country to start the development process. 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, the demand channel: agricultural productivity growth rises income per capita, which generates demand for manufacturing goods if preferences are non-homotetic [Murphy, Shleifer, Vishny (1989), Kongsamut, Rebelo and Xie (2001), Gollin, Parente and Rogerson (2002)]. The higher relative demand for manufactures generates a reallocation of labor away from agriculture. Second, the supply channel: if productivity growth in agriculture is faster than in manufacturing and these goods are complements in consumption, then the relative demand of agriculture does not grow as fast as productivity and labor reallocates towards manufacturing [Baumol (1967), Ngai and

[5]Because the size of municipalities is small in coastal areas of Brazil, we show that our results are robust to using a larger unit of observation, Micro-regions.

Pissarides (2007)].[6,7]

The view that agricultural productivity can generate manufacturing growth was challenged by scholars studying industrialization experiences in open economies. These scholars argued that high agricultural productivity can retard industrial growth as labor reallocates towards the comparative advantage sector [Mokyr (1976), Field (1978) and Wright (1979)] . Matsuyama (1992) formalized these ideas by showing how the demand and supply channels are not operative in a small open economy that faces a perfectly elastic demand for both goods at world prices. The open economy model we present in this paper differs from Matsuyama's in one key dimension. In his model, there is only one type of labor thus technical change is, by definition, Hicks-neutral. In our model agricultural production uses both land and labor, and technical change can be factor-biased. Thus, a new prediction emerges: when technical change is strongly labor saving an increase in agricultural productivity leads to industrial growth even in open economies.

Our work also builds on the empirical literature studying the links between agricultural productivity and economic development.[8] The closest precedent to our work is Foster and Rosenzweig (2004, 2008) who study the effects of the adoption of high-yielding-varieties (HYV) of corn, rice, sorghum, and wheat during the Green Revolution in India. To guide empirical work, they present a model where agricultural and manufacturing goods are tradable and technical change is Hicks-neutral. Consistent with the model, they find that villages with higher improvements in crop yields experienced lower manufacturing growth. Our findings are in line with theirs in the case of Maize, where technical change is labor-biased. However, we find the opposite effects in the case of soy, where technical change in strongly labor saving. Thus, relative to theirs, our work highlights the importance of the factor bias of technical change in shaping the relationship between agricultural productivity and industrial development in open economies.

Finally, our work is also related to recent empirical papers studying the effects of agricultural productivity on urbanization [Nunn and Qian (2011)], the links between structural transformation and urbanization [Michaels, Rauch and Redding (2012)], and the effects of agriculture on local economic activity [Hornbeck and Keskin (2012)].

The remaining of the paper is organized as follows. Section 2 gives background information on agriculture in Brazil. Section 3 presents the theoretical model. Section 4 describes the data.

[6]The agricultural and manufacturing goods are complements in consumption of the elasticity of substitution between the two goods is less than one.

[7]Another mechanism generating a reallocation of labor from agriculture to manufacturing is faster growth in the relative supply of one production factor when there are differences in factor intensity across sectors [See Caselli and Coleman (2001), and Acemoglu and Guerrieri (2008)]. For a recent survey of the structural transformation literature see Herrendorf, Valentinyi and Rogerson (2013).

[8]This literature is surveyed by Syrquin (1988) and Foster and Rosensezweig (2008).

Section 5 presents the empirical strategy and results. Section 7 concludes.

2 Agriculture in Brazil

In this section we provide background information about recent developments in the Brazilian agricultural sector. As Figure 1 shows, in the last decade, Brazilian labor force has been shifting away from agriculture and increasing in manufacturing and services. At the end of the 1990s, agriculture employed around 16 million workers, while manufacturing less than 8 million. By 2011, this gap was almost closed with agriculture and manufacturing employing, respectively, 12 and 10.5 million workers.

During the same period, agricultural productivity increased significantly. Figures 2 and 3 compare the distributions of, respectively, average soy yields and average maize yields (expressed in tons per hectare) across Brazilian municipalities in 1996 and 2006. The figures show a clear shift to the right in the distribution of average yields for both soy and maize, the two major crops produced in Brazil. Productivity growth went hand-in-hand with an expansion in the area planted. Table 1 shows that the land cultivated with seasonal crops – i.e. crops produced from plants that need to be replanted after each harvest, such as soy and maize – increased by 10.4 million hectares between 1996 and 2006. Out of these 10.4 million, 6.2 million hectares were converted to soy cultivation.

During this period new agricultural technologies were adopted in the cultivation of both soy and maize. In the case of soy, Brazilian farmers started introducing on a large scale genetically engineered (GE) seeds. In the case of maize, Brazilian farmers started introducing a second harvesting season, which requires the use of advanced cultivation techniques.

2.1 Technical Change in Soy: Genetically Engineered Seeds

The first generation of GE soy seeds, the Roundup Ready (RR) variety, was commercially released in the U.S. in 1996 by the agricultural biotechnology firm Monsanto. In 1998 the Brazilian National Technical Commission on Biosecurity (CTNBio) authorized Monsanto to field-test GE soy in Brazil for 5-years as a first step before commercialization. However, reports from the Foreign Agricultural Service of the United States Department of Agriculture (USDA) document that smuggling of GE soy seeds from Argentina – where they were approved for cultivation since 1996 – was already taking place from 2001 (USDA, 2001, p. 63). Eventually, pressure from soy farmers led the Brazilian government to legalize cultivation of GE soy seeds in 2003.[9]

[9] In 2003, law 10.688 allowed the commercialization of GE soy for one harvesting season, requiring farmers to burn all unsold stocks after the harvest. This temporary measure was renewed in 2004. Finally, in 2005, law 11.105 – the

The main advantage of GE soy seeds relative to traditional seeds is that they are herbicide resistant. This allows the use of no-tillage planting techniques.[10] The planting of traditional seeds is preceded by soil preparation in the form of "tillage", the operation of removing the weeds in the seedbed that would otherwise crowd out the crop or compete with it for water and nutrients. In contrast, planting GE soy seeds requires no tillage, as the application of herbicide will selectively eliminate all unwanted weeds without harming the crop. As a result, GE soy seeds can be applied directly on last season's crop residue, allowing farmers to save on production costs since less labor is required per unit of land to obtain the same output.[11]

The new technology spread quickly: in 2006 GE seeds were planted in 46.4% of the area cultivated with soy in Brazil, according to the last Agricultural Census (IBGE, 2006, p.144). In the following years the technology continued spreading to the point that it covered 85% of the area planted with soy in Brazil in the 2011-2012 harvesting season, according to the Foreign Agricultural Service of the USDA (USDA, 2012). The timing of adoption of GE soy coincides with a fast expansion in the area planted with soy in Brazil. Figure 4 documents the evolution of the area planted with soy since 1980. The figure shows that this area grew slightly between 1980 and 1996, but experienced a fast expansion afterwards. In particular, note that growth in the soy area accelerated after 2001 when the USDA documents that GE soy seeds started to be smuggled from Argentina.

The expansion of the area planted with soy can affect labor demand in the agricultural sector through two channels. First, soybean production is one of the least labor-intensive agricultural activities, as documented in Table 2.[12] As a result, the expansion of soy cultivation over areas previously devoted to other agricultural activities tends to reduce the labor intensity of agricultural production (*across-crops effect*). Second, during the period under study there was a reduction in

New Bio-Safety Law – authorized production and commercialization of GE soy in its Roundup Ready variety (art. 35).

[10]Genetic engineering (GE) techniques allow a precise alteration of a plant's traits. This allows to target a single plant's trait, facilitating the development of plant characteristics with a precision not attainable through traditional plant breeding. In the case of herbicide resistant GE soy seeds, soy genes were altered to include those of a bacteria that was herbicide resistant.

[11]GE soybeans seeds allow farmers to adopt a new "package" of techniques that lowers labor intensity for several reasons. First, since GE soybeans are resistant to herbicides, weed control can be done more flexibly. Herbicides can be applied at any time during the season, even after the emergence of the plant (Duffy and Smith, 2001). Second, GE soybeans are resistant to a specific herbicide (glyphosate), which needs fewer applications: fields cultivated with GE soybeans require an average of 1.55 sprayer trips against 2.45 of conventional soybeans (Duffy and Smith, 2001; Fernandez-Cornejo et al., 2002). Third, no-tillage production techniques require less labor. This is because the application of chemicals needs fewer and shorter trips than tillage. In addition, no-tillage allows greater density of the crop on the field (Huggins and Reganold, 2008). Finally, farmers that adopt GE soybeans report gains in the time to harvest (Duffy and Smith, 2001). These cost savings might explain why the technology spread fast, even though experimental evidence in the U.S. reports no improvements in yield with respect to conventional soybeans (Fernandez-Cornejo and Caswell, 2006)

[12]In 2006 it required less than 20 workers per 1000 hectares against the 84 of the average seasonal crop and the 127 of the average permanent crop.

the labor intensity of soy cultivation, which also tends to reduce the labor intensity of agricultural production (*within-crop effect*), as documented in Table 2 and Figure 5.

2.2 Technical Change in Maize: Second Harvesting Season

During the last two decades Brazilian agriculture experienced also important changes in maize cultivation. Maize used to be cultivated as soy, during the summer season that takes place between August and December. At the beginning of the 1980s a few farmers in the South-East started producing maize after the summer harvest, between March and July. This second season of maize cultivation spread across Brazil, where it is now known as *milho safrinha* (small-harvest maize).

Cultivation of a second season of maize requires the use of modern cultivation techniques for several reasons. First, more intensive land-use removes nitrogen from the soil, which needs to be replaced by fertilizers (EMBRAPA, 2006). Second, the planting of a second crop requires careful timing, as yields drop considerably due to late planting. Then, herbicides are used to remove residuals from the first harvest on time to plant the second crop. In addition, the second season crop needs to be planted one month faster than the first, which usually requires higher mechanization (CONAB, 2012). Finally, because a second-harvest implies a more intensive use of the soil, farmers have to rely mostly on no-tillage techniques (EMBRAPA, 2006).

Note that, even with advanced cultivation techniques, maize is still more labor intensive than both soy and other agricultural activities like cattle ranching (see Table 2). In the USDA Agricultural Resources Management Survey (ARMS) labor cost of maize cultivation in 2001 and 2005 were on average 1.8 and 1.4 times higher than the labor cost for soy cultivation.[13,14]

Figure 7 documents the evolution of the area cultivated with maize since 1980. The figure shows that, although the total area devoted to maize has increased only slightly, the area devoted to second season maize has expanded steadily since the beginning of the 1990s.[15]

3 Model

In this section we present a simple model to illustrate the effects of factor-biased technical change on structural transformation in open economies. We consider a small open economy where there are two sectors, agriculture and manufacturing, and two production factors, land and labor.

[13] Maize (corn) survey years are 2001 and 2005, soybean producers were surveyed by the USDA in 2002 and 2006.

[14] In Table 2 we do not report productivity for Brazilian farms whose main activity was maize cultivation because publicly available data on area in farms and number of workers by principal activity is available only for farms whose principal activity is either soy or cereals, a category that includes rice, wheat, maize and other cereals.

[15] Data on area cultivated with maize broken down by the season of harvest of maize are available only at the aggregate level. For this reason in section 5, when we study municipality-level data, we will not be able to distinguish between the two maize cultivation seasons.

3.1 Setup

This small open economy has a mass one of residents, each endowed with L units of labor. There are two goods, *manufactures* and *agriculture*, both of which are tradable. Production of the manufactured good requires only labor and labor productivity in manufacturing is A_m, so that

$$Q_m = A_m L_m \tag{1}$$

where Q_m denotes production of the manufactured good and L_m denotes labor allocated to the manufacturing sector. Production of the agricultural good requires both labor and land, and takes the CES form:

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

where Q_a denotes production of the agricultural good, the two production factors are labor (L_a) and land (T_a), A_a is hicks-neutral technical change, A_L is labor-augmenting technical change and A_T is land-augmenting technical change. The parameter $\gamma \in (0,1)$, and the parameter $\sigma > 0$ captures the elasticity of substitution between land and labor. The production function described by equation (2) implies the following ratio of marginal product of land to marginal product of labor:

$$\frac{MPT_a}{MPL_a} = \frac{1-\gamma}{\gamma}\left(\frac{A_T}{A_L}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{T_a}{L_a}\right)^{-\frac{1}{\sigma}}$$

Thus, if land and labor are complements in production ($\sigma < 1$), labor-augmenting technical change is land-biased. That is, increases in A_L rise the marginal product of land relative to labor for a given amount of land per worker. Similarly, land-augmenting technical change is labor-biased. Finally, technical change is strongly labor-saving if improvements in technology reduce the marginal product of labor. In the case of labour-augmenting technical change, this requires $\frac{\partial MPL_a}{\partial A_L} < 0$, which imposes a stronger condition on the elasticity of substituiton:[16]

$$\sigma < \frac{(1-\gamma)\left(A_T T\right)^{\frac{\sigma-1}{\sigma}}}{\gamma\left(A_L L_a\right)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)\left(A_T T\right)^{\frac{\sigma-1}{\sigma}}} < 1. \tag{3}$$

Note that this condition is more likely to be satisfied the more complementary are land and labor in production and the more important is land relative to labor in production.[17]

Consumers have homotetic preferences over the agricultural and manufacturng good: $U(C_a, C_m)$ where $\frac{\partial U}{\partial C_i} > 0$ and $\frac{\partial^2 U}{\partial C_i^2} < 0$ for $i = a, m$.

[16] See Acemoglu (2010) for a discussion and more general definition of strongly labor-saving technical change.
[17] See Appendix A for a formal proof.

3.2 Equilibrium

We consider a small open economy that trades with a world economy where the relative price of the agricultural good is $\frac{P_a}{P_m} = \left(\frac{P_a}{P_m}\right)^*$.Profit maximization implies that the value of the marginal product of labor must equal the wage in both sectors, thus:

$$P_a MPL_a = w = P_m MPL_m. \tag{4}$$

This implies that, in equilibrium, the marginal product of labor is determined by international prices and manufacturing productivity:

$$MPL_a = \left(\frac{P_m}{P_a}\right)^* A_m. \tag{5}$$

The equilibrium allocation of labor can be determined by substituting the land market clearing condition, $T_a = T$, in equation 5:

$$A_a \left[\gamma \left(A_L L_a\right)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)\left(A_T T\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}-1} \gamma \left(A_L L_a\right)^{\frac{\sigma-1}{\sigma}-1} A_L = \left(\frac{P_m}{P_a}\right)^* A_m. \tag{6}$$

The above equation 6 implicitely defines the equilibrium level of employment in agriculture, L_a^{eq}. In turn, the equilibrium level of employment in manufacturing, L_m^{eq}, can be determined using the labor market clearing condition, $L_m + L_a = L$. Once L_m^{eq} and L_a^{eq} are determined output in each sector can be found using the production functions described in equations 2 and 1. Equilibrium consumption is finally determined by: $\frac{\partial U/\partial C_a}{\partial U/\partial C_m} = \left(\frac{P_a}{P_m}\right)^*$ and the zero trade balance condition $(Q_a - C_a) = \left(\frac{P_m}{P_a}\right)^* (Q_m - C_m)$.

3.3 Technological Change and Structural Transformation

In this section we asess the response of the employment share of agriculture to three types of technological change: Hicks-neutral, labor-augmenting and land-augmenting. We assume that land and labor are complements in production, thus labor-augmenting technical change is land-biased and land-augmenting technical change is labor-biased.

Hicks-neutral technical change

An increase in A_a generates a reallocation of labor from manufacturing to agriculture, that is $\frac{\partial L_a^{eq}}{\partial A_a} > 0$ and $\frac{\partial L_m^{eq}}{\partial A_a} < 0$. To see why this is the case, note that, in equlibrium, the marginal product of labor in agriculture is given by international prices and manufacturing productivity, thus it must stay constant when A_a increases. However, the increase in agricultural productivity rises the marginal product of labor in agriculture because $\frac{\partial MPL_a}{\partial A_a} > 0$. Thus, employment in agriculture must increase to reduce the marginal product of labor to its equilibrium level, because $\frac{\partial MPL_a}{\partial L_a} < 0$ (see Appendix A for a proof).

Land-augmenting technical change (labor-biased)

An increase in A_T generates a reallocation of labor from manufacturing to agriculture, that is $\frac{\partial L_a^{eq}}{\partial A_T} > 0$ and $\frac{\partial L_m^{eq}}{\partial A_T} < 0$. To see why this is the case, note that the land-augmenting technical change rises the marginal product of labor in agriculture because $\frac{\partial MPL_a}{\partial A_T} > 0$ as long as $\sigma < 1$ (see Appendix A for a proof). Thus, employment in agriculture must increase to bring the marginal product of labor back to its equilibrium level, because $\frac{\partial MPL_a}{\partial L_a} < 0$.

Labor-augmenting technical change (land-biased)

A. Strongly labor saving

If land and labor are strong complements in production, that is, the elasticity of substitution, σ, satisfies the condition stated in equation (3), labor-augmenting technical change is not only land-biased but also strongly labor-saving. In this case, an increase in A_L generates a reallocation of labor from agriculture to manufacturing, that is $\frac{\partial L_a^{eq}}{\partial A_L} < 0$ and $\frac{\partial L_m^{eq}}{\partial A_L} > 0$. This is because technical change induces a reduction in the marginal product of labor in agriculture, that is $\frac{\partial MPL_a}{\partial A_L} < 0$. However, in equlibrium, the marginal product of labor in agriculture is given by international prices and manufacturing productivity, thus it must stay constant when A_L changes. Thus, as $\frac{\partial MPL_a}{\partial L_a} < 0$, employment in agriculture must fall to bring the marginal product of labor back to its equilibrium level.

B. *Weakly labor saving*

If the elasticity of substitution, σ, is smaller than one but does not satisfy the condition stated in equation (3), labor-augmenting technical change is land-biased but not strongly labor-saving. Thus, an increase in A_L generates a reallocation of labor from manufacturing to agricluture, that is $\frac{\partial L_a^{eq}}{\partial A_L} > 0$ and $\frac{\partial L_m^{eq}}{\partial A_L} < 0$. This is because technical change induces an increase in the marginal product of labor in agriculture, that is $\frac{\partial MPL_a}{\partial A_L} > 0$. Thus, agricultural employment must increase to bring the marginal product of labor back to its equilibrium level.

3.4 Empirical Predictions

The model predicts that, in a small open economy, a Hicks-neutral increase in agricultural productivity induces a reduction in the size of the industrial sector as labor reallocates towards agriculture, as in Matsuyama (1992). Similar results are obtained when technical change is labor-biased. However, if technical change is strongly labor-saving, labor demand in agriculture falls and workers reallocate towards manufacturing. In sum, the model predicts that the effects of agricultural productivity on structural transformation in open economies depend on the factor-bias of technical change.

In the following section, we test the predictions of the model by studying the simultaneous expansion of two new agricultural technologies: GE soy and second-harvest maize. In the case of soy, the advantage of GE seeds relative to traditional ones is that they are herbicide resistant, which reduces the need to plow the land. As a result, this new technology requires less labor per unit of land to yield the same output and can be characterized as labor-augmenting technical change. As discussed above, the effect of labor-augmenting technical change on structural transformation depends on the elasticity of substitution between land and labor in the agricultural production function. In the case where land and labor are strong complements, then technical change is expected to reduce the labor intensity of agricultural production and employment in agriculture as labor reallocates towards manufacturing. Thus, in this case, we expect that the adoption of GE soy reduces the labor intensity of agricultural production and reallocates labor from agriculture towards manufacturing. Note, however, that if the complementarity between land and labor is not strong enough, we obtain the opposite prediction: the labor intensity of agricultural production increases and labor reallocates towards agriculture. In the case of maize, farmers started introducing a second harvesting season, which requires the use of advanced cultivation techniques and inputs. Second-harvest maize (*milho safrinha*) permits to grow two crops a year, effectively increasing the land endowment. In the case where land and labor are complements in production, land-augmenting technical change can be characterized as labor-biased. Thus, we expect that the adoption of second-harvest maize increases the labor intensity of agricultural production and reallocates labor from manufacturing towards agriculture.

4 Data

In this paper we use three main data sources: the Agricultural Census for data on agriculture, the Population Census for data on the sectoral composition of employment and wages, and the FAO Global Agro-Ecological Zones database for potential yields of soy and maize. To perform robustness checks we also use manufacturing plant-level data from the Brazilian Yearly Industrial Survey (PIA).[18]

The Agricultural Census is released at intervals of 10 years by the *Instituto Brasileiro de Geografia e Estatística* (IBGE), the Brazilian National Statistical Office. We use data from the last

[18]In this section we briefly discuss the main data sources and variables of interest. For detailed variable definition and data sources please refer to Appendix B.

two rounds of the census that have been carried out in 1996 and in 2006. This allows us to observe agricultural variables both before and after the introduction of genetically engineered soybean seeds, which were commercially released in the U.S. in 1996 and legalized in Brazil in 2003. The census data is collected through direct interviews with the managers of each agricultural establishment and is made available online by the IBGE aggregated at municipality level. The main variables we use from the Census are: the value of agricultural production, the number of agricultural workers and the area devoted to agriculture in each municipality. Out of the area devoted to agriculture in each municipality we are able to distinguish the area devoted to each crop in a given Census year. This allows us to monitor how land use has changed between 1996 and 2006.

Data on the sectoral composition of the economy and average wages is constructed using the Brazilian Population Census. The Census is carried out every 10 years and it covers the entire Brazilian population. We use data from the last two rounds of the census (2000 and 2010) so that we can observe the variables of interest both before and after the legalization of the new technology.[19] Data on the sector of employment is collected both in 2000 and 2010 through a special survey that is administered to a sample of around 11% of the Brazilian population (*questionário da amostra*). The sample is selected to be representative of the Brazilian population within narrow cells defined by geographical district, sex, age and urban or rural situation. The variables we focus on are the sector in which the person was working during the previous week and its wage. [20] For each municipality, we compute the employment share in manufacturing as the number of people working in CNAE sectors from 15 to 37 divided by the total number of people employed in that municipality.

Our third source of data is the Global Agro-Ecological Zones database produced by the FAO, which provides data on potential yields for soy and maize. Potential yields are the maximum yields attainable for a crop in a certain geographical area. They depend on the climate and soil conditions of that geographical area, and the level of technology available. The FAO-GAEZ database provides estimates of potential yields under different theoretical levels of technology. We focus on the two extreme levels of technological inputs used in production: *low* and *high*. When the level of technology is assumed to be *low*, agriculture is not mechanized, it uses traditional cultivars and does not use nutrients or chemicals for pest and weed control. When the level of technology is *high* instead, production is fully mechanized, it uses improved or high yielding varieties and "optimum" application of nutrients and chemical pest, disease and weed control. The database reports potential yields for each crop under low and high technological levels for a worldwide grid at a resolution of

[19] To perform some of the robustness checks we also use the 1991 Population Census.

[20] The sector classification is comparable across the census of 2000 and 2010 and it is the CNAE Domiciliar 1.0. The broader categories of CNAE Domiciliar 1.0 follow the structure of the ISIC classification version 3.1.

9.25 × 9.25 km. Figures 8 and 9 show the potential yields for soybean in Brazil under, respectively, low and high technology. Figure 10 and 11 show the correspondent maps for maize.

In order to match the potential yields data with agriculture and industry variables we superimposed each of the potential yields' maps with political maps of Brazil reporting the boundaries of either municipality or micro-regions (a larger administrative unit of observation that encompass several municipalities). Next, we compute the average potential yield of all cells falling within the boundaries of every geographical unit. We repeated this operation for both soy and maize and for each of the two levels of technology. Our measure of technical change in soy or maize production within each municipality is obtained as the potential yield under high technology minus the potential yield under low technology. Figure 12 illustrates the resulting measure of technical change in soy at the municipality level, while Figure 13 shows the same measure at the micro-region level.

Finally, in order to perform some robustness checks, we use data from the *Pesquisa Industrial Anual* (PIA), the Yearly Industrial Survey carried out by the IBGE. This survey monitors the performance of Brazilian firms in the extractive and manufacturing sectors. We focus on the manufacturing sector as defined by CNAE 1.0 (sectors 15 to 37).[21] We use yearly data from 1996 to 2006. The population of firms eligible for the survey is composed by all firms with more than 5 employees registered in the national firm registry (CEMPRE, Cadastro Central de Empresas). The survey is constructed using two strata: the first includes a sample of firms having between 5 and 29 employees (*estrato amostrado*) and it is representative at the sector and state level. The second includes all firms having 30 or more employees (*estrato certo*). We focus on the sample of firms with 30 or more employees which is representative at municipality level. The variables we focus on are: total employment and average wages.

5 Empirics

In this section we study the effects of the adoption of new agricultural technologies on structural transformation in Brazil. For this purpose, we first study the effect of the adoption of GE soy and second season maize on agricultural productivity and the factor intensity of agricultural production. This first step permits to characterize the factor-bias of technical change. Next, we asses the impact of technical change on the allocation of labor across sectors. We start by reporting simple correlations between the expansion of the area planted with soy and maize and agricultural and industrial labor market outcomes. Then, to establish causality, we exploit the timing of adoption and the differential impact of the new technology on potential yields across geographical areas.

[21] The broad category of CNAE 1.0 are identical to the broad categories of CNAE Domiciliar version 1.0 and of the ISIC classification version 1.0.

Note that our empirical strategy relies on the assumption that, although goods can move across geographical areas of Brazil, labor markets are local. This research design allows us to investigate whether exogenous shocks to local agricultural productivity lead to changes in the size of the local industrial sector. Thus, our ideal unit of observation would be a region containing a city and its hinterland with limited migration across regions. In this section we attempt to approximate this ideal using municipalities as our main level of geographical aggregation. Municipalities include both rural and urban areas in the interior of the country, but tend to be mostly urban in more densely populated coastal areas. To address this concern we show that our results are robust to using a larger unit of observation: micro-regions. These are groups of several municipalities created by the 1988 Brazilian Constitution and used for statistical purposes by IBGE. Figures 12 and 13 contain maps of Brazil displaying both levels of aggregation.

5.1 Basic Correlations in the Data

We start by documenting how the expansion of soy and maize cultivation during the 1996-2006 period relates to changes in agricultural production and industrial employment. In section 5.1.1 we present a set of OLS estimates of equations relating agricultural outcomes to the percentage of farm land cultivated with soy and maize. In section 5.1.2 we present a second set of OLS estimates of equations relating manufacturing outcomes to the percentage of farm land cultivated with soy and maize. These basic correlations in the data attempt to answer the following question: did areas where soy expanded experience faster structural transformation? Note that these correlations are not informative about the causal relation between these variables. In section (5.2) we present an empirical strategy that attempts to establish the direction of causality.

The basic form of the equations to be estimated in this section is:

$$y_{jt} = \alpha_j + \alpha_t + \beta \left(\frac{\text{Soy Area}}{\text{Agricultural Area}} \right)_{jt} + \gamma \left(\frac{\text{Maize Area}}{\text{Agricultural Area}} \right)_{jt} + \varepsilon_{jt} \tag{7}$$

where y_{jt} is an outcome that varies across municipalities and time, j indexes municipalities, t indexes time, α_j are municipality fixed effects, α_t are time fixed effects, $\frac{\text{Soy (Maize) Area}}{\text{Agricultural Area}}$ is the total area reaped with soy (maize) divided by total farm land.[22,23] Our source for agricultural variables is the Agricultural Census, thus we observe them for the years 1996 and 2006. Because fixed effects and first difference estimates are identical when considering only two periods, we estimate (7) in

[22]Total farm land includes areas devoted to crop cultivation (both permanent and seasonal crops), animal breeding and logging.

[23]Borders of municipalities often change, thus, to make them comparable across time, IBGE has defined *Área Mínima Comparável* (AMC), smallest comparable areas, which we use as our unit of observation.

first differences:

$$\Delta y_j = \Delta\alpha + \beta\ \Delta \left(\frac{\text{Soy Area}}{\text{Agricultural Area}} \right)_j + \gamma\ \Delta \left(\frac{\text{Maize Area}}{\text{Agricultural Area}} \right)_j + \Delta\varepsilon_j \tag{8}$$

5.1.1 Agricultural Outcomes: Productivity, Labor Intensity and Employment Share

Table 4 reports OLS estimates of equation 8 for three agricultural outcomes. The first is labor productivity, measured as the value of output per worker in farms whose main activity is seasonal crops.[24,25] The second is labor intensity, measured as the number of workers per unit of land in agriculture. The third outcome is the employment share of agriculture, which attempts to capture the extent of structural transformation.[26]

The first column of Table 4 shows that in areas where soy and maize cultivation expanded, the value of agricultural production per worker increased. Column 2 shows that labor intensity in agriculture decreased in areas where soy cultivation expanded. In contrast, labor intensity increased in areas where maize expanded. This evidence is consistent with our characterization of technical change in soy as land-biased and technical change in maize as labor-biased. The estimated coefficient on the effect of the expansion of soy cultivation in labor intensity implies that a municipality experiencing a one standard deviation increase in the area cultivated with soy, had a decrease in agricultural labor intensity of 4% of a standard deviation.[27]

To illustrate the magnitude of our estimate, we perform a simple calculation that measures how much of the aggregate decrease in agricultural employment can be explained by the increase in the area planted with soy. The estimate reported in column 2 implies that the change in area devoted to soy cultivation as a share of total agricultural area can explain 20% of the aggregate reduction in agricultural employment in Brazil between the years 1996 and 2006, which amounted to roughly 1.3 million workers.[28] Maize expansion is instead positively correlated with agricultural

[24] Both soy and maize are seasonal crops.

[25] This is the most precise measure of labor productivity that can be obtained using the publicly available municipality-level data. This is because employment is not reported at individual level but at farm-level.

[26] The share of workers employed in agriculture is defined as total number of workers in agriculture divided by total number of workers in all sectors. This variable is obtained from the Population Census and its first difference is computed between the years 2000 and 2010.

[27] Note that the share of soy area on agricultural area is constructed using as a denominator the sum of the areas devoted to all agricultural activities including seasonal and permanent crops, cattle ranching and forest. A one standard deviation increase in this share corresponds to roughly 3,500 more hectares of agricultural land cultivated with soy.

[28] To obtain this number we first multiply the average change in soy area share between the years 1996 and 2006 by the estimated coefficient reported in column 2. Then we multiply this number by the initial average level of agricultural labor intensity in 1996, obtaining the percentage decrease in agricultural labor intensity due to an increase in soy area share in the average municipality. Finally we multiply this number by the average level of agricultural land in a municipality in 1996, finding an average reduction of 66 agricultural workers per municipality that is attributable to soy expansion. Multiplying this number by the number of municipalities used to estimate our coefficient we obtain that soy expansion can explain a reduction of around 260,000 agricultural workers across Brazil between the years

labor intensity. The estimated coefficient on the effect of the expansion of maize cultivation in labor intensity implies that a municipality experiencing a 1 standard deviation increase in the area cultivated with maize, had an increase in agricultural labor intensity of around 10% of a standard deviation.

Finally, column 3 shows that the employment share of agriculture decreased in places where soy expanded. In contrast, the employment share of agriculture increased in areas where maize expanded, although this change is not statistically significant.

5.1.2 Manufacturing Outcomes: Employment Share, Total Employment and Wages

We now turn to the question of whether manufacturing employment expanded (contracted) in areas where soy (maize) expanded. Table 5 reports OLS estimates of equation 8 for three manufacturing outcomes: manufacturing employment share, the level of employment in manufacturing, and the average wage in the manufacturing sector.

Note that the timing of Population and Agricultural Censi do not coincide, thus our estimation of equation (8) relates changes in manufacturing outcomes between 2000 and 2010 to changes in the area planted with soy and maize between 1996 and 2006. In both cases the initial year precedes the timing of legalization of soybean seeds in Brazil (2003), as well as the first date in which smuggling of GE soy seeds was documented (2001).

The first column of Table 5 shows that municipalities where soy expanded experienced a faster increase in the employment share in manufacturing. In contrast, this share remained unchanged in municipalities where maize expanded. The estimated coefficient on the effect of the expansion of soy cultivation in manufacturing employment share implies that a municipality experiencing a 1 standard deviation increase in the area cultivated with soy had an increase in the manufacturing employment share of 7% of a standard deviation. Interestingly, in areas where soy expanded, not only the share but also the level of manufacturing employment increased, as shown in column 2.

To illustrate the magnitude of our estimate, we perform a simple calculation that measures how much of the aggregate increase in manufacturing employment can be explained by the expansion in the area planted with soy. The estimate reported in column 2 implies that the change in area devoted to soy cultivation as a share of total agricultural area can explain 6% of the aggregate increase in manufacturing employment in Brazil between the years 2000 and 2010, which amounted to roughly 1.6 million workers in the sample used to estimate our coefficient.[29] The last column

1996 and 2006.

[29] To obtain this number we first multiply the average change in soy area share between the years 1996 and 2006 by the estimated coefficient reported in column 2. Then we multiply this number by the initial average level of manufacturing employment across municipalities in 1996, finding an average increase of around 24 manufacturing workers per

of Table 5 reports estimated coefficients of the correlation between the expansion in soy and maize area and wages in manufacturing, which are both not statistically different from zero.

The finding that manufacturing employment increased in areas where soy expanded suggests that soy technical change is not only land-biased but also strongly labor-saving. In this case, our model predicts that technology adoption reduces labor demand in agriculture inducing a reallocation of labor towards manufacturing.

5.2 The Effect of Agricultural Technological Change on Structural Transformation

In this section we provide direct empirical evidence on the causal effects of the widespread adoption of new agricultural technologies on industrial development in Brazil. The basic correlations in the data reported in the previous section show that areas where soy expanded experienced an increase in output per worker and a reduction in labor intensity in agriculture while industrial employment expanded. However, these correlations are not informative about the direction of causality. Indeed, these findings could reflect the two following different sequences of events. First, the adoption of strongly labour saving agricultural technologies reduces labor demand in the agricultural sector and induces a reallocation of labor towards the industrial sector. Second, productivity growth in the industrial sector increases labor demand and wages, inducing agricultural firms to switch to less labor-intensive crops, like soy. To establish the direction of causality we exploit the timing of adoption and the differential impact of the new technology on potential yields across geographical areas.

First, we discuss the timing of adoption. GE soy seeds were patented in the U.S. in 1996, and legalized in Brazil in 2003. Given that GE seeds were developed in the U.S., their date of invention, 1996, is exogenous with respect to developments in the Brazilian economy. In contrast, the date of legalization, 2003, responded partly to pressure from Brazilian farmers. In addition, smuggling of GE soy seeds across the border with Argentina is reported since 2001. Thus, in our empirical analysis we will compare outcomes before and after 1996 whenever possible.[30] The cultivation techniques necessary to introduce the second harvest maize, instead, were developed within Brazil. Thus, the timing of its expansion can not be considered exogenous to other developments in the Brazilian economy. Nevertheless, since the diffusion of this new technology across space depends

municipality that is attributable to soy expansion. Multiplying this number by the number of municipalities used to estimate our coefficient we obtain that soy expansion can explain an increase of around 92,000 manufacturing workers across Brazil between the years 1996 and 2006.

[30]For some data sources we will compare outcomes before and after 2001 or 2003, due to data availability constraints. In those cases, however, the potential effect of smuggling can only bias downward our estimates.

on exogenous local soil and weather characteristics, we think it is reasonable to argue that this diffusion is exogenous to developments in the local industrial sector.

Second, these new technologies have a differential impact on potential yields depending on soil and weather characteristics. Thus, we exploit these exogenous differences on potential yields across geographical areas as our source of cross-sectional variation in the intensity of the treatment.

To implement this strategy, we need an exogenous measure of potential yields for soy and maize, which we obtain from the FAO-GAEZ database. These potential yields are estimated by FAO using an agricultural model that predicts yields for each crop given climate and soil conditions. As potential yields are a function of weather and soil characteristics, not of actual yields in Brazil, they can be used as a source of exogenous variation in agricultural productivity across geographical areas. Crucially for our analysis, the database reports potential yields under different technologies or input combinations. Yields under low inputs are described as those obtained using traditional seeds and no use of chemicals, while yields under high inputs are obtained using high yielding varieties and optimum application of fertilizers and herbicides. Thus, the difference in yields between the high and low technology captures the effect of moving from traditional agriculture to a technology that uses optimum weed control, among other characteristics.[31] We expect this increase in yields to be a good predictor of the profitability of adopting herbicide resistant GE soy seeds.

More formally, our basic empirical strategy consists in estimating the following equation:

$$y_{jt} = \alpha_j + \alpha_t + \beta \ A_{jt}^{soy} + \varepsilon_{jt} \tag{9}$$

where y_{jt} is an outcome that varies across municipalities and time, j indexes municipalities, t indexes time, α_j are municipality fixed effects, α_t are time fixed effects and A_{jt}^{soy} is equal to the potential soy yield under high inputs from 2003 onwards and to the potential soy yield under low inputs in the years before 2003. A_{jt}^{soy} can be thought of as the empirical counterpart of the labor augmenting technical change A_L presented in our model.

In the case of maize, we follow a similar strategy. As noted in Section 2, the cultivation of second harvest maize requires the use of modern techniques that are intensive in the use of fertilizers, herbicides and tractors. Thus, we expect that the the difference in FAO-GAEZ potential yields

[31] The description of each technology in the FAO-GAEZ dataset documentation is as follows. Low-level inputs/traditional management: "Under the low input, traditional management assumption, the farming system is largely subsistence based and not necessarily market oriented. Production is based on the use of traditional cultivars (if improved cultivars are used, they are treated in the same way as local cultivars), labor intensive techniques, and no application of nutrients, no use of chemicals for pest and disease control and minimum conservation measures." High-level inputs/advanced management: "Under the high input, advanced management assumption, the farming system is mainly market oriented. Commercial production is a management objective. Production is based on improved high yielding varieties, is fully mechanized with low labor intensity and uses optimum applications of nutrients and chemical pest, disease and weed control."

between the high and low technology captures the profitability of planting second season maize. Thus, we augment the equation described above to include the following variable: A_{jt}^{maize} which is equal to the potential maize yield under high inputs from 2003 onwards and to the potential maize yield under low inputs in the years before 2003. A_{jt}^{maize} can be thought of as the empirical counterpart of the land augmenting technical change A_T presented in our model.

$$y_{jt} = \alpha_j + \alpha_t + \beta A_{jt}^{soy} + \gamma A_{jt}^{maize} + \varepsilon_{jt} \ . \tag{10}$$

In the following subsections we report the results of using our measure of technical change to explain changes in agricultural production and in the sectoral composition of the economy. Section 5.2.1 reports the relationship between our measure of technical change and the expansion of soy and maize cultivation. Section 5.2.2 shows the relationship between this measure and other agricultural outcomes. Finally, section 5.2.3 presents results using manufacturing outcomes.

5.2.1 Agricultural Outcomes: Soy and Maize Expansion

In this section we document the relationship between technical change measured by the increase in the FAO-GAEZ potential yield of soy and maize, and the actual change in agricultural area cultivated with each crop. The objective of this exercise is to check whether the change in potential yields is a good proxy of the profitability of the adoption of new agricultural technologies. If this is the case, we expect the increase in the potential yield of a given crop to predict the actual expansion in the area cultivated with that crop between 1996 and 2006. With this purpose, we estimate a first-difference version of equation 10:

$$\Delta y_j = \Delta\alpha + \beta\Delta A_j^{soy} + \gamma\Delta A_j^{maize} + \Delta\varepsilon_j \tag{11}$$

where the outcome of interest, Δy_j is the change in share of farm land reaped with either soy or maize between 1996 and 2006, and A_j^{soy} is potential yield of soy under high inputs minus potential yields of soy under low inputs (A_j^{soy} is its equivalent for maize).

Column 1 in Table 6 shows that the increase in potential soy yield predicts the expansion in soy area as a share of agricultural area between 1996 and 2006. Column 2 shows that this estimate is robust to controlling for the increase in potential maize yield. The size of the estimated coefficient reported in column 3 implies that a one standard deviation increase in potential soy yield corresponds to an increase in the share of soy in agricultural land of almost 30% of a standard deviation. Notice also that the estimated effect of the increase in potential maize yield on the expansion of soy area is negative and statistically significant.

Similarly, the estimates reported in column 3 imply that the increase in potential maize yield predicts the expansion in maize area as a share of agricultural area between 1996 and 2006. Column 4 shows that this estimate is robust to controlling for the increase in potential soy yield, which in turn has a negative effect on the expansion of maize area as a share of agricultural area. The size of the estimated coefficient implies that a one standard deviation increase in potential maize yield corresponds to an increase in the share of maize in agricultural area of 14% of a standard deviation.

The fact that our measure of technical change correctly predicts the expansion or retrenchment of specific crops suggests that it captures the benefits of adoption of new agricultural technologies. Taken together, the results reported in Table 6 suggest that technical change measured as the increase in a crop potential yield had large effects on land allocation.

Next, we investigate whether the expansion in soy area is driven by the adoption of GE soy. For this purpose, we check whether our measure of technical change in soy predicts actual adoption of GE seeds.[32] In principle, we expect that areas with a higher increase in FAO-GAEZ potential soy yields are those switching to genetically engineered soy on a larger scale. Column 1 of Table 7 shows that this is indeed the case. The size of the estimated coefficient implies that a one standard deviation increase in potential soy yield corresponds to an increase in GE soy area as a share of agricultural area of 25% of a standard deviation. In column 2 we perform a falsification test, by looking at the correlation between the change in potential soy yield and the expansion in non-GE soy area. In this case, the coefficient is negative and significant. This finding suggests that the change in potential soy yield correctly captures the benefits of adopting GE soy vis-à-vis traditional soy seeds.

5.2.2 Agricultural Outcomes: Productivity, Labor Intensity and Employment Share

In this section we study the effect of agricultural technical change on production and employment in agriculture. Table 8 reports the results of estimating equation (11) where the dependent variables are three agricultural outcomes: the value of agricultural production per worker in seasonal crops, labor intensity, and the share of workers employed in agriculture, all defined as in section 5.1.1.

The estimated coefficients reported in column 1 of Table 8 indicate that in areas where the potential soy yield increased relatively more, the value of agricultural production per worker increased. The size of the estimated coefficient implies that a one standard deviation increase in potential soy yield corresponds to an increase in the value of agricultural production per worker of 7% of a standard deviation. On the other hand, an increase in potential maize yield seems

[32] Unfortunately, we can not perform the same test for maize given that the publicly available Agricultural Census data does not contain information on the season of planting of maize at the municipality level.

negatively associated with the value of agricultural production per worker, but this effect is not statistically significant.

The estimated coefficients reported in column 2 indicate that in areas where potential soy yield increased relatively more, agricultural labor intensity decreased. The size of the coefficient implies that a one standard deviation increase in potential soy yield corresponds to a decrease in the ratio of workers per unit of land in agriculture of 5% of a standard deviation. In contrast, the estimated coefficient of the increase in potential maize yield is positive and significant, indicating that in areas where potential maize yield increased relatively more agricultural labor intensity increased. The size of the coefficient implies that a one standard deviation increase in potential maize yield corresponds to an increase in agricultural labor intensity of 8% of a standard deviation. Notice that the effects of potential soy and maize yields on labor intensity in agriculture are consistent with the correlations presented in section 5.1.1.

Finally, the estimated coefficients reported in column 3 suggest that an increase in the potential soy yield have no statistically significant effect on agricultural employment share. Note that these results contrast with the simple correlations in the data reported in section 5.1.1, according to which areas where soy expanded experienced a reduction in the employment share in agriculture. This inconsistency might respond to two causes. First, potential soy yields are estimated, thus they might not correctly capture the benefits of GE soy adoption. Second, the agricultural employment share is measured with error in the Population Census. Individuals interviewed for the Brazilian Population Census are classified in different sectors depending on the occupation they report in the week preceding the interview. This is a potential problem when measuring employment, especially in agriculture, where employment is more seasonal than in other sectors.

Taken together, the results presented in Table 8 suggest that the introduction of new agricultural technologies in Brazil had a sizable impact in agricultural labor markets. Areas where the potential impact of GE soy adoption was higher experienced an increase in the value of agricultural production per worker and a reduction in the number of workers per unit of land. These findings are consistent with our characterization of the adoption of GE soy as a land-biased technical change. In the case of maize, areas where the potential impact of the introduction of a second harvesting season was higher experienced an increase in the number of workers per unit of land. This result is also consistent with our characterization of the introduction of a second harvesting season as labor-biased technical change.

5.2.3 Manufacturing Outcomes: Employment Share, Employment and Wages

In this section we study the effect of agricultural technical change on manufacturing employment and wages. Table 9 reports the results of estimating equation (11) where the dependent variables are three manufacturing outcomes: the employment share of manufacturing, the level of manufacturing employment, and the average wage in manufacturing as defined in section 5.1.2.

The estimates reported in column 1 indicate that areas where potential soy yield increased relatively more, experienced a larger increase in the employment share of manufacturing. The size of the estimated coefficient implies that a one standard deviation increase in potential soy yield corresponds to an increase in manufacturing employment share of 30% of a standard deviation. On the other hand, areas with higher increase in potential maize yield experienced a larger decrease in the manufacturing employment share. . The size of the estimated coefficient implies that a one standard deviation increase in potential maize yield corresponds to a decrease in manufacturing employment share of 12% of a standard deviation.

When looking at the level of manufacturing employment instead of its share in total employment we find very similar results. The estimates reported in column 2 suggest that areas where potential soy yield increased relatively more, experienced a larger increase in the level of manufacturing employment. The estimated coefficient implies that a one standard deviation increase in potential soy yield corresponds to an increase in the level of manufacturing employment of 34% of a standard deviation. Again, we observe the opposite result for the potential maize yield: areas with higher increase in potential maize yield experienced a larger decrease in the level of manufacturing employment. The size of the estimated coefficient is such that one standard deviation increase in potential maize yield corresponds to a decrease in the level of manufacturing employment of almost 20% of a standard deviation.

Finally, we study the effect of potential soy and maize yields on manufacturing wages. The results reported in column 3 indicate that areas where potential soy yields increased relatively more, experienced a larger decrease in average manufacturing wages. The estimated coefficient implies that a one standard deviation increase in potential soy yields corresponds to a decrease in average manufacturing wages of 16% of a standard deviation. An increase in potential maize yield has the opposite effect on manufacturing wages: in areas where potential maize yield increased relatively more, average manufacturing wages also increased (15% of a standard deviation for a one standard deviation increase in potential maize yield).

Taken together, the estimates reported in this section are consistent with the empirical predictions of our model. They show that the effects of agricultural productivity on the industrial sector depend on the factor bias of technical change. In the case of soy, our estimates indicate that strongly labor saving technologies (like GE seeds), by reducing the demand for labor in agriculture, promote the growth of the manufacturing sector through an increase in labor supply and lower wages. On the other hand, in the case of maize, our estimates show that land-augmenting technical change (like the introduction of a second harvesting season), by increasing the labor intensity of agriculture, result in a decrease of manufacturing employment and increasing wages.

6 Robustness Checks

6.1 Robustness to Using a Larger Unit of Observation: Micro-Regions

In the empirical analysis performed so far we assumed that municipalities are the best approximation of the relevant labor market faced by Brazilian agricultural workers. A potential issue is that local labor market boundaries do not overlap with a municipality's administrative boundaries. In particular, some municipalities might be too small to properly capture labor flows between urban and rural areas, provided manufacturing activities take place in the former, and agricultural activities in the latter. In order to take into account this concern we aggregate our data at a larger unit of observation: the micro-regions. Table 10 and 11 show that the results reported in Tables 5 and 9 are robust to using the 557 micro-regions for which data are available as units of observation.

6.2 Falsification Test: Checking for Pre-Existing Trends

In this section we address the possibility that our results are driven by pre-existing trends. If municipalities with the largest increase in potential soy and maize yields were already experiencing faster structural transformation before 2000, the results shown in the previous section may not be caused entirely by the technical changes introduced by GE soy seeds and the second harvesting season in maize.

Table 12 reports the results of our falsification test. We replicate the estimation of equation 11 as reported in Table 9 but using differences in manufacturing outcomes between 1991 and 2000 instead of between 2000 and 2010. We perform this test for manufacturing employment and average manufacturing wages but not for the manufacturing employment share on total employment that we are unable to measure consistently across the 1991 and 2000 censi due to a change in the definition of employment introduced by the IBGE after the 1991 Census.[33]

[33]Between the 1991 and 2000 censi the Brazilian Statistical Institute (IBGE) changed its definition of employment in two important ways. First, it started to count zero-income workers as employed. In order to homogenize the Brazilian Census with international practices, the IBGE started to consider employed anyone who helped another household member with no formal compensation, as well as agricultural workers that produced only for their own

Table 12 shows that that our measures of technical change in agriculture do not explain variation in manufacturing employment or wages before 2000. The estimated coefficients on potential soy and maize yields are not statistically different from zero. The only exception is the estimated coefficient of potential maize yield on wages in column 2, which is positive and marginally significant.[34] This falsification test validates our interpretation that the effect of our measures of technical change on structural transformation is due to the introduction of new agricultural technologies rather than to pre-existing trends in the areas that were mostly affected by these new technologies.

6.3 Robustness to Controlling for Commodity Prices

Another potential concern is that our results might be driven by the evolution of commodity prices, soy and maize in particular, and not by technical change. For example, an increase in the price of soy could induce an expansion in the area planted with this crop and generate income spent on manufacturing goods produced in the same area. The evolution of international prices for soy and maize is depicted in Figures 14 and 15. Both soy and maize prices are relatively stable in the period 1996-2006, and they both start growing from 2007. Thus, throughout the period of analysis for agricultural variables (1996-2006) prices were relatively stable. Still, the period of analysis of manufacturing variables (2000-2010) includes these years of high prices. This is in principle problematic because, although international commodity prices should affect all Brazilian municipalities at the same time, they might still have heterogeneous effects in places that are more suitable to the cultivation of a particular crop.

To address this concern, we use an alternative source of data on manufacturing employment that, unlike the Population Census, has a yearly frequency. This permits to both exclude the years where prices are high from the analysis and fully control for yearly prices.

The source of these data is the yearly industry survey (PIA), which covers the universe of firms

consumption (IBGE, 2003; p. 218). Zero-income workers are more common in agriculture than in other sectors, and in 1991 were only partially included in the labor force. In the 1991 Census 15% of agricultural workers reported zero income, against 34% in 2000 and 35% in 2010 (the corresponding numbers for people employed in fishery are 3% in 1991, 22% in 2000 and 28% in 2010). Second, the IBGE changed the reference period for considering a person employed: while in 1991 such period included the last 12 months, in 2000 it only included the reference week of the Census. This new rule implied that workers performing temporary and seasonal activities that were not employed during the reference week were counted in the 1991 census but not the in the 2000 census. The IBGE felt that inquiring into temporary employment entailed too many additional questions, and that smaller surveys would be more suitable to deal with the matter (IBGE, 2003; p. 218). Also this second change is likely to be especially problematic for the agricultural sector, also considering that the reference week in the 2000 Census was in the middle of the Brazilian winter. This is why, to test for pre-existing trends, we focus on the absolute number of workers employed in manufacturing as an outcome (instead of its share in total employment). This measure is less likely to be affected by the changes introduced between the two censi, because: (1) there are virtually no zero-income workers in manufacturing (only 0.5%, 1.9% and 1% of manufacturing workers declare zero income in 1991, 2000 and 2010, respectively) and (2) manufacturing is less seasonal than other sectors.

[34] This could reflect the fact that a second harvesting season for maize was introduced in several areas of Brazil already before 2000.

with at least 30 employees in Brazil and it is therefore, for this class of firms, representative at municipality level. We focus on two variables from this survey: total manufacturing employment and average wage.[35]

We estimate an equation of the following form:

$$y_{jt} = \alpha_j + \alpha_t + \beta A_{jt}^{soy} + \gamma A_{jt}^{maize} + \sum_z \theta_z P_t^z A_{j0}^z + \varepsilon_{jt} \tag{12}$$

where y_{jt} is total employment or average wage in a given municipality; A_{jt}^{soy} is equal to the potential soy yield under low inputs for all years before 2003 and to the potential soy yield under high inputs starting from 2003 (same criteria is used to define A_{jt}^{maize}). We observe all years from 1996 to 2006 and control for the prices of soy and maize multiplied by the potential yield under low inputs of these crops. In all specifications we control for both municipality and year fixed effects (α_j and α_t) and cluster standard errors at the municipality level to address potential serial correlation in the error term (Bertrand, et al., 2004).

The results obtained using data from the industrial survey are consistent with those obtained using the Population Census data (see Table 9): areas where potential soy yields increased relatively more, experienced a larger increase in manufacturing employment and a larger decrease in average manufacturing wages. To compare the magnitude of the estimated coefficients with those obtained using the Population Census data we calculate how much of the change in manufacturing employment and wages between the years 1996 and 2006 can be explained by the change in potential soy and maize yields in the same years. The estimated coefficients in column 2 and 4 imply that a one standard deviation increase in potential soy yield corresponds to an increase in manufacturing employment of 6% of a standard deviation and a decrease in average manufacturing wages of 6% of a standard deviation. An increase in potential maize yield has instead the opposite effect when the outcome is the average manufacturing wage (6.5% of a standard deviation for a one standard deviation increase in potential maize yield) while its effect is negative but not statistically significant when the outcome is total manufacturing employment.[36]

[35] The average wage is defined as the aggregate wage bill (in real terms) divided by the total number of workers employed in a municipality.

[36] The fact that these effects are quantitatively smaller with respect to those obtained with the Population Census can be attributed to the following reasons: (1) the yearly industrial survey, differently from the Population Census, does not cover informal employment (2) the changes in manufacturing employment and wages in the Population Census are calculated between the years 2000 and 2010, while in the industrial survey they are calculated between the years 1996 and 2006 (i.e. this data covers a shorter period after the introduction of the new technology), (3) the industrial survey tends to over represent larger firms that are more likely to hire high skilled workers with respect to low skilled workers, and are therefore less likely to be hiring former agricultural workers.

7 Final Remarks

The process of modern economic growth is accompanied by structural transformation, i.e. the reallocation of economic activity from agriculture to industry. Identifying the forces behind structural transformation is therefore key to our understanding of economic development. Based on the experience of England during the industrial revolution, economists have argued that increases in agricultural productivity is one important force behind structural transformation. However, as underlined by Matsuyama (1992), in open economies a comparative advantage in agriculture could instead slow down industrial growth. Despite the importance of the question, there is so far scarce evidence on the channels through which agricultural productivity can shape the reallocation of economic activity across sectors in an open economy.

In this paper we argue that the effect of agricultural productivity on industrial development depends crucially on the factor-bias of technical change. In particular, predictions of models of structural transformation in open economies hold when technical change is hicks neutral or labor-biased, but are reversed when land-biased technical change is strongly labor saving.

We provide direct empirical evidence on these mechanisms by isolating the effects of adoption of two new agricultural technologies in Brazil: genetically engineered soybean seeds and a second harvesting season for maize. We argue that the first technical change is land-biased, while the second is labor-biased, and exploit this setup to study the effect of the diffusion of these agricultural technologies on the manufacturing sector. To identify the causal effects of this new technology, we exploit the timing of adoption and the differential impact of the new technologies on potential yields across geographical areas.

We find that in municipalities where the new technology had a larger potential impact on soy yields, there was faster GE soy adoption, a reduction of labor intensity in agriculture and an expansion of manufacturing employment. In contrast, in municipalities where the new technology had a larger potential impact on maize yields, there was an increase of labor intensity in agriculture and a contraction of manufacturing employment. These different effects documented for soy and maize indicate that the factor bias of technical change is a key factor in the relationship between agricultural productivity and industrial growth in open economies.

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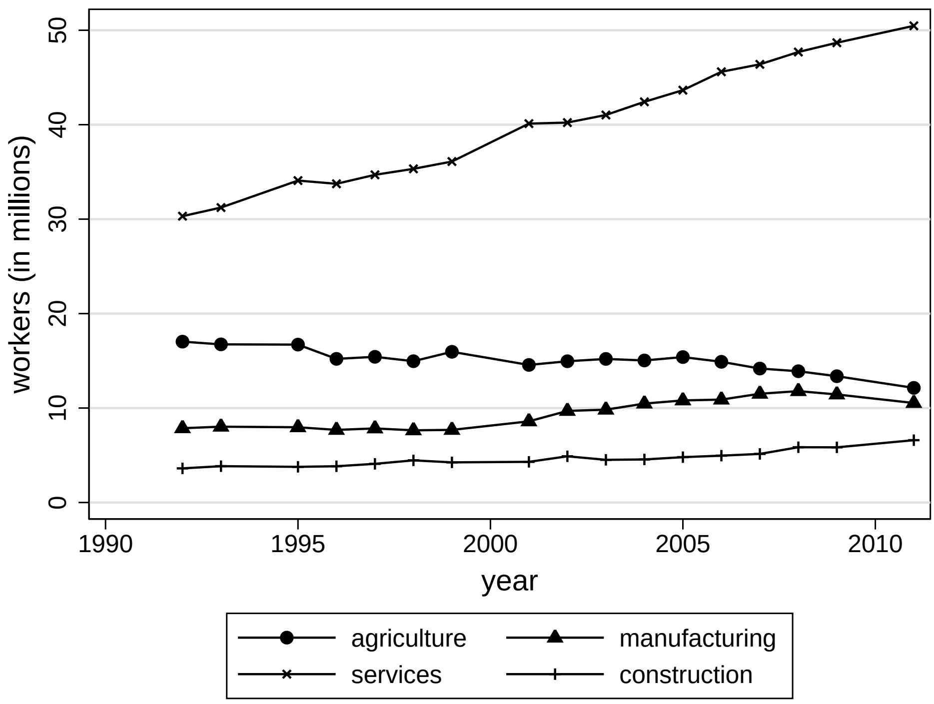
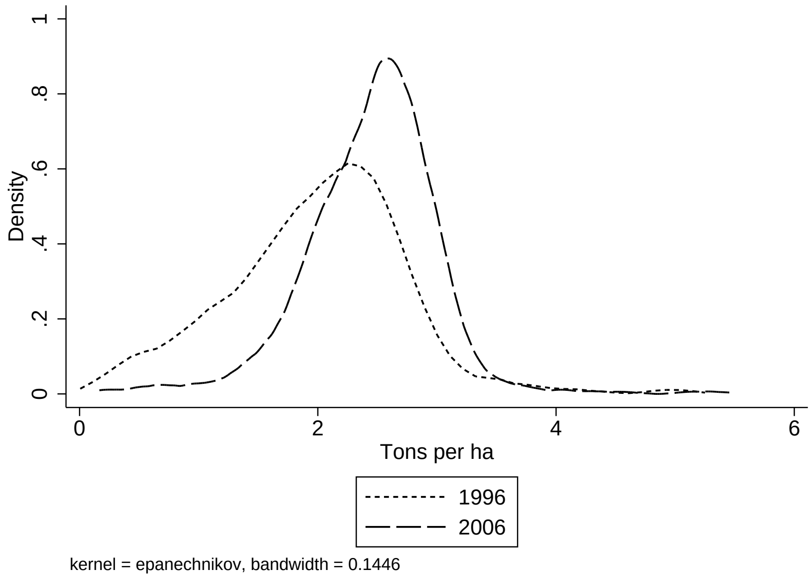
Figures and Tables

Figure 1
Employment in agriculture, industry, services and construction (1992-2011)



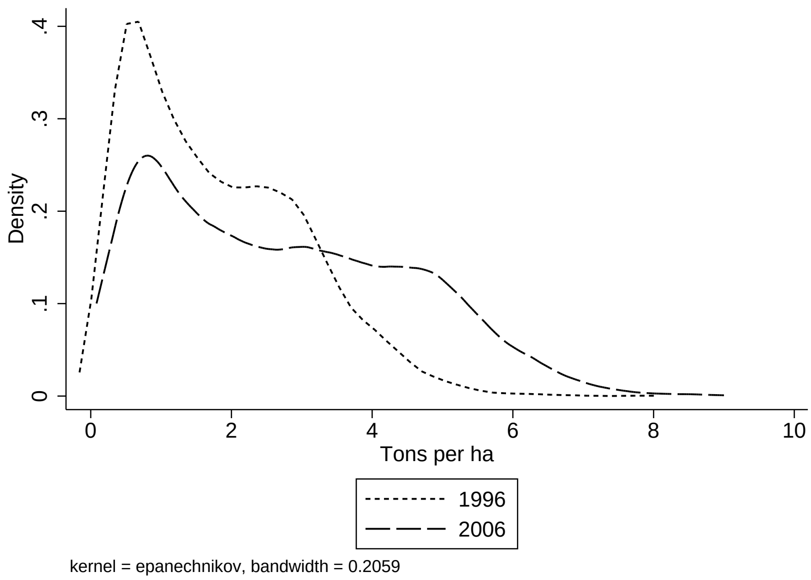
Notes: The Figure shows the evolution between 1992 and 2011 of the total number of workers (expressed in million) employed by sector in Brazil. The sectors are: Agriculture (codes A and B in the CNAE-Domiciliar classification), Industry (code D), Services (codes: G, H, I, J, K, L, M, N, O, P, Q, E) and Construction (code: F). Workers in the Extractive Industry (code C) are not included in any of the categories above. Data is from PNAD, a national household survey representative at country level carried out yearly by the IBGE (the survey was not carried out in 1994 and in the census years: 1991, 2000 and 2010). Since the PNAD coverage changed over time, to harmonize the sample across years we exclude: (i) workers located in the states of: Rondonia, Acre, Amazonas, Roraima, Pará and Amapá (North macro-region) because only urban areas (and not rural areas) of these states were covered until 2004; (ii) workers located in the states of: Tocantins, Mato Grosso do Sul, Goias and the Distrito Federal because the sample of households in these states is not complete in the years from 1992 to 1997.

Figure 2
Distribution of soy yields across municipalities (1996-2006)



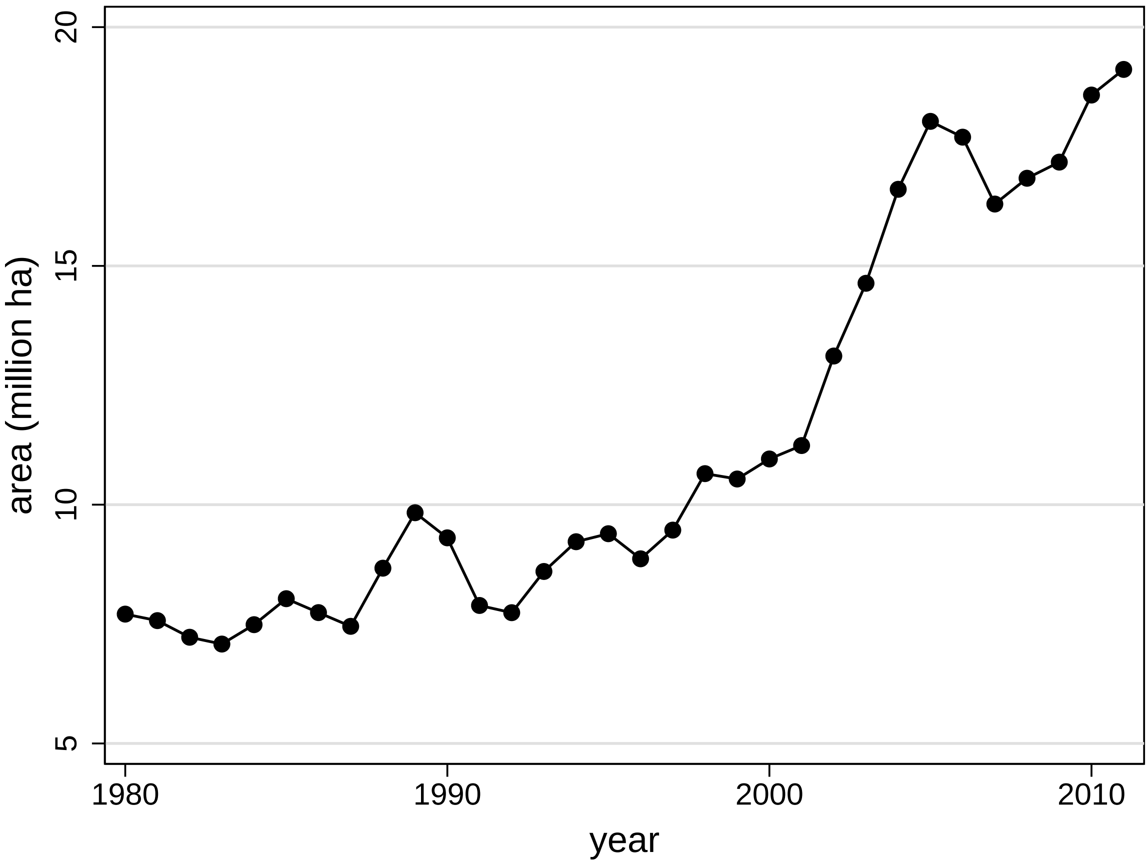
Notes: Data sources are the Brazilian Agricultural Censi of 1996 and 2006, IBGE.

Figure 3
Distribution of maize yields across municipalities (1996-2006)



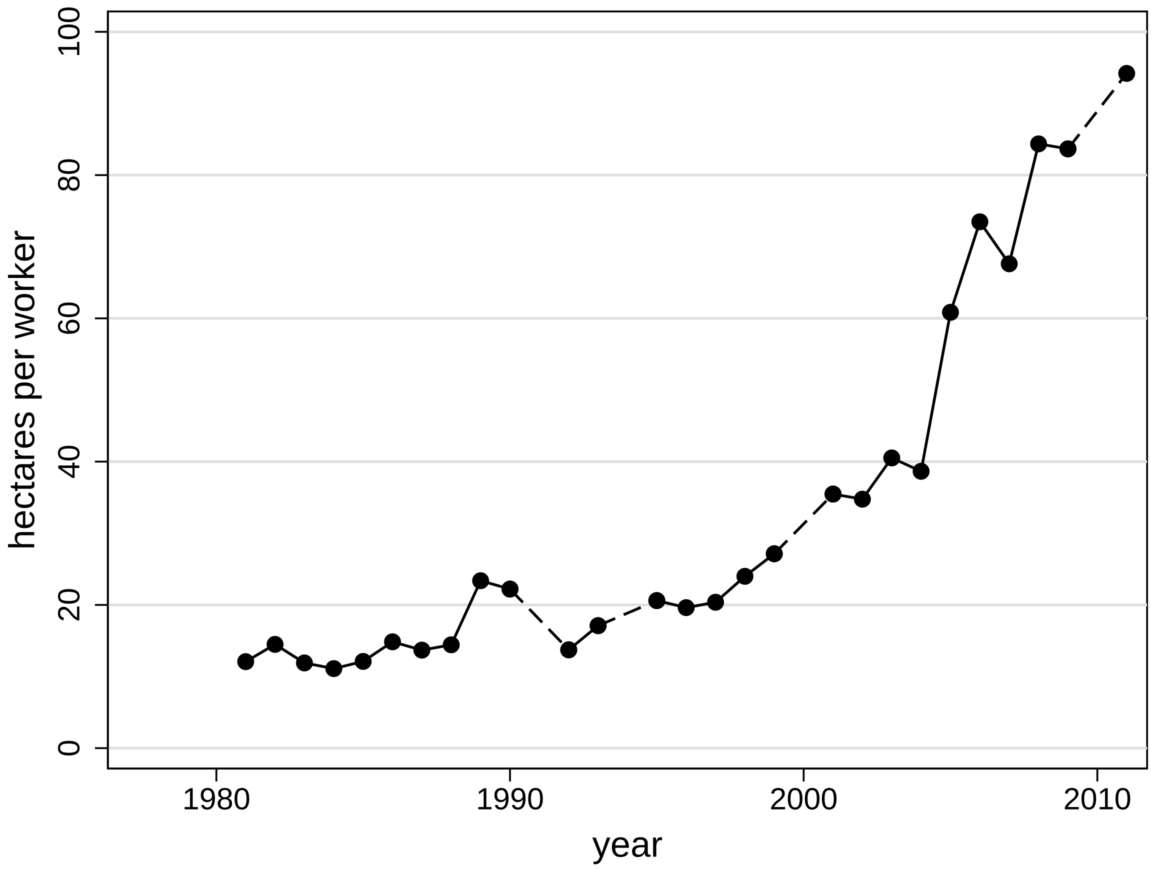
Notes: Data sources are the Brazilian Agricultural Censi of 1996 and 2006, IBGE.

Figure 4
Area planted with soy (1980-2011)



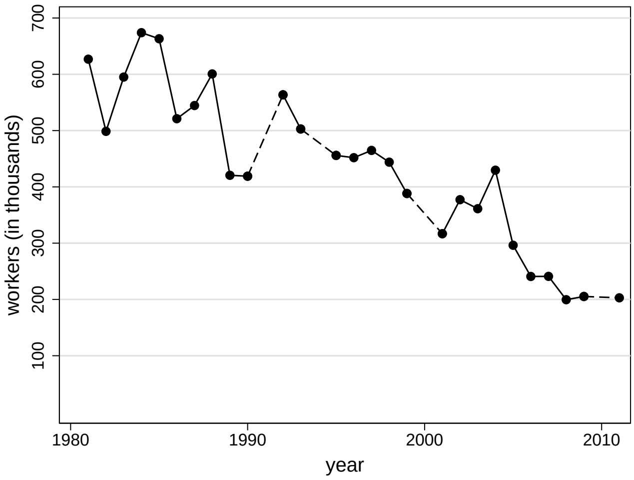
Notes: The Figure depicts the evolution between 1980 and 2011 of the total area planted with soy in Brazil (expressed in million hectares). Data sources are monthly surveys carried out by CONAB, Companhia Nacional de Abastecimento, an agency created by the Brazilian Ministry of Agriculture. Data is constructed by interviewing on the ground farmers, agronomists and financial agents in the main cities of the country.

Figure 5
Area planted per worker in soy production (1980-2011)



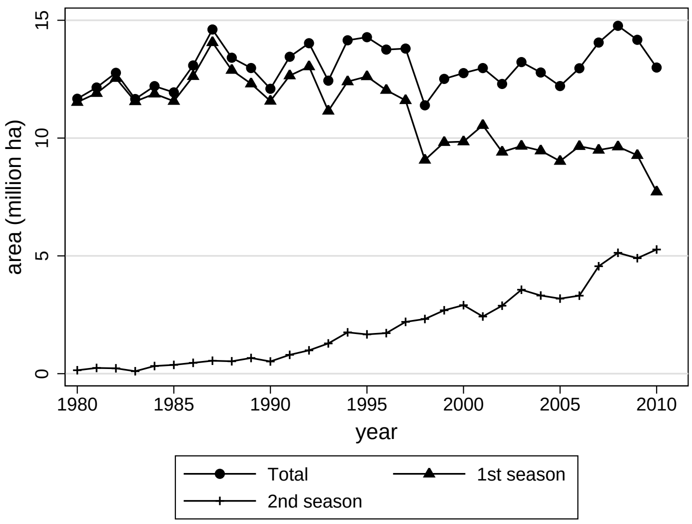
Notes: The Figure depicts the evolution between 1980 and 2011 of the area planted with soy divided by the total number of workers employed in soy production in Brazil. Data sources are CONAB for area planted with soy and PNAD for the total number of workers in soy production. CONAB, Companhia Nacional de Abastecimento, is an agency created by the Brazilian Ministry of Agriculture. Data is constructed by interviewing on the ground farmers, agronomists and financial agents in the main cities of the country. PNAD is a national household survey representative at country level carried out yearly by the IBGE (the survey was not carried out in 1994 and in the census years: 1991, 2000 and 2010). Since the PNAD coverage changed over time, to harmonize the sample across years we exclude: (i) workers located in the states of: Rondonia, Acre, Amazonas, Roraima, Pará and Amapá (North macro-region) because only urban areas (and not rural areas) of these states were covered until 2004; (ii) workers located in the states of: Tocantins, Mato Grosso do Sul, Goias and the Distrito Federal because the sample of households in these states is not complete in the years from 1992 to 1997. We harmonized data from CONAB with the PNAD coverage such data numerator and denominator are constructed using the same subset of states.

Figure 6
Employment in soy production (1980-2011)



Notes: The Figure depicts the evolution between 1980 and 2011 of the total number of workers employed in soy production (expressed in thousands) in Brazil. Data source is PNAD, see the Note under Figure 1 for a detailed description.

Figure 7
Area planted with maize (1980-2010)



Notes: The Figure depicts the evolution between 1980 and 2010 of the area planted with maize in Brazil (expressed in million hectares). The series show the total area planted with maize as well as the breakdown by the season of harvest (1st or 2nd season). Data sources are monthly surveys carried out by CONAB, Companhia Nacional de Abastecimento, an agency created by the Brazilian Ministry of Agriculture.

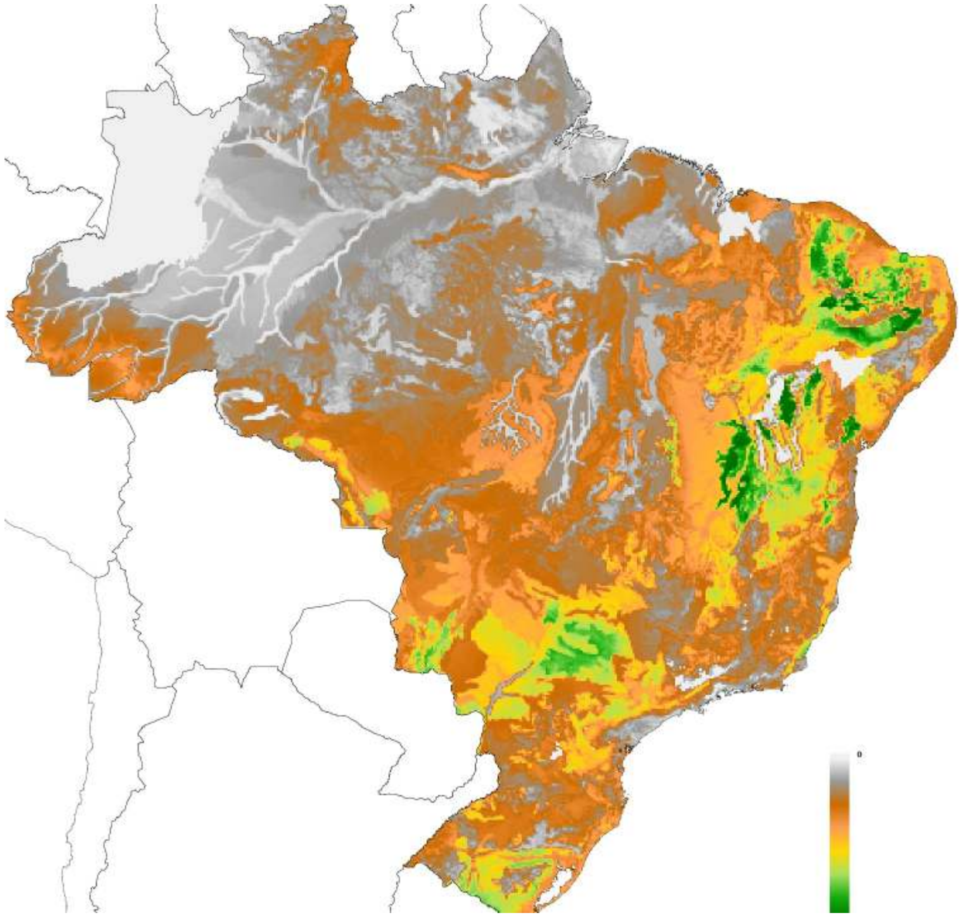


Figure 8

Potential soy yield under low agricultural technology

Notes: Data source is FAO-GAEZ.

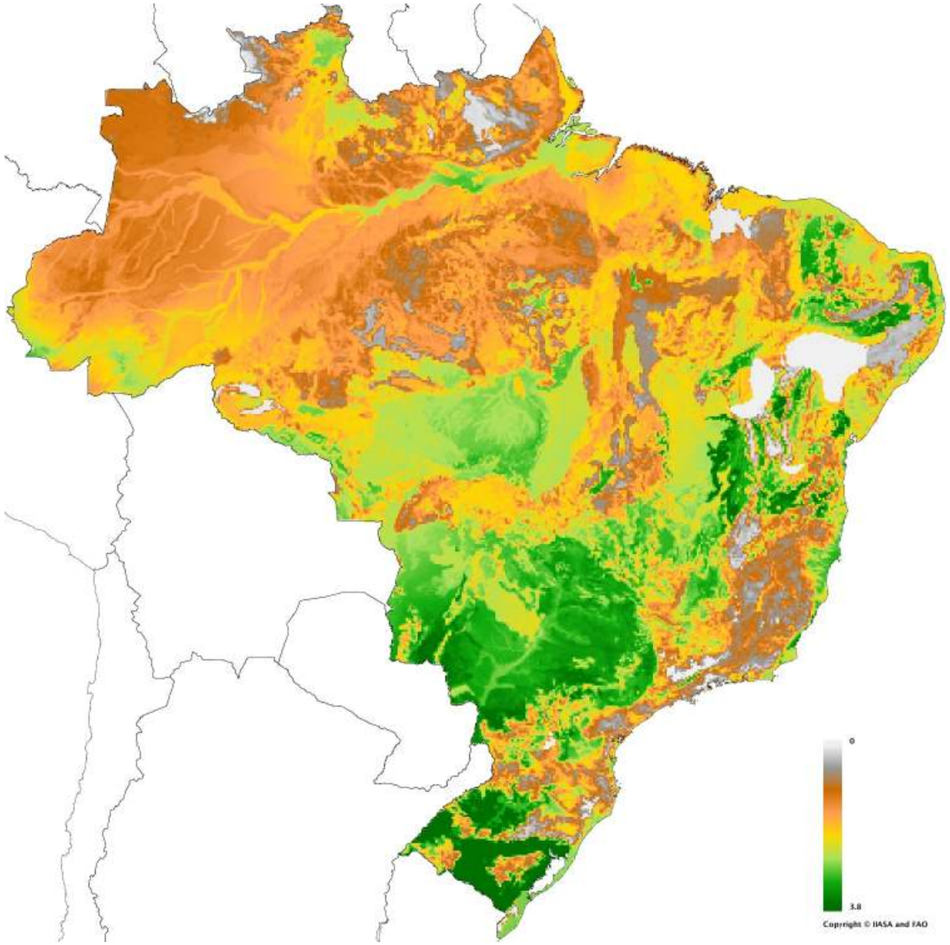


Figure 9

Potential soy yield under high agricultural technology

Notes: Data source is FAO-GAEZ.

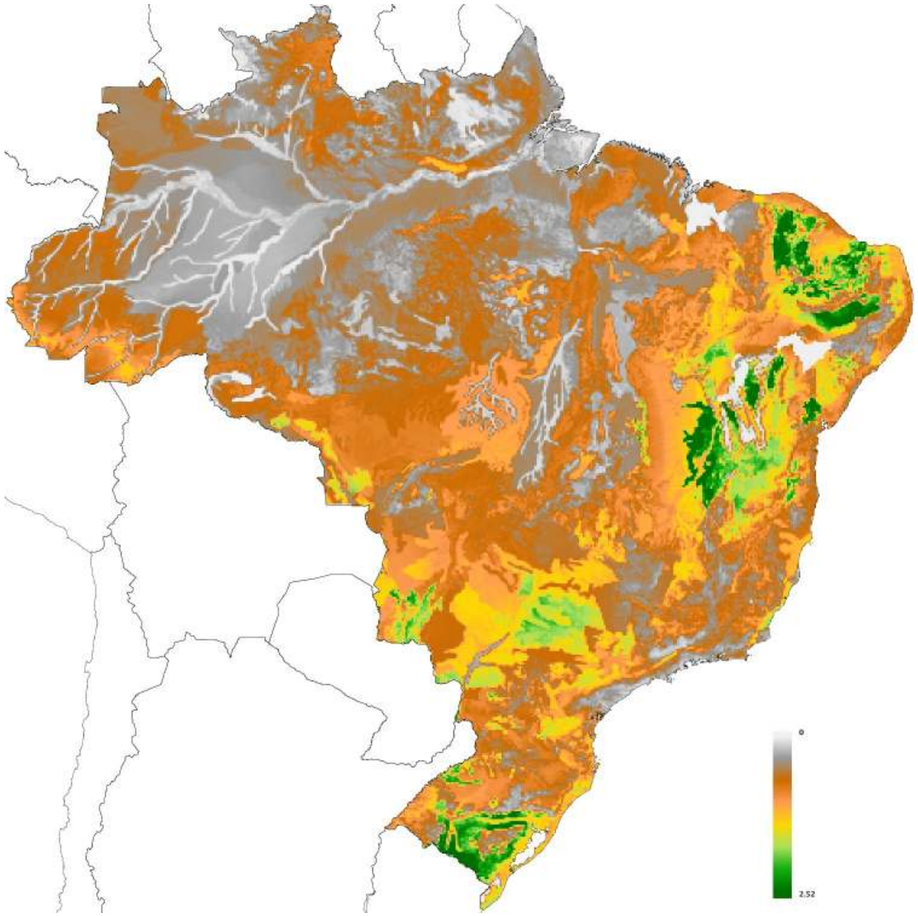


Figure 10

Potential maize yield under low agricultural technology

Notes: Data source is FAO-GAEZ.

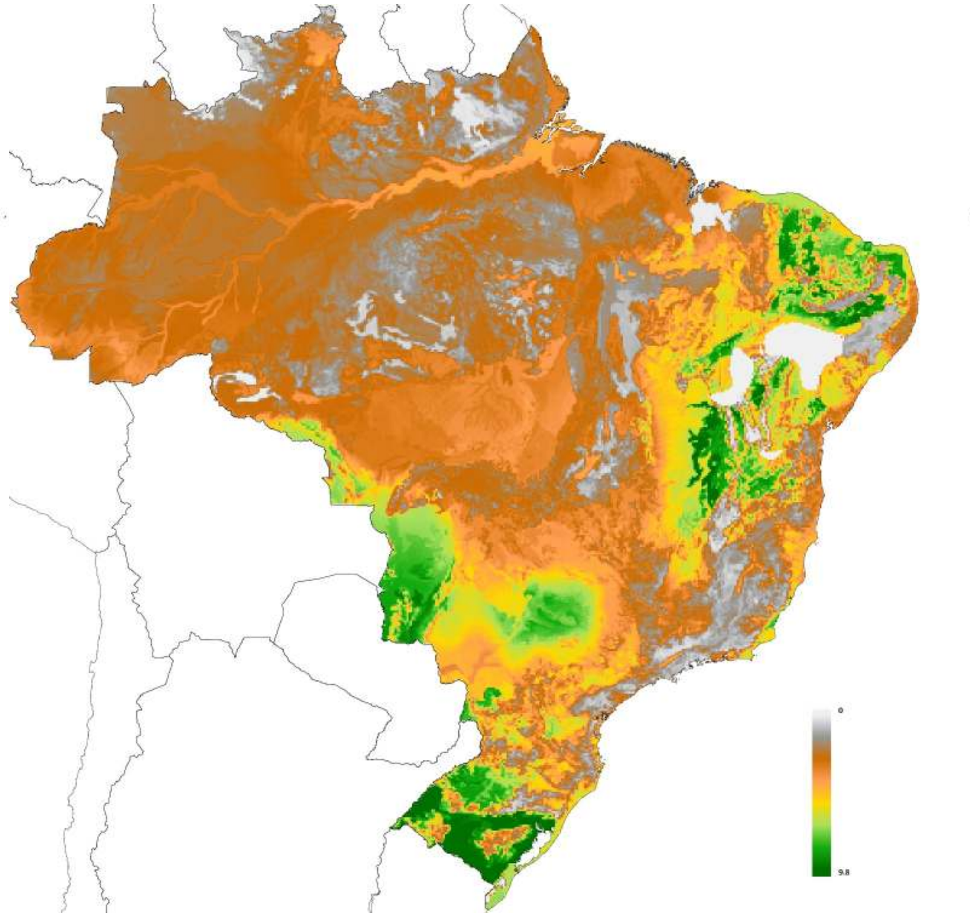


Figure 11

Potential maize yield under high agricultural technology

Notes: Data source is FAO-GAEZ.

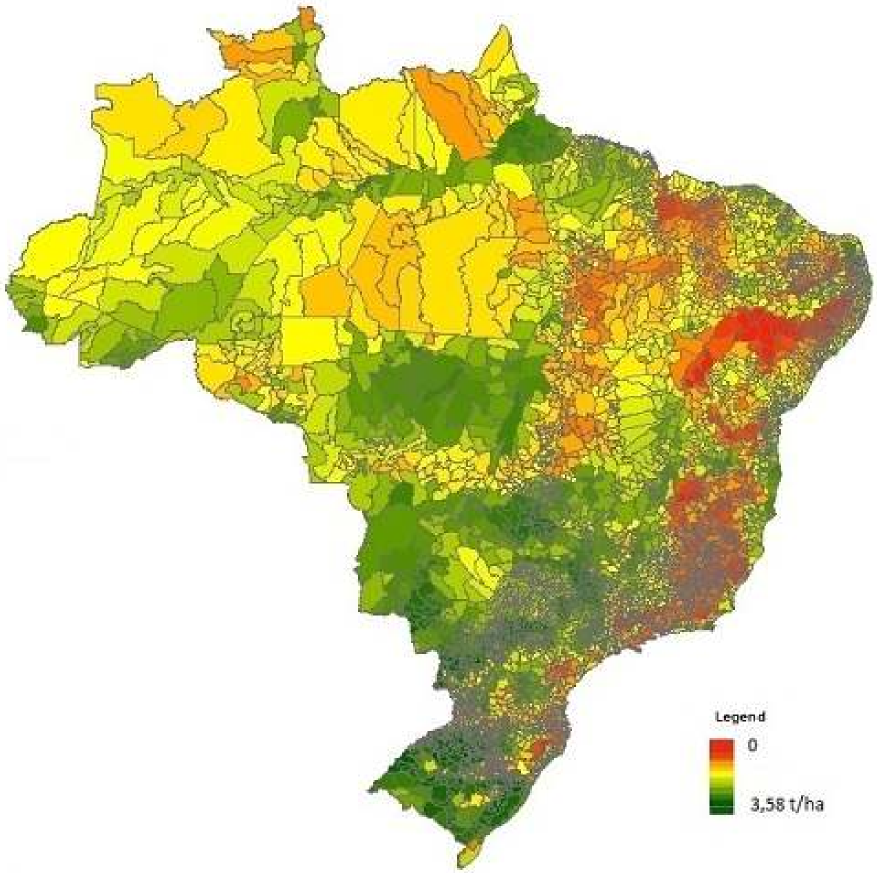


Figure 12
Technological change in soy
Potential yield under high technology minus potential yield under low technology
Municipalities

Notes: Authors' calculations from FAO-GAEZ data.

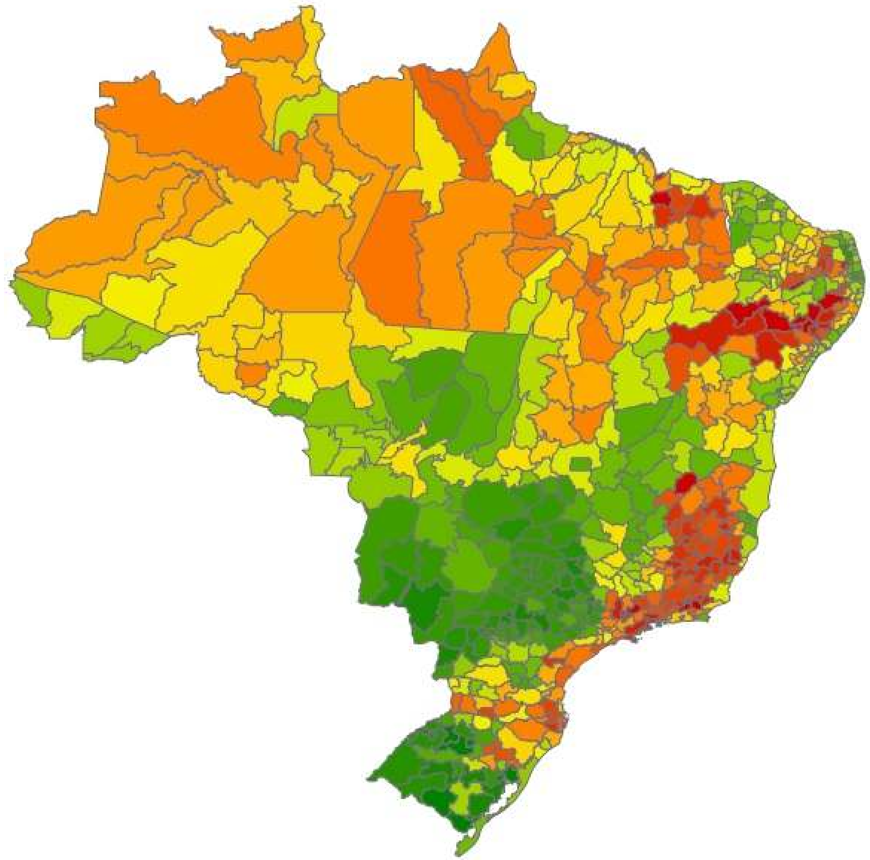
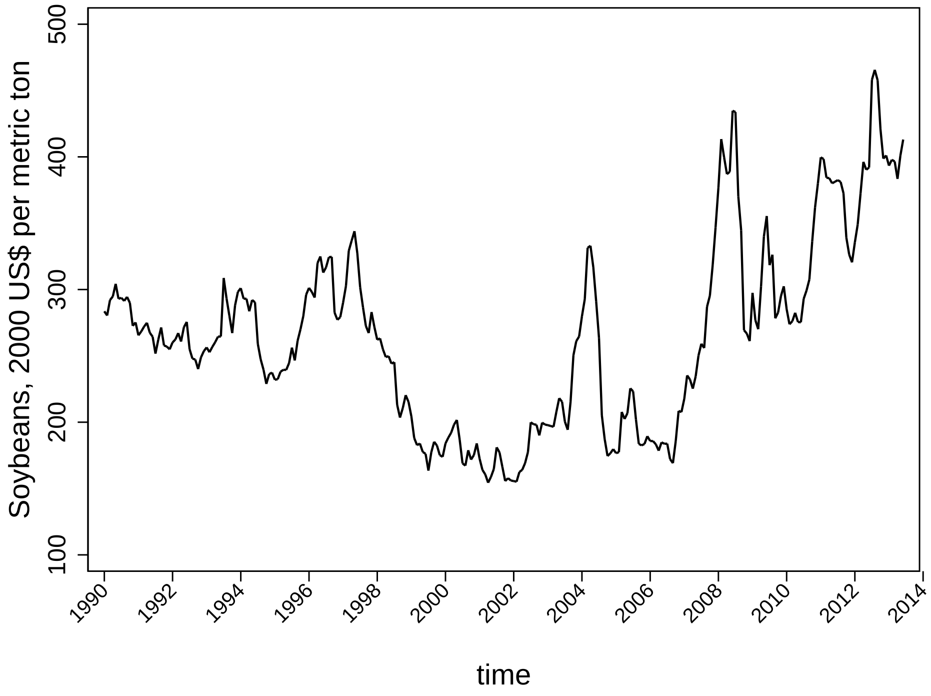


Figure 13
Technological change in soy
Potential yield under high technology minus potential yield under low technology
Micro-regions

Notes: Authors' calculations from FAO-GAEZ data.



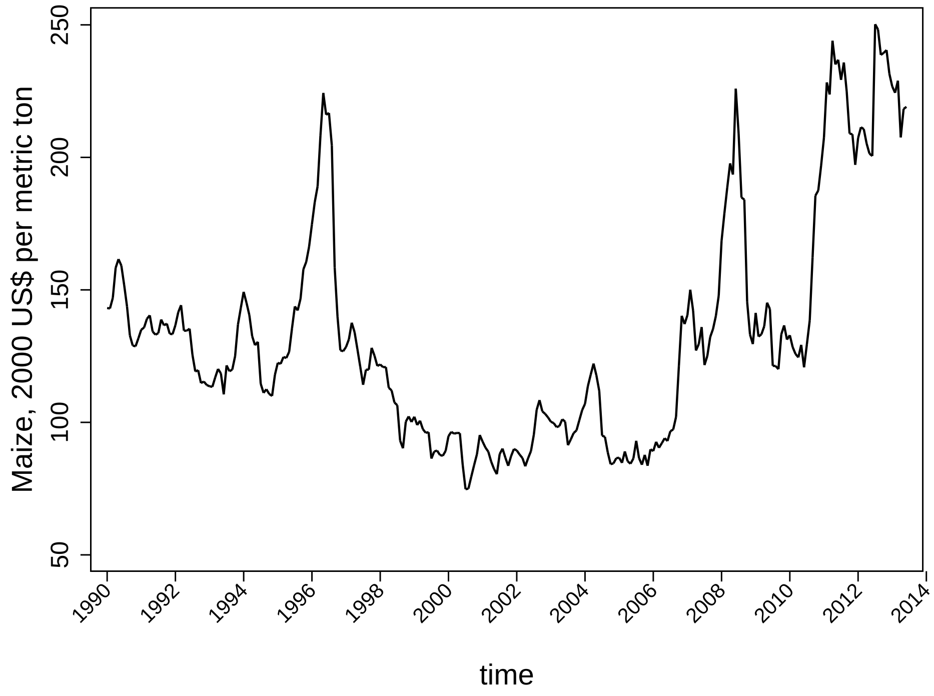


Figure 14
Evolution of soy price (1990-2013)

Notes: The Figure shows the monthly evolution of soy real price between 1990 and 2013. Data are from the IMF Primary Commodity Prices database, series code: *PSOYB_USD*, expressed in nominal US$ per metric ton. We deflate the series using the US *Consumer Price Index for All Urban Consumers: All Items*, source: Federal Reserve St. Louis, series code: *CPIAUCNS*, rescaled so that 2000 is the base year.

Figure 15
Evolution of maize price (1990-2013)

Notes: The Figure shows the monthly evolution of maize real price between 1990 and 2013. Data are from the IMF Primary Commodity Prices database, series code: *PMAIZMT_US*, expressed in nominal US$ per metric ton. We deflate the series using the US *Consumer Price Index for All Urban Consumers: All Items*, source: Federal Reserve St. Louis, series code: *CPIAUCNS*, rescaled so that 2000 is the base year.

Table 1
Land use (million ha)

	1996	2006	Change	% change
Permanent crops	7.5	11.7	4.1	55%
Seasonal crops	34.3	44.6	10.4	30%
Cattle ranching	177.7	168.3	-9.4	-5%
Forest	110.7	91.4	-19.2	-17%
Not usable	15.2	8.2	-6.9	-46%
Other	8.3	9.0	0.7	8%
Total	353.6	333.2	-20.4	-6%

Notes: The Table reports the total land use in Brazil (expressed in million hectares). Data is available for 1996 and 2006 and come from the last two Brazilian Agricultural Censi carried out by the Brazilian National Statistical Institute and it is sourced from the the IBGE Sidra repository (table 317 for 1996 and table 1011 for 2006). Seasonal crops include (among others) cereals (e.g. maize, wheat and rice), soybean, cotton, sugar cane and tobacco. Permanent crops include (among others) coffee and cocoa. Not usable land includes lakes and areas that are not suitable for neither crop cultivation nor cattle ranching. Other uses is not exactly comparable across years: in 1996 it includes resting area for seasonal crops; in 2006 it includes area devoted to pasture, flowers and buildings.

Table 2
Labor intensity in Brazilian agriculture (1996-2006)

	Labor intensity		Change in labor intensity	
Principal activity:	1996	2006	Absolute	Relative
Seasonal crops	107.6	83.7	-23.9	-22%
soy	*28.6*	*17.9*	*-10.7*	*-37%*
all cereals	*92.4*	*76.8*	*-15.6*	*-17%*
other	*159.2*	*145.4*	*-13.8*	*-9%*
Permanent crops	126.8	127.4	0.6	0%
Cattle ranching	22.6	30.6	8.1	36%
Forest	33.9	46.1	12.2	36%

Note: The table reports labor intensity in agriculture by principal activity of the farm. Labor intensity is computed as number of workers per 1000 hectares. Data are sourced from the IBGE Sidra repository. Land in farm by principal activity in 1996 comes from table 491 and for 2006 from table 797. Total number of workers in 1996 is reported in table 321 and in 2006 in table 956. Cereals are rice, wheat, maize and other cereals. The definition of "principal activity" of the farm changed somehow between 1996 and 2006. In 1996 higher specialization was required for farms to be classified under one of the categories reported, and those that did not produce at least 2/3 of the value within a single category were classified under the "mixed activity" category. In 2006 farms were classified according to the activity that accounted for the simple majority of production and no "mixed activity" category existed (**?**).

Table 3
Summary statistics of main variables at AMC level

Variable Name	1996		1996-2010 Change		Obs.
	mean	st.dev.	mean	st.dev.	
Log value of agric. production per worker	0.938	1.411	0.853	1.059	4,149
Log labor intensity in agriculture	-2.594	1.054	-0.025	0.556	4,231
Soy area share	0.028	0.099	0.012	0.043	3,920
Maize area share	0.050	0.069	0.008	0.067	4,111
GE soy area share	0.000	0.000	0.013	0.059	3,769

Variable Name	2000		2000-2010 Change		Obs.
	mean	st.dev.	mean	st.dev.	
Employment share in manufacturing	0.098	0.086	0.007	0.052	4,255
Employment share in agriculture	0.405	0.197	-0.066	0.075	4,255
Log employment in manufacturing	6.006	1.597	0.213	0.603	4,249
Log wage in manufacturing	5.753	0.555	0.128	0.426	4,249

Variable Name	Low inputs		High inputs		Difference		Obs.
	mean	st.dev.	mean	st.dev.	mean	st.dev.	
Potential yield in soy	0.301	0.154	2.105	0.936	1.804	0.849	4,255
Potential yield in maize	0.989	0.493	4.047	2.195	3.058	1.811	4,255

Table 4
Basic correlations in the data: agriculture
Productivity, labor intensity and employment share

VARIABLES	(1) Δ Value per worker	(2) Δ Labor intensity	(3) Δ Employment share
Δ Soy area share	2.350***	-0.484***	-0.058**
	(0.297)	(0.154)	(0.027)
Δ Maize area share	2.410***	0.746***	-0.024
	(0.229)	(0.119)	(0.019)
Constant	0.120***	-0.029***	-0.066***
	(0.018)	(0.009)	(0.001)
Observations	3,753	3,805	3,805

Note: The table reports the OLS estimated coefficients of equation 8 in the text. The independent variables are defined as the share of farm land reaped with soy and maize. The dependent variables are reported on top of the respective columns. Value per worker is defined as total value of output in farms whose main activity is seasonal crop cultivation divided by the total number of workers employed by these farms. Labor intensity is the total number of workers employed in agriculture divided by total area in farms. Share of workers employed in agriculture is defined as total number of workers in agriculture divided by total number of workers in all sectors. The source of data for the independent variables and the dependent variables reported in columns 1 and 2 are the agricultural censi of 1996 and 2006. Thus, changes are calculated over the years 1996 and 2006. The source for the employment share reported in column 3 are the population censi of 2000 and 2010. In this case, changes in the dependent variable are calculated over the years 2000 and 2010. The unit of observation are municipalities. Robust standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 5
Basic correlations in the data: manufacturing

Employment share, employment and wages

VARIABLES	(1) Δ Employment share	(2) Δ Employment	(3) Δ Wage
Δ Soy area share	0.084***	0.982***	0.047
	(0.020)	(0.224)	(0.121)
Δ Maize area share	0.005	-0.004	-0.040
	(0.011)	(0.142)	(0.085)
Constant	0.005***	0.195***	0.307***
	(0.001)	(0.010)	(0.006)
Observations	3,805	3,799	3,777

Note: The table reports the OLS estimates of the coefficients in equation 8 in the text. The independent variables are defined as the share of farm land reaped with soy and maize. The dependent variables are reported on top of the respective columns. Employment share in manufacturing is defined as number of people employed in the manufacturing sector (CNAE codes between 15 and 37) divided by total number of people employed in all sectors. Employment in manufacturing is the natural logarithm of people employed in the manufacturing sector. Wage is calculated as the logarithm of the average wage of manufacturing workers in 2000 Reais. The source of data for the independent variables are the agricultural censi of 1996 and 2006. Thus, changes are calculated over the years 1996 and 2006. The source for the dependent variables are the population censi of 2000 and 2010. In this case, changes in the dependent variable are calculated over the years 2000 and 2010. The unit of observation is the AMC. Robust standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 6
The effect of technological change on agriculture
Soy and maize expansion

VARIABLES	(1) Δ Soy area share	(2)	(3) Δ Maize area share	(4)
ΔA^{soy}	0.012***	0.014***		-0.006***
	(0.001)	(0.002)		(0.002)
ΔA^{maize}		-0.002**	0.003***	0.005***
		(0.001)	(0.001)	(0.001)
Constant	-0.009***	-0.009***	-0.000	0.004
	(0.001)	(0.001)	(0.002)	(0.002)
Observations	3,920	3,920	4,111	4,111

Note: The table reports the OLS estimates of the coefficients in equation 11 in the text. Dependent variables – reported on top of the respective columns – are defined as the share of farm land reaped with soy and maize. ΔA^{soy} is defined as potential soy yield under high inputs minus potential soy yield under low inputs. ΔA^{maize} is defined as potential maize yield under high inputs minus potential maize yield under low inputs. The source of data for the dependent variables are the agricultural censi of 1996 and 2006. Thus, changes are calculated over the years 1996 and 2006. The source of data for the independent variables is the FAO-GAEZ v3.0 dataset. The unit of observation is the AMC. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7
The effect of technological change on agriculture
GE soy adoption

VARIABLES	(1) Δ GE soy area share	(2) Δ Non-GE soy area share
ΔA^{soy}	0.017***	-0.007***
	(0.002)	(0.002)
Constant	-0.017***	0.011***
	(0.002)	(0.002)
Observations	3,769	3,769

Note: The table reports the OLS estimates of the coefficients in equation 11 in the text where the dependent variable is defined as the share of farm land reaped with GE soy (column 1) and non-GE soy (column 2). ΔA^{soy} is defined as potential soy yield under high inputs minus potential soy yield under low inputs. The source of data for the independent variables are the agricultural censi of 1996 and 2006. Thus, changes are calculated over the years 1996 and 2006. The source of data for the independent variables is the FAO-GAEZ v3.0 dataset. The unit of observation is the AMC. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8
The effect of technological change on agriculture
Productivity, labor intensity and employment share

	(1)	(2)	(3)
VARIABLES	Δ Value per worker	Δ Labor intensity	Δ Employment share
ΔA^{soy}	0.090***	-0.034**	0.000
	(0.031)	(0.016)	(0.002)
ΔA^{maize}	-0.017	0.024***	-0.001
	(0.015)	(0.008)	(0.001)
Constant	0.045	-0.037*	-0.063***
	(0.037)	(0.019)	(0.003)
Observations	4,149	4,231	4,255

Note: The table reports the OLS estimates of the coefficients in equation 11 in the text. The dependent variables are reported on top of the respective columns. Value per worker is defined as total value of output in farms whose main activity is seasonal crop cultivation divided by the total number of workers employed by these farms. Labor intensity is the total number of workers employed in agriculture divided by total area in farms. Share of workers employed in agriculture is defined as total number of workers in agriculture divided by total number of workers in all sectors. ΔA^{soy} is defined as potential soy yield under high inputs minus potential soy yield under low inputs. ΔA^{maize} is defined as potential maize yield under high inputs minus potential maize yield under low inputs. The source of data for the dependent variables reported in columns 1 and 2 are the agricultural censi of 1996 and 2006. Thus, changes are calculated over the years 1996 and 2006. The source for the employment share reported in column 3 are the population censi of 2000 and 2010. In this case, changes in the dependent variable are calculated over the years 2000 and 2010. The source of data for the independent variables is the FAO-GAEZ v3.0 dataset. The unit of observation is the AMC. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9
The effect of technological change on manufacturing
Employment share, employment and wages

VARIABLES	(1) Δ Employment share	(2) Δ Employment	(3) Δ Wage
ΔA^{soy}	0.018***	0.241***	-0.071***
	(0.002)	(0.016)	(0.012)
ΔA^{maize}	-0.003***	-0.062***	0.030***
	(0.001)	(0.008)	(0.005)
Constant	-0.015***	-0.032	0.339***
	(0.002)	(0.021)	(0.014)
Observations	4,255	4,249	4,226

Note: The table reports the OLS estimates of the coefficients in equation 11 in the text. The dependent variables are reported on top of the respective columns. Employment share in manufacturing is defined as number of people employed in the manufacturing sector (CNAE codes between 15 and 37) divided by total number of people employed in all sectors. Employment in manufacturing is the natural logarithm of people employed in the manufacturing sector. Wage is calculated as the logarithm of the average wage of manufacturing workers in 2000 Reais. ΔA^{soy} is defined as potential soy yield under high inputs minus potential soy yield under low inputs. ΔA^{maize} is defined as potential maize yield under high inputs minus potential maize yield under low inputs. The source for the dependent variables are the population censi of 2000 and 2010. In this case, changes in the dependent variable are calculated over the years 2000 and 2010. The source of data for the independent variables is the FAO-GAEZ v3.0 dataset.The unit of observation is the AMC. Robust standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 10
Basic correlations in the data: manufacturing

Employment share, employment and wages

Robustness of results reported in Table 5 to a larger unit of observation: micro-regions

VARIABLES	(1) Δ Employment share	(2) Δ Employment	(3) Δ Wage
Δ Soy area share	0.093*	0.906**	0.043
	(0.049)	(0.396)	(0.228)
Δ Maize area share	0.038	0.126	0.259
	(0.032)	(0.468)	(0.207)
Constant	-0.003**	0.170***	0.262***
	(0.001)	(0.015)	(0.009)
Observations	557	557	556

Note: The table reports the OLS estimates of the coefficients in equation 8 in the text. The independent variables are defined as the share of farm land reaped with soy and maize. The dependent variables are reported on top of the respective columns. Employment share in manufacturing is defined as number of people employed in the manufacturing sector (CNAE codes between 15 and 37) divided by total number of people employed in all sectors. Employment in manufacturing is the natural logarithm of people employed in the manufacturing sector. Wage is calculated as the logarithm of the average wage of manufacturing workers in 2000 Reais. The source of data for the independent variables are the agricultural censi of 1996 and 2006. Thus, changes are calculated over the years 1996 and 2006. The source for the dependent variables are the population censi of 2000 and 2010. In this case, changes in the dependent variable are calculated over the years 2000 and 2010. The unit of observation is the micro-region. Robust standard errors are reported in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 11
The effect of technological change on manufacturing

Employment share, employment and wages

Robustness of results reported in Table 9 to a larger unit of observation: micro-regions

VARIABLES	(1) Δ Employment share	(2) Δ Employment	(3) Δ Wage
ΔA^{soy}	0.009***	0.171***	-0.092***
	(0.003)	(0.024)	(0.015)
ΔA^{maize}	-0.000	-0.048***	0.042***
	(0.001)	(0.011)	(0.007)
Constant	-0.018***	0.020	0.302***
	(0.003)	(0.032)	(0.020)
Observations	557	557	557

Note: The table reports the OLS estimates of the coefficients in equation 11 in the text. The dependent variables are reported on top of the respective columns. Employment share in manufacturing is defined as number of people employed in the manufacturing sector (CNAE codes between 15 and 37) divided by total number of people employed in all sectors. Employment in manufacturing is the natural logarithm of people employed in the manufacturing sector. Wage is calculated as the logarithm of the average wage of manufacturing workers in 2000 Reais. ΔA^{soy} is defined as potential soy yield under high inputs minus potential soy yield under low inputs. ΔA^{maize} is defined as potential maize yield under high inputs minus potential maize yield under low inputs. The source for the dependent variables are the population censi of 2000 and 2010. In this case, changes in the dependent variable are calculated over the years 2000 and 2010. The source of data for the independent variables is the FAO-GAEZ v3.0 dataset. The unit of observation is the micro-region. Robust standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 12
The effect of technological change on manufacturing

Employment and wages

Falsification test of results reported in Table 9: checking for pre-existing trends

VARIABLES	(1) Δ Employment	(2) Δ Wage
ΔA^{soy}	-0.019	-0.001
	(0.020)	(0.026)
ΔA^{maize}	0.001	0.020*
	(0.009)	(0.012)
Constant	0.246***	-0.157***
	(0.025)	(0.033)
Observations	4,231	4,096

Note: The table reports the OLS estimates of the coefficients in equation 11 in the text. The dependent variables are reported on top of the respective columns. Employment in manufacturing is the natural logarithm of people employed in the manufacturing sector. Wage is calculated as the logarithm of the average wage of manufacturing workers in 2000 Reais. ΔA^{soy} is defined as potential soy yield under high inputs minus potential soy yield under low inputs. ΔA^{maize} is defined as potential maize yield under high inputs minus potential maize yield under low inputs. The source for the dependent variables are the population censi of 1991 and 2000. In this case, changes in the dependent variable are calculated over the years 1991 and 2000. The source of data for the independent variables is the FAO-GAEZ v3.0 dataset. The unit of observation is the AMC. Robust standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 13
The effect of technological change on manufacturing

Employment and wages

Robustness of results reported in Table 9 to controlling for commodity prices

VARIABLES	(1) Total Employment	(2) Total Employment	(3) Wage	(4) Wage
A^{soy}	0.073**	0.077***	-0.046***	-0.040***
	(0.029)	(0.028)	(0.014)	(0.014)
A^{maize}	-0.013	-0.016	0.020***	0.019***
	(0.015)	(0.015)	(0.007)	(0.007)
$P^z A^z$ controls	No	Yes	No	Yes
AMC & year FE	Yes	Yes	Yes	Yes
Observations	20,740	20,740	20,718	20,718

Note: The table reports the OLS estimates of the coefficients in equation 12 in the text. The dependent variables are reported on top of the respective columns. Total employment is the natural logarithm of the total number of workers employed in manufacturing plants (CNAE 1.0 codes 15 to 37) owned by firms that employ at least 30 employees within an AMC. The average wage is computed from manufacturing plants (CNAE 1.0 codes 15 to 37) owned by firms that employ at least 30 employees. Wage is defined as the aggregate wage bill (in real terms) across firm within an AMC divided by total number of workers across the same firms within the same AMC. A^{soy} is defined as potential soy yield under high inputs for the years between 2003 and 2006, and the potential soy yield under low inputs for the years between 1996 and 2002. A^{maize} is defined as potential maize yield under high inputs for the years between 2003 and 2006, and potential maize yield under low inputs for the years between 1996 and 2002. $P^z A^z$ *controls* stand for the interaction of the potential yield of soy and maize under low inputs interacted with price levels of these crops between 1996 and 2006. The source for the dependent variables is the plant-level supplement of the yearly industrial survey (PIA) for the years 1996 to 2006. The source of data for the independent variables is the FAO-GAEZ v3.0 dataset. The unit of observation is the AMC. Standard errors clustered at AMC level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.