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Agricultural composition and labor productivity

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ABSTRACT

Labor productivity differences between developing and developed countries are much larger in agriculture than in non-agriculture. We show that differences in agricultural composition across countries explain a substantial part of these labor productivity differences. To this end, we group agricultural products into two sectors: capital-intensive and labor-intensive agriculture. As the economy develops and capital accumulates, the price of labor-intensive agricultural goods relative to capital-intensive agricultural goods increases. This price change drives a process of structural change that moves land and farmers to the capital-intensive sector, increasing labor productivity in agriculture. We illustrate this mechanism using a multisector growth model that generates transitional dynamics consistent with patterns of structural change observed in Brazil and also differences in agricultural composition and labor productivity consistent with cross-country data.

1. Introduction

A recent branch of the growth literature claims that a substantial part of cross-country income differences can be explained by differences in agricultural labor productivity across countries.[2] This claim is based on two observations. First, employment in agriculture is large in developing countries. Second, labor productivity differences between developed and developing countries are much larger in agriculture than in non-agriculture. In particular, Caselli (2005) finds that agricultural labor productivity in countries in the 90th percentile of the world income distribution is 45 times larger than that of countries in the 10th percentile of the distribution. In contrast, non-agricultural labor productivity is only 4 times larger in advanced countries. This implies that agricultural labor productivity relative to non-agricultural labor productivity increases along the development process.

A central issue to understand economic growth is, therefore, to explain the increase of relative productivity between agriculture and non-agriculture along the development path. In this paper, we identify a process of substitution of crops associated with development, which we denote as structural change within agriculture, and show that this process explains a significant fraction of the rise in relative productivity. Consequently, we show that crop diversity is a key element to consider in explaining the relationship between agricultural productivity and development.

We use data from the US Census of Agriculture and the Food and Agriculture Organization (FAO) to group crops into two different sectors: a capital-intensive and a labor-intensive agricultural sector. Using this classification of crops, we document two novel facts. First, countries with a high share of land in capital-intensive agriculture have higher relative productivity. Second, developed countries have more land allocated to capital-intensive agriculture. These facts suggest a relationship between economic development, changes in the composition of agriculture and agricultural productivity. We propose the following mechanism to explain this relationship. As the economy develops, capital becomes more abundant and less expensive, which reduces the production cost in the capital-intensive agricultural sector more than in the labor-intensive agricultural sector. As a result, the price of labor-intensive crops relative to capital-intensive crops increases. If the two crops are imperfect substitutes in preferences, the consumption and, hence, the production of labor-intensive crops relative to capital-intensive crops declines. As a consequence, the composition of agriculture shifts towards the capital-intensive sector, which increases capital intensity in agriculture and, therefore, capital intensity in agriculture increases relative to non-agriculture.[3] This contributes to explain the increase in labor productivity in agriculture relative to labor productivity in non-agriculture. Therefore, according to our

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[1] The two authors have the same contributions and roles in the elaboration of this paper.

[2] See Cao and Birchenall (2013), Chanda and Dalgaard (2008), Caselli (2005), Gollin et al. (2002, 2014a,b), Restuccia et al. (2008) and Vollrath (2009).

[3] The increase of capital intensity in agriculture relative to non-agriculture, along the process of economic development, is consistent with evidence provided by Chen (2020) and Alvarez-Cuadrado et al. (2017). In particular, Chen (2020) indicates that the capital–output ratio in agriculture is 2.9 times larger in developed countries than in developing countries, whereas it is only 2.1 times larger in non-agriculture.

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mechanism, relative labor productivity increases due to changes in the composition of the agricultural sector that occur along economic development.

We introduce this mechanism in a multisector overlapping generations model, in which a continuum of individuals is born in each period. These individuals have heterogeneous agricultural abilities and homogeneous ability for non-agricultural work. As in Lucas (1978), individuals with low abilities choose to become workers, whereas individuals with high abilities become entrepreneurs. In our framework, workers are employed in non-agriculture, while entrepreneurs are farmers specialized in the production of either labor or capital-intensive crops. Since technologies exhibit complementarity between ability and capital, only farmers endowed with high abilities choose to produce capital-intensive crops. Individuals consume both an agricultural and a non-agricultural good. To introduce substitution in consumption between agricultural sectors, we define the agricultural good as a constant elasticity of substitution aggregate of the goods produced in the two agricultural sectors.

In the model, exogenous technological progress causes economic development and drives two different processes of structural change: between sectors and within agriculture. Structural change between sectors depends on a minimum consumption requirement in the agricultural good. This minimum consumption introduces an income effect that reduces the number of farmers as the economy grows. The remaining farmers have larger farms and higher abilities. This is consistent with evidence provided by Adamopoulos and Restuccia (2014), who report that the average farm size in the poorest 20% of countries is 34 times smaller than in the richest 20% of countries. It is also consistent with Lagakos and Waugh (2013), who argue that selection amplifies labor productivity differences between sectors. On the other hand, structural change within agriculture depends on the elasticity of substitution between the two types of agricultural goods. When it is larger than one, the two types of agricultural goods are imperfect substitutes. In this case, as the economy develops and capital becomes more abundant, the price of labor-intensive crops relative to capital-intensive crops increases, which causes a process of structural change that turns aggregate agriculture more capital intensive. This increases labor productivity in the agricultural sector. This second process of structural change and its relation with labor productivity in agriculture are the main contributions of this paper.

The model is calibrated to match data from Brazil and we simulate the dynamic transition. Along the transition, which is driven by exogenous sector-specific technological progress, the economy develops, capital accumulates and this results in the following patterns: (i) a reduction in the number of farmers; (ii) an increase in the average farm size; (iii) a reduction in the fraction of harvested land in the labor-intensive sector; (iv) an increase in the capital intensity of agriculture relative to non-agriculture; and (v) an increase in the productivity of agriculture relative to non-agriculture. We show that these development patterns are consistent with patterns observed in Brazil during the period 1960–2018. Moreover, we show that the model accounts for 66.2% of the increase in the relative productivity of Brazil, measured at constant prices, observed during this period.

Relative productivity increases due to different mechanisms: (i) sector-specific technological progress that can be faster in agriculture, (ii) the reduction in the number of farmers that increases average farm size and increases the ability of the average farmer, and (iii) structural change within agriculture that increases capital intensity in agriculture relative to non-agriculture. This third mechanism is the focus of this paper and to determine its significance we measure the fraction of the increase in relative productivity that is explained by structural change within agriculture. To this end, we simulate a counterfactual economy in which the elasticity of substitution between crops is set equal to one and, hence, there is no structural change within the agricultural sector and capital intensity in agriculture relative to non-agriculture remains constant even though the relative price between labor-intensive agriculture and capital-intensive agriculture increases. From the comparison between the benchmark and the counterfactual economies, we conclude that structural change within agriculture explains 24.8% of the increase in relative productivity observed in Brazil.

We also provide cross-country evidence, for a large sample including developing and developed countries, that supports the patterns of development implied by our model. The cross-country data shows a positive correlation between (i) GDP per worker and the fraction of harvested land in capital-intensive agriculture, and (ii) between this fraction and relative productivity. We calibrate the model to match the cross-country correlation between GDP per worker and the fraction of harvested land in capital-intensive agriculture. More precisely, we use the calibration of Brazil and adjust sectoral TFPs to match cross-country differences in income, land in the capital-intensive sector and also employment in agriculture. We show that the model can generate these differences and can also explain the positive correlation between GDP per worker and relative productivity. In particular, the data shows that relative productivity between agriculture and non-agriculture of countries in the top quartile of the world income distribution is 7.05 times larger than relative productivity of countries in the bottom quartile. We show that the model generates a 6.36-fold gap in relative productivity between rich and poor countries and that structural change within agriculture accounts for 27.5% of this gap.

This paper is related to three branches of the literature. First, it is related to the structural change literature that introduces income and price effects to explain changes in the sectoral composition of an economy (see Kongsamut et al., 2001; Ngai and Pissarides, 2007; Acemoglu and Guerrieri, 2008). We consider price and income effects to account for structural change among broad sectors and within agriculture.

Second, it is related to the literature on agricultural productivity differences across countries. This literature has considered misallocations of production factors (Chen, 2017; Gottlieb and Grobovsek, 2019; Hayashi and Prescott, 2008; Restuccia et al., 2008; Restuccia and Santaeulalia-Llopis, 2017), differences in farm sizes (Adamopoulos and Restuccia, 2014), differences in technology (Chen, 2020; Gollin et al., 2007; Manuelli and Seshadri, 2014; Yang and Zhu, 2013), selection (Lagakos and Waugh, 2013), uninsurable risk and incomplete capital markets (Donovan, 2020), and differences in the quality of capital (Caunedo and Keller, 2021). This literature considers an aggregate agricultural sector producing a single commodity. However, agricultural products are in fact diverse, they can be produced with different technologies and the consumption composition of these products can change along economic development. Recent papers examine agricultural product diversity. For example, Sotelo (2020) considers a model of regional specialization, Adamopoulos and Restuccia (2020) study how land reforms affect farmers' decisions between producing cash or food crops, and Rivera-Padilla (2020) shows that the crop choice is affected by subsistence requirements and trade costs. We contribute to this literature by studying how crop diversity affects agricultural productivity.

Third, it is also related to the literature that studies the increase in the capital intensity of agriculture relative to non-agriculture driven by technological change (see Gollin et al., 2007; Alvarez-Cuadrado et al., 2017). In particular, it is closely related to Chen (2020), who links the increase in both capital intensity and average farm size in agriculture to technology adoption. In Chen (2020), there is a single agricultural product and, as the cost to adopt technology declines, farmers switch to a more capital-intensive technology. This explains the increase of capital per worker in agriculture. As in our paper, the increase of agricultural capital-intensity is behind the increase in relative productivity. Our paper provides a different, but complementary, explanation for the increase in capital intensity. In our framework, agricultural capital-intensity increases, not as consequence of technology adoption but because of substitution between different crops. Capital-intensity of agriculture grows because the share of agriculture produced in the more capital-intensive sector expands. This is an important difference

Table 1
Capital intensity for main crop categories.

Capital/Value added	1978	1982	1992	1997	2002	2012
Oilseed and grain	1.52	1.62	1.62	1.53	1.73	1.43
Other crop	1.28	1.19	1.10	1.21	3.92	2.55
Vegetable and melon	0.50	0.47	0.48	0.44	0.53	0.58
Fruit and tree nut	0.55	0.59	0.49	0.44	0.53	0.44

Note:
[1] We use data from the US Census of Agriculture for the following years: 1978, 1982, 1992, 1997, 2002, and 2012. The last three censuses classify crops according to the North American Industry Classification System (NAICS). The first 3 censuses use the Standard Industrial Classification System (SIC), however, we reclassify crops in these censuses according to categories in NAICS. We exclude hay, greenhouse and floriculture production, which are not considered in the FAO dataset.
[2] Capital intensity is defined as capital over value added. We compute the value added as the market value of crops excluding government payments and expenditures in fertilizers, chemicals, seeds, gasoline, utilities, supplies, maintenance and all other production expenses. Capital is defined as the value of equipment and machinery.

Table 2
Capital intensity by crop.

Oilseed and grain farming	0.93	Vegetable and melon farming	0.35
Soybean	1.16	Potato	0.41
Oilseed (ex soybean)	1.15	Other vegetable and melon	0.34
Dry pea and bean	0.95	Fruit and tree nut farming	0.29
Wheat	1.16	Orange groves	0.23
Corn	0.86	Citrus (ex. orange) groves	0.25
Rice	0.66	Noncitrus fruit and tree nut	0.44
Other grain	0.93	Apple orchards	0.29
Other crop farming	1.44	Grape vineyards	0.24
Tobacco	0.73	Strawberry	0.11
Cotton	0.89	Berry (except strawberry)	0.53
Sugarcane	0.40	Tree nut	0.32
All other crop	1.33	Other non-citrus fruit farming	0.44

Note: Data is from the 2012 US Census of Agriculture. This census provides data on production and capital at crop-level. For this reason, we compare the ratio between capital and production, instead of capital and value added.

that affects not only the model, but also the calibration targets. In the technological change literature, the model is calibrated to match a technological adoption curve or a measure of capital intensity. Instead, we calibrate the model to account for the change in the sectoral composition of agriculture observed in the data and documented in this paper. We see both explanations as complementary, since we could consider a single model including substitution between agricultural goods and technological adoption within each agricultural sector to account for the increase in agricultural capital-intensity.

The rest of the paper is organized as follows. Section 2 shows the empirical strategy followed to construct the two agricultural subsectors and introduces the main facts. Section 3 introduces the model. Section 4 characterizes the equilibrium. Section 5 describes the quantitative analysis and shows that the model explains a sizable part of the increase in relative productivity observed in Brazil and that it also accounts for a large part of cross-country differences in relative productivity observed in the data. Finally, Section 6 concludes.

2. Agricultural sectors

In this section, we classify crops according to capital intensity. Using this classification, we first show that, in a cross-section of countries, using more land in capital-intensive agriculture correlates with capital intensity in agriculture relative to non-agriculture and with relative productivity. We then focus on development patterns of Brazil during the period 1960–2018 and show that both the fraction of land in capital-intensive agriculture and relative productivity increase in this country.

We use the US Census of Agriculture to obtain the ratio between capital and value added by crop, which is a standard measure of capital intensity. Table 1 shows the value of this ratio for different years in which the census is available and for the main crop categories under the North American Industry Classification System (NAICS). Although there are some important changes in capital intensity among censuses, a clear pattern emerges: the first two categories, Oilseed and grain farming and Other crop farming, have a capital intensity, on average, larger than 1.5, whereas the last two categories, Vegetable and melon farming and Fruit and tree nut farming, have an average capital intensity of 0.5. Therefore, there is a large and persistent gap in the capital intensities across different categories of crops.

This gap remains if we consider crops within categories. Table 2 shows that capital intensity, defined as the ratio between capital and production, of crops in the first two categories is in general larger than capital intensity of any crop in the last two categories.[4] Given these findings, we distinguish between two agricultural sectors. We group crops in the first two categories of Table 1 in the capital-intensive agricultural sector, whereas crops in the other two categories are grouped in the labor-intensive agricultural sector.[5] We assume that this classification remains stable through time and across countries.

Next, we use the Food and Agriculture Organization (FAO) dataset, that provides crop-level data on production, prices and area harvested for a large number of countries. We consider the period 1961–2018. Using the classification of crops obtained from the US Census of Agriculture, we classify all crops in the FAO dataset in order to construct the two agricultural sectors. This gives us the value of production, the price index and the fraction of total harvested land in both capital and labor-intensive agriculture, for each country and time period. The classification of all crops is shown in detail in the supplementary appendix.

In Fig. 1 we show cross-country evidence that supports the mechanism in our model. In particular, Panel (a) of Fig. 1 shows a positive correlation between the fraction of harvested land in capital-intensive agriculture and relative capital intensity between agriculture and non-agriculture. Relative capital intensity is defined as capital per worker in agriculture divided by capital per worker in non-agriculture. We combine data on capital by sector from Larson et al. (2000) with data on employment by sector from the Groningen Growth and Development Centre (GGDC) 10-Sector Database. This results in a sample of 25 countries. Although data is limited, we obtain a positive correlation that is statistically significant. This positive correlation provides support to our classification of crops: economies with more land in capital-intensive agriculture, according to our classification, are also the ones with higher capital intensity in agriculture relative to non-agriculture.

The mechanism in our model implies that the fraction of harvested land in capital-intensive agriculture increases as the economy develops. It also implies that agricultural productivity relative to non-agricultural productivity increases as the fraction of harvested land

[4] The US Census of Agriculture provides crop-level data on production and capital. Therefore, we compare the ratio between capital and production, instead of capital and value added, which is the standard measure of capital intensity.

[5] Using Table 1, we distinguish between a more capital-intensive sector and a less capital-intensive sector. In the model of Section 3, the less capital-intensive sector is also the labor-intensive sector.

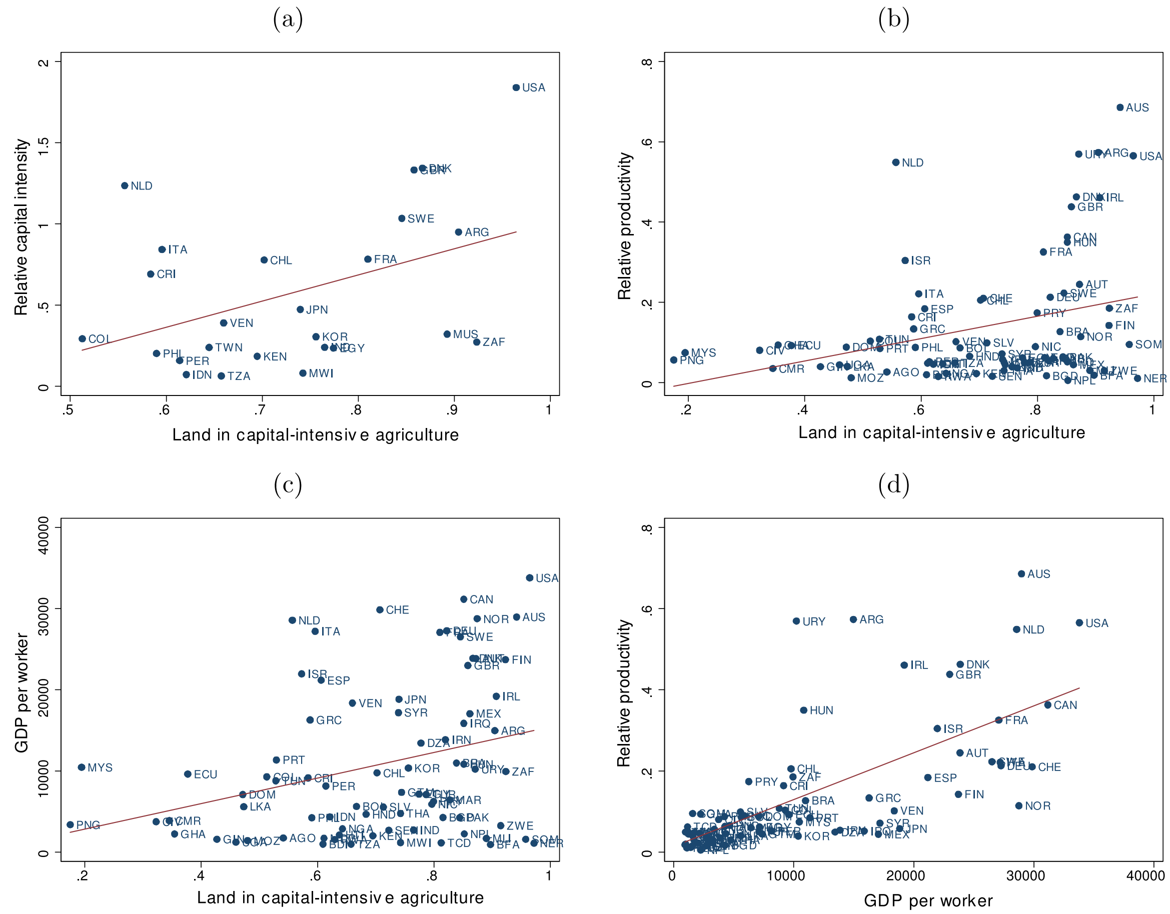

Fig. 1. Cross-country comparisons. Note: [1] This figure shows correlations between: (a) Relative capital intensity between agriculture and non-agriculture and the fraction of land in capital-intensive agriculture (L_k/L), (b) Relative productivity between agriculture and non-agriculture and L_k/L, (c) GDP per worker and L_k/L, and (d) Relative productivity between agriculture and non-agriculture and GDP per worker. Relative productivity and GDP per worker are PPP-adjusted. [2] Data for relative productivity between agriculture and non-agriculture and GDP per worker is obtained from Restuccia et al. (2008). Relative capital intensity between agriculture and non-agriculture is from Larson et al. (2000) and the GGDC 10-Sector Database. The fraction of land in capital-intensive agriculture is computed from FAO. All data is for year 1985.

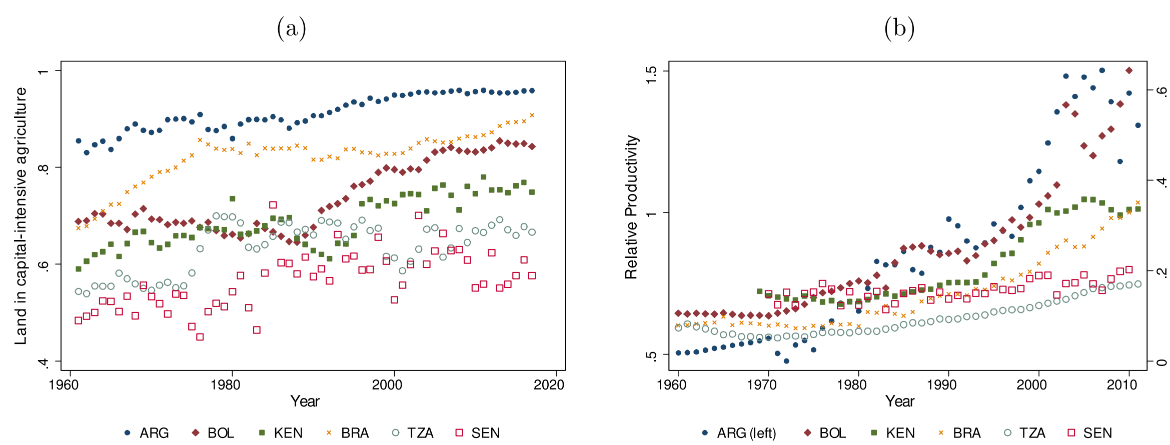

Fig. 2. Development patterns. Note: [1] Panel (a) shows the increase in the fraction of land in capital-intensive agriculture (L_k/L) and Panel (b) shows the increase in relative productivity between agriculture and non-agriculture $(Y_a/N_a)/(Y_m/N_m)$ in 6 developing countries. [2] Data for L_k/L is computed from FAO and relative productivity at 2005 constant prices is obtained from the GGDC 10-Sector Database. We include all developing countries for which we have relative productivity data from GGDC 10-Sector Database since the 1960s and for which both L_k/L and $(Y_a/N_a)/(Y_m/N_m)$ increase. Countries included are: Argentina, Bolivia, Kenya, Brazil, Tanzania, Senegal.

in capital-intensive agriculture increases. Therefore, this mechanism involves a positive correlation between: (i) the fraction of harvested land in capital-intensive agriculture and relative labor productivity; (ii) between this fraction and GDP per worker; and (iii) between GDP per worker and relative labor productivity. Panels (b), (c) and (d) of Fig. 1 illustrate these three positive correlations, using the cross-country comparable measure of relative productivity provided by Restuccia et al. (2008). These authors provide GDP per worker and labor productivity in each sector, measured at Purchasing Power Parity (PPP) adjusted prices, for a large sample of countries for the year 1985. Using this

Table 3
Relative productivity across countries.

Dependent variable: Relative productivity	(1)	(2)	(3)
Constant	−0.0589 (0.0675)	−0.6733*** (0.1170)	0.0264 (0.0414)
Fraction of land in capital-intensive agriculture	0.2791*** (0.0931)	–	0.2305*** (0.0490)
Log real GDP per worker	–	0.0920*** (0.0131)	–
Country fixed effects	–	–	Yes
Time fixed effects	–	–	Yes
Countries	80	80	37
Observations	80	80	1802
R^2	0.103	0.385	0.388

Note:
[1] Standard errors in parenthesis.
[2] This table shows that relative productivity ($Y_a/N_a/Y_m/N_m$) is correlated with the fraction of land in capital-intensive agriculture (L_k/L) and with real GDP per worker (Y/N). Regressions in columns (1) and (2) use cross-section data, while the regression in column (3) uses a panel of 37 countries. Data on relative productivity and real GDP per worker in columns (1) and (2) is from Restuccia et al. (2008) and is PPP-adjusted, the fraction of land in capital-intensive agriculture is constructed from FAO data, and relative productivity at constant prices in column (3) is from GGDC 10-Sector Database.
***Indicates p-value < 0.01.

Table 4
Agricultural composition across countries.

Dependent variable: Land in capital-intensive agriculture	(1)	(2)
Constant	0.3575** (0.1673)	0.5170*** (0.0216)
Log real GDP per worker	0.0392** (0.0188)	0.0181*** (0.0024)
Countries	80	82
Observations	80	4897
R^2	0.053	0.012

Note:
[1] Standard errors in parenthesis
[2] This table shows that the fraction of land in capital-intensive agriculture (L_k/L) is correlated with real GDP per worker (Y/N). The regression in column (1) uses cross-section data and the one in column (2) uses panel data from 82 countries. Data on the fraction of land in capital-intensive agriculture is constructed from FAO. Real GDP per worker in column (1) is from Restuccia et al. (2008) and is PPP-adjusted. Real GDP per capita in columns (2) is from Penn World Table 10.0.
**Indicates p-value < 0.05.
***Indicates p-value < 0.01.

data, in the first two columns of Table 3 and in the first column of Table 4 we show that the three positive correlations in Panels (b), (c) and (d) of Fig. 1 are statistically significant.

We complement the previous cross-country analysis with two additional linear regressions using panel data. First, we run a regression between relative productivity and the fraction of harvested land in capital-intensive crops, using a panel of 37 countries during the period 1961–2011. Data on relative productivity is from the GGDC 10-Sector Database and is not PPP-adjusted; therefore, it is not directly comparable across countries.[6] This justifies the introduction of country and time fixed effects in the regression. The results from this regression are in the third column of Table 3 and show a positive and statistically significant correlation. Second, in the second column of Table 4, we run a regression between the fraction of land in capital-intensive agriculture and real GDP per capita. This regression includes 82 countries during the period 1960–2020. The results from this regression also show a positive and statistically significant correlation.

From this evidence, it can be argued that as countries move to higher income levels, land shifts towards capital-intensive crops, and this shift involves an increase in relative productivity. Therefore, we find evidence that supports the mechanism proposed in this paper.

[6] We exclude the following 5 countries for which data is unavailable during the entire period: Germany, Hong-Kong, Ethiopia, Mauritius and Singapore.

In Fig. 2, we provide time series evidence for selected developing countries. This figure shows countries that exhibit a process of development in which both the fraction of land in capital-intensive agriculture and relative productivity increase over time. Among these countries, we select Brazil to calibrate the model and perform numerical simulations.

We choose Brazil because it is a large country with a diversified agricultural sector that exhibits the classical patterns of development, including structural change and a large increase in relative productivity. These patterns are documented in Fig. 3 for the period 1960–2018. Panels (a) and (b) of this figure show that Brazil has experienced two important patterns of structural change. First, there is structural change across broad sectors, which is measured by the fraction of total employment in agriculture. This fraction, obtained from the GGDC 10-Sector Database for 1960–2011 and the GGDC/UNU-WIDER Economic Transformation Database for 2012–2018, exhibits a major decline during this period, from 59% to 12%. Second, there is structural change within agriculture, which is measured by the fraction of total land in the labor-intensive sector. This fraction also exhibits a pronounced decline, from 30% to 8.2%.

In Panel (c), we report a steep increase in relative capital intensity between agriculture and non-agriculture. Data on relative capital intensity for Brazil is obtained from the 2012 World Input–Output Database and it is available for the period 1995–2009.

Panel (d) shows the increase of agricultural productivity relative to non-agricultural productivity in Brazil from 7.9% in 1960 to 53.8% in 2018. This is a considerable increase of 45.9 percentage points. Relative productivity is measured at 2015 constant prices and is obtained from the GGDC 10-Sector Database for the period 1960–2011 and from the GGDC-UNU/WIDER Economic Transformation database for the period 2012–2018. In Section 5.2, we study how much of the increase observed in this variable is due to the process of structural change within agriculture reported in Panel (b).

In Fig. 4, we calculate the price index and the value of production for both agricultural sectors using data from FAO and show that the relative price between labor and capital-intensive agriculture exhibits a rising trend (despite large fluctuations), whereas the relative value of production between these two sectors declines. This evidence suggests imperfect substitution in consumption between agricultural goods, which is a feature implied by the mechanism in our paper. At this point, we clarify that production is not measured in value added terms, hence, it cannot be used to calibrate the model.

In the analysis that follows, we assume that the driver of structural change within agriculture is domestic consumption demand. The substitution of consumption from labor to capital-intensive agricultural products changes the composition of agriculture. Cockx et al. (2018), Huang and David (1993), Kearney (2019) and Rae (1998) provide evidence on this substitution. They document that, as economies develop, diets shift from traditional staples such as cassava, potatoes, bananas and other starchy foods to consumption of rice, bread, pasta, cereals and prepared foods. This is consistent with our classification of crops, in which the first group is considered labor-intensive and the second is considered capital-intensive. In the supplementary appendix, we provide further evidence on this substitution based on findings in the literature and on data from FAO. An alternative potential driver of structural change within agriculture, not considered in our analysis, could be exports of agricultural products. However, in the supplementary appendix, we show that exports are not the main driver of structural change within agriculture in Brazil. Therefore, in the following sections we present a multisector growth model of a closed economy and analyze the effect of structural change within agriculture on relative productivity in Brazil.

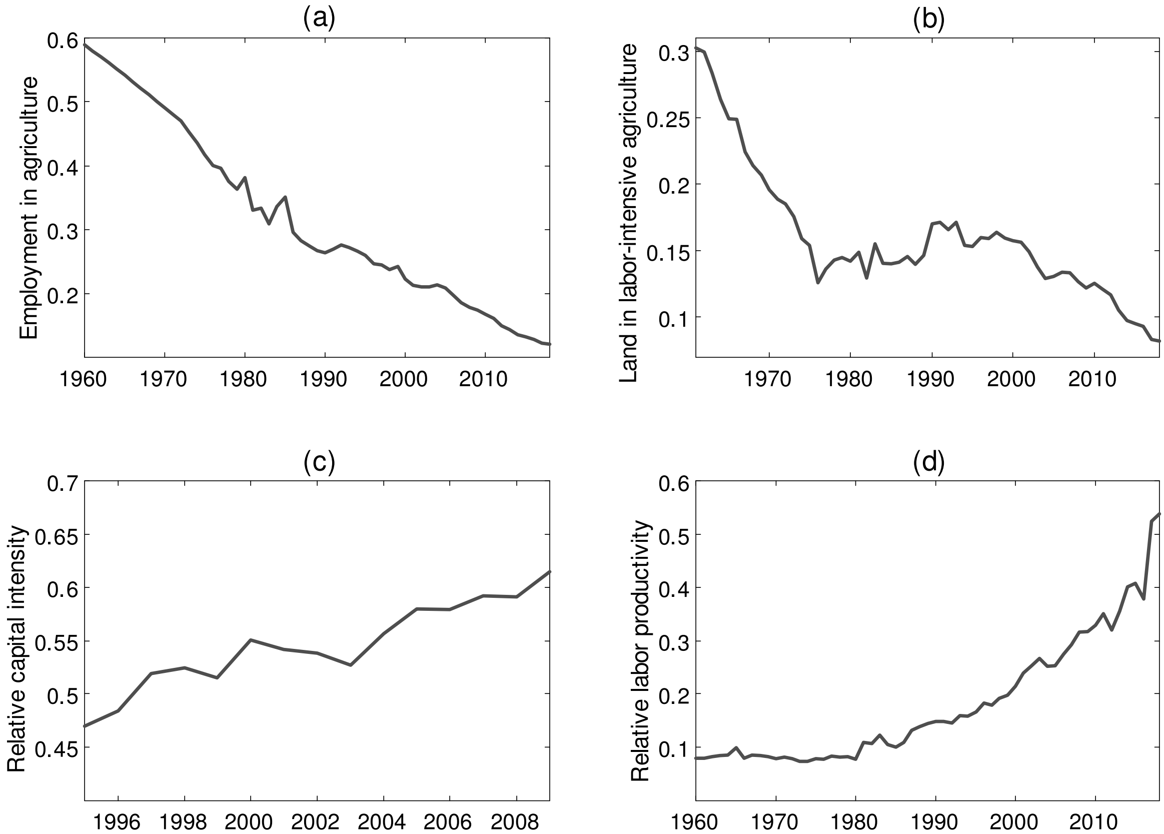

Fig. 3. Development patterns of Brazil. Note: Panel (a) shows the fraction of employment in agriculture using data from GGDC 10-Sector Database (1960–2011) and GGDC/UNU-WIDER Economic Transformation Database (2012–2018). Panel (b) shows the fraction of land in labor-intensive agriculture during 1961–2018, using data from FAO. Panel (c) shows capital intensity in agriculture relative to non-agriculture using data from the World Input–Output Database 2012, available for 1995–2009. Panel (d) shows agricultural productivity relative to non-agricultural productivity at 2015 constant prices using data from GGDC 10-Sector Database (1960–2011) and GGDC/UNU-WIDER Economic Transformation Database (2012–2018). All data is for Brazil.

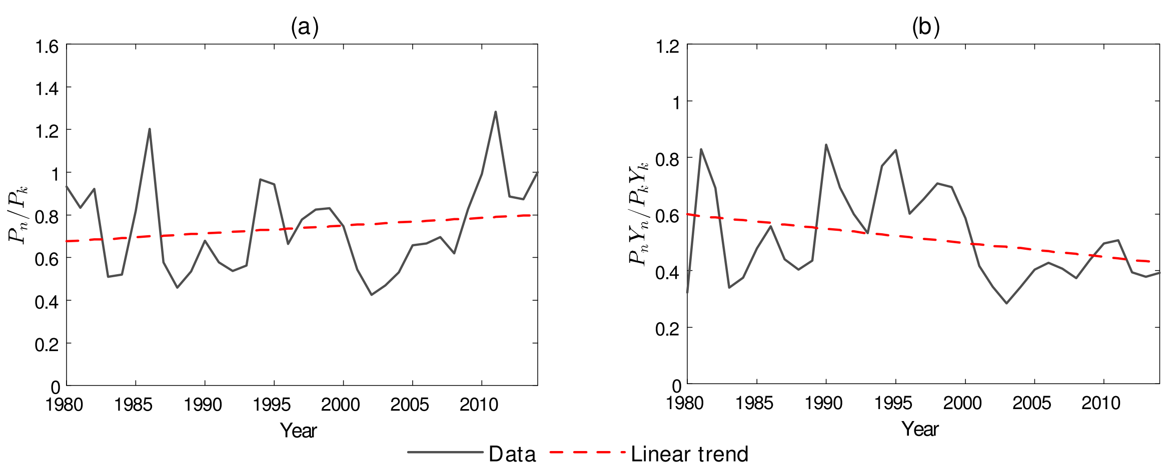

Fig. 4. Relative price and value of production in Brazil. Note: [1] This figure shows evidence on crop substitution. Panel (a) shows an increase in the linear trend of the relative price. Panel (b) shows a decline in the linear trend of the relative value of production. [2] Data for the relative price of labor-intensive agriculture to capital-intensive agriculture (P_n/P_k) and for the relative value of production in labor-intensive agriculture to capital-intensive agriculture (P_nY_n/P_kY_k) are computed from FAO.

3. The model

3.1. Individuals

The economy is populated by a continuum of individuals of mass N_t. Individuals live for two periods. In the first period, they are young, they choose the sector of activity, they work and save buying capital and land. Therefore, young individuals supply the capital that will be productive next period. We assume that capital and land are perfect substitute assets and, therefore, the return of land equals the return of capital, R_{t+1}. In the second period of life, individuals are old, they do not work and consume the accumulated savings. As in Laitner (2000), individuals consume only when they are old. As a result, young individuals save all their income and, therefore, consumption expenditures of old individuals in period $t+1$ are given by $E^i_{t+1} = R_{t+1}I^i_t$, where R_{t+1} is the return of savings and I^i_t is the income obtained by young individual i at period t.

Young individuals are differentiated by their ability in agriculture, which we denote by a^i. In every generation, these abilities follow the same Pareto distribution with density function $f\left(a^i\right) = \lambda\eta^{\lambda}\left(a^i\right)^{-(1+\lambda)}$ and cumulative function $F\left(a^i\right) = 1-\left(\eta/a^i\right)^{\lambda}$, with $\eta > 0$ and $\lambda > 1$. The parameter η is the minimum ability and λ determines the shape of the distribution. We assume that all individuals have the same ability for non-farm work.

An individual i born at period t derives utility from consumption in the second period of his life according to the following non-homothetic utility function:

$$U_t^i = \omega \ln\left(c_{a,t+1}^i - \overline{c}\right) + (1-\omega)\ln c_{m,t+1}^i, \tag{1}$$

where $c_{a,t+1}^i$ is the consumption of agricultural goods, $c_{m,t+1}^i$ is the consumption of non-agricultural goods, $\overline{c}$ is a subsistence level of agricultural consumption, and $\omega \in (0,1)$ is the weight of agricultural consumption in the utility function. The agricultural good is defined as the following aggregate of goods produced in the capital and labor-intensive sectors:

$$c_{a,t+1}^i = \left[\mu\left(c_{n,t+1}^i\right)^{\frac{\varepsilon-1}{\varepsilon}} + (1-\mu)\left(c_{k,t+1}^i\right)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{2}$$

where $\mu \in (0,1)$ is the weight of labor-intensive goods, and $\varepsilon > 0$ is the elasticity of substitution between the consumption of labor-intensive agricultural goods, c_n^i, and capital-intensive agricultural goods, c_k^i.

Let total consumption expenditure be defined as

$$E_{t+1}^i = P_{n,t+1}c_{n,t+1}^i + P_{k,t+1}c_{k,t+1}^i + P_{m,t+1}c_{m,t+1}^i, \tag{3}$$

where $P_{n,t+1}$ is the price of the labor-intensive goods, $P_{k,t+1}$ is the price of the capital-intensive goods and $P_{m,t+1} = 1$ for all t, since the output of the non-agricultural sector is assumed to be the numeraire. In Appendix A, we obtain the individuals' consumption demands from maximizing utility subject to (3).

3.2. Technology

We distinguish between three production sectors: two agricultural sectors that produce consumption goods and one non-agricultural sector that produces both a consumption good and productive capital. Firms in the non-agricultural sector produce combining capital and labor according to the following constant returns to scale production function:

$$Y_{m,t} = A_{m,t}K_{m,t}^{\alpha_m}N_{m,t}^{1-\alpha_m}, \tag{4}$$

where $Y_{m,t}$ is output in non-agriculture, $A_{m,t}$ is total factor productivity (TFP) in the non-agricultural sector, $K_{m,t}$ is the capital stock employed in this sector, $N_{m,t}$ is the total amount of workers employed in this sector and $\alpha_m \in (0,1)$ is the capital–output elasticity. We assume that capital completely depreciates after one period. We also assume perfect competition and, hence, the wage and the rental price of capital satisfy

$$w_t = \left(1-\alpha_m\right)A_{m,t}K_{m,t}^{\alpha_m}N_{m,t}^{-\alpha_m}, \tag{5}$$

and

$$R_t = \alpha_m A_{m,t}K_{m,t}^{\alpha_m-1}N_{m,t}^{1-\alpha_m}. \tag{6}$$

Individuals working in agriculture are the owners of farms. Farmers can produce either labor or capital-intensive crops using the following technology:

$$y_{s,t}^i = A_{s,t}a^i\left(L_{s,t}^i\right)^{\beta_s}\left(K_{s,t}^i\right)^{\alpha_s}, \quad s = \{k,n\},$$

where $y_{s,t}^i$ is the output produced in the agricultural sector s by a farmer with ability a^i, $A_{s,t}$ is the TFP in sector s, $L_{s,t}^i$ and $K_{s,t}^i$ are the amount of land and capital that a farmer with ability a^i rents, $\beta_s \in (0,1)$ measures the land output elasticity and $\alpha_s \in (0,1)$ measures the capital–output elasticity. The subindex s equals n for labor-intensive agriculture and k for capital-intensive agriculture. We assume that $\alpha_k > \alpha_n$, $\beta_s+\alpha_s < 1$ for all s and $\beta_k+\alpha_k > \beta_n+\alpha_n$. The first inequality is consistent with sector k being capital intensive. The second one implies that both production functions exhibit decreasing returns to scale. In what follows, we show that the third inequality implies that sector n is labor intensive.

Since the production functions exhibit decreasing returns to scale, farmers make positive profits that can be interpreted as the labor income of the farmer. Profit is given by

$$\pi_{s,t}^i = (1-\tau)P_{s,t}y_{s,t}^i - x_tL_{s,t}^i - R_tK_{s,t}^i, \tag{7}$$

where x_t is the rental cost of land and $\tau \in (0,1)$ is a tax on agricultural production. This tax introduces a wedge between the marginal product of capital in agriculture and in non-agriculture, that we use in the calibration to match the level of relative capital intensity between agriculture and non-agriculture in Brazil. The farmers' optimal demands of land and capital are

$$L_{s,t}^i = \left[\left(\frac{\alpha_s}{R_t}\right)^{\alpha_s}\left(\frac{\beta_s}{x_t}\right)^{1-\alpha_s}(1-\tau)P_{s,t}A_{s,t}a^i\right]^{\frac{1}{1-\beta_s-\alpha_s}}, \tag{8}$$

$$K_{s,t}^i = \left[\left(\frac{\alpha_s}{R_t}\right)^{1-\beta_s}\left(\frac{\beta_s}{x_t}\right)^{\beta_s}(1-\tau)P_{s,t}A_{s,t}a^i\right]^{\frac{1}{1-\beta_s-\alpha_s}}, \tag{9}$$

and the amount produced is

$$y_{s,t}^i = A_{s,t}a^i\left[\left(\frac{\alpha_s}{R_t}\right)^{\alpha_s}\left(\frac{\beta_s}{x_t}\right)^{\beta_s}\left[(1-\tau)P_{s,t}A_{s,t}a^i\right]^{\alpha_s+\beta_s}\right]^{\frac{1}{1-\beta_s-\alpha_s}}. \tag{10}$$

Note that the size of a farm, measured by $L_{s,t}^i$, increases with farmer's ability, but decreases with the rental cost of land and capital. Finally, we replace (8), (9) and (10) in the profit function to obtain

$$\pi_{s,t}^i\left(a^i\right) = \left(1-\beta_s-\alpha_s\right)\left[\left(\frac{\alpha_s}{R_t}\right)^{\alpha_s}\left(\frac{\beta_s}{x_t}\right)^{\beta_s}(1-\tau)P_{s,t}A_{s,t}a^i\right]^{\frac{1}{1-\beta_s-\alpha_s}}. \tag{11}$$

Using (11), we observe that profits are an increasing function of abilities. Using the same equation, it is immediate to show that the assumption $\beta_k+\alpha_k > \beta_n+\alpha_n$ implies that the fraction of the after tax value of production that the farmer obtains as labor income is larger in labor-intensive agriculture.

3.3. Individuals' decisions

Young individuals' decision regarding the sector of activity depends on their abilities. To understand this decision, we first obtain the ability of the two marginal individuals that are indifferent between two sectors of activity. We denote by $\underline{a}_t$ the ability of the first marginal individual, who is indifferent between working in non-agriculture and in labor-intensive agriculture. Therefore, this ability is obtained from solving the following equation: $\pi_{n,t}^i\left(\underline{a}_t\right) = (1-\phi)w_t$, where $\phi \in (0,1)$ is a labor income tax that workers in the non-agricultural sector must pay. This tax introduces a wedge between agricultural and non-agricultural labor income that we use in the calibration to match the difference in labor productivity between agriculture and non-agriculture, when labor productivity is measured at current prices. We find that

$$\underline{a}_t = \left(\frac{1}{(1-\tau)P_{n,t}A_{n,t}}\right)\left(\frac{(1-\phi)w_t}{1-\beta_n-\alpha_n}\right)^{1-\beta_n-\alpha_n}\left(\frac{x_t}{\beta_n}\right)^{\beta_n}\left(\frac{R_t}{\alpha_n}\right)^{\alpha_n}. \tag{12}$$

We denote by $\overline{a}_t$ the ability of the second marginal individual, who is indifferent between being a farmer in labor and in capital-intensive agriculture. Therefore, this ability is obtained from solving the following equation: $\pi_{n,t}^i\left(\overline{a}_t\right) = \pi_{k,t}^i\left(\overline{a}_t\right)$. We obtain

$$\overline{a}_t = \Psi\frac{\left[\left(\frac{\alpha_n}{R_t}\right)^{\alpha_n}\left(\frac{\beta_n}{x_t}\right)^{\beta_n}(1-\tau)P_{n,t}A_{n,t}\right]^{\frac{1-\beta_k-\alpha_k}{\beta_k+\alpha_k-\beta_n-\alpha_n}}}{\left[\left(\frac{\alpha_k}{R_t}\right)^{\alpha_k}\left(\frac{\beta_k}{x_t}\right)^{\beta_k}(1-\tau)P_{k,t}A_{k,t}\right]^{\frac{1-\beta_n-\alpha_n}{\beta_k+\alpha_k-\beta_n-\alpha_n}}}, \tag{13}$$

where $\Psi = \left[\left(1-\beta_n-\alpha_n\right)/\left(1-\beta_k-\alpha_k\right)\right]^{(1-\beta_n-\alpha_n)(1-\beta_k-\alpha_k)/(\beta_k+\alpha_k-\beta_n-\alpha_n)}$.

The assumption $\beta_n+\alpha_n<\beta_k+\alpha_k$ implies that the profit of capital-intensive farms as a function of abilities is steeper than the profit function of labor-intensive farms at $a^i=\overline{a}_t$. Given that individuals choose the sector to maximize their labor income, it follows that we can only have both types of farms if $\overline{a}_t>\underline{a}_t$. Therefore, as shown in Fig. 5, individuals with $a^i\in\left[\eta,\underline{a}_t\right]$ will be workers in the non-agricultural sector, individuals with $a^i\in\left[\underline{a}_t,\overline{a}_t\right]$ will be farmers in the labor-intensive sector and individuals with $a^i\in\left[\overline{a}_t,\infty\right]$ will be farmers in the capital-intensive sector. Note that since the distribution of abilities is unbounded, there are always capital-intensive farmers. In contrast, if $\overline{a}_t<\underline{a}_t$ then all farmers will produce capital-intensive crops. In our simulations, the condition $\overline{a}_t>\underline{a}_t$ will always be satisfied along the dynamic equilibrium.

The abilities of the marginal farmers determine structural change along economic development. Eq. (12) sets the value of $\underline{a}_t$, which determines the number of non-agricultural workers. This number increases with the wage and decreases with profits of the labor-intensive sector. In fact, Eq. (12) shows that the number of non-agricultural workers increases ($\underline{a}_t$ increases) when the rental cost of land or capital increases, or when either the price or the TFP of the labor-intensive agriculture decline. These changes reduce profits in labor-intensive agriculture, making it more attractive to become a worker in the non-agricultural sector. Finally, the wage and rental cost of land increase with economic development, which explains the shift of workers from agriculture to non-agriculture.

Eq. (13) sets the value of $\overline{a}_t$, which determines the fraction of agricultural workers in the labor-intensive sector. This fraction increases when profits in labor-intensive agriculture increase and decreases when profits in capital-intensive agriculture increase. Eq. (13) shows that this fraction increases ($\overline{a}_t$ increases) if the price or the TFP of the labor-intensive sector increase and declines if the price or the TFP of the capital-intensive sector increase. The fraction also increases with the rental cost of capital, R_t. When R_t increases, profits in capital-intensive agriculture suffer a larger reduction than in labor-intensive agriculture and, as a result, more individuals prefer to be labor-intensive farmers. The effect of an increase in the rental cost of land, x_t, depends on the relationship between β_k and β_n. If $\beta_k>\beta_n$ then the capital-intensive sector is also land-intensive and, as a result, an increase in the rental cost of land reduces to a larger extend profits of this sector, which increases the number of labor-intensive farmers.

Finally, the assumption $\beta_n+\alpha_n<\beta_k+\alpha_k$ implies that the marginal individual with ability $\overline{a}_t$ satisfies $P_{n,t}y^i_{n,t}\left(\overline{a}_t\right)<P_{k,t}y^i_{k,t}\left(\overline{a}_t\right)$. Thus, there is a productivity gain when the marginal farmer moves from the labor to the capital-intensive sector. This productivity gain is mainly explained by the increase in the stock of capital that occurs when the farmer chooses to produce capital-intensive crops. The existence of a productivity gain implies that the sectoral composition that results from individuals decisions is not the one that maximizes the value of agricultural production. In fact, given that $\beta_n+\alpha_n<\beta_k+\alpha_k$, the size of the labor-intensive agricultural sector is larger than the size that would maximize the value of agricultural production.

4. Equilibrium

In this section, we characterize the equilibrium of the model. To this end, we first obtain aggregate factor demands, aggregate production and aggregate consumption demands for each sector.

Using (8) and (9), in Appendix B we obtain the following aggregate demands of land and capital in each agricultural sector:

$$L_{s,t}=N_t\left[\left(\frac{\alpha_s}{R_t}\right)^{\alpha_s}\left(\frac{\beta_s}{x_t}\right)^{1-\alpha_s}(1-\tau)\,P_{s,t}A_{s,t}\right]^{\frac{1}{1-\beta_s-\alpha_s}}\Delta_{s,t}, \tag{14}$$

and

$$K_{s,t}=N_t\left[\left(\frac{\alpha_s}{R_t}\right)^{1-\beta_s}\left(\frac{\beta_s}{x_t}\right)^{\beta_s}(1-\tau)\,P_{s,t}A_{s,t}\right]^{\frac{1}{1-\beta_s-\alpha_s}}\Delta_{s,t}, \tag{15}$$

for $s=\{n,k\}$, where $\Delta_{n,t}$ and $\Delta_{k,t}$, defined in Appendix B, are both positive when $\lambda>1/\left(1-\beta_k-\alpha_k\right)$. This condition is satisfied in the numerical exercises of Section 5.

We use (6) to obtain the demand of capital in the non-agricultural sector

$$K_{m,t}=\left(\frac{\alpha_m A_{m,t}}{R_t}\right)^{\frac{1}{1-\alpha_m}}N_{m,t}, \tag{16}$$

where the amount of workers in this sector is given by $N_{m,t}=F\left(\underline{a}_t\right)N_t=\left(1-\eta^{\lambda}\underline{a}_t^{-\lambda}\right)N_t$.

In equilibrium, the total amount of agricultural land, L_t, equals the sum of the aggregate demands of land of each sector. Therefore, the following equation is satisfied: $L_{k,t}+L_{n,t}=L_t$. Regarding the market for capital, young individuals supply the capital that will be productive next period. In equilibrium, the aggregate supply of capital, K_t, equals the sum of the aggregate demands of capital of each sector. Therefore, the following equation is satisfied:

$$K_t=K_{n,t}+K_{k,t}+K_{m,t}. \tag{17}$$

Next, using (10), in Appendix B we obtain that the aggregate production of agricultural goods in each sector is

$$Y_{s,t}=A_{s,t}N_t\left[\left(\frac{\alpha_s}{R_t}\right)^{\alpha_s}\left(\frac{\beta_s}{x_t}\right)^{\beta_s}\left[(1-\tau)\,P_{s,t}A_{s,t}\right]^{\beta_s+\alpha_s}\right]^{\frac{1}{1-\beta_s-\alpha_s}}\Delta_{s,t}. \tag{18}$$

Finally, we obtain aggregate consumption demands, which depend on consumption expenditure. As noted above, young individuals do not consume and save all their income. Therefore, consumption expenditure of an old individual is $E^i_{t+1}=R_{t+1}I^i_t$, where I^i_t is the income obtained by young individual i in period t that depends on ability and the sector of activity. Consequently, the consumption expenditure of an old individual that was a non-agricultural worker in period t is $E^{m,i}_{t+1}=R_{t+1}\left[(1-\phi)\,w_t+T^i_t\right]$, where T^i_t is a transfer from the government. The consumption expenditure of an old individual that was a labor-intensive farmer is $E^{n,i}_{t+1}=R_{t+1}\left[\pi^i_{n,t}\left(a^i\right)+T^i_t\right]$. Similarly, the consumption expenditure of an old individual that was a capital-intensive farmer is $E^{k,i}_{t+1}=R_{t+1}\left[\pi^i_{k,t}\left(a^i\right)+T^i_t\right]$. Aggregate consumption expenditure is then given by

$$E_{t+1}=N_t\left(\int_{\eta}^{\underline{a}_t}E^{m,i}_{t+1}f\left(a^i\right)da^i+\int_{\underline{a}_t}^{\overline{a}_t}E^{n,i}_{t+1}f\left(a^i\right)da^i+\int_{\overline{a}_t}^{\infty}E^{k,i}_{t+1}f\left(a^i\right)da^i\right). \tag{19}$$

We assume that tax revenues are returned to individuals as a transfer and that the government budget constraint is balanced in each period. Using the balanced government budget constraint and (19), in Appendix C we obtain the following equation for aggregate consumption expenditure:

$$E_{t+1}=R_{t+1}\left\{\begin{array}{c}\left(1-\alpha_m\right)Y_{m,t}+\left[1-(1-\tau)\left(\alpha_n+\beta_n\right)\right]P_{n,t}Y_{n,t}\\+\left[1-(1-\tau)\left(\alpha_k+\beta_k\right)\right]P_{k,t}Y_{k,t}\end{array}\right\}. \tag{20}$$

Given that the utility function in the model belongs to the class of Gorman preferences, the aggregate demand of the different consumption goods does not depend on the distribution of consumption expenditures, but on aggregate consumption expenditure only. Using the individuals' consumption demands obtained in Appendix A, we obtain the aggregate consumption demands of labor and capital-intensive agricultural goods and of non-agricultural goods that, respectively, are given by

$$C_{n,t+1}=\omega\mu^{\varepsilon}\left(\frac{P_{n,t+1}}{P_{a,t+1}}\right)^{1-\varepsilon}\frac{E_{t+1}}{P_{n,t+1}}+(1-\omega)\,\mu^{\varepsilon}\left(\frac{P_{a,t+1}}{P_{n,t+1}}\right)^{\varepsilon}\overline{c}N_t, \tag{21}$$

$$C_{k,t+1}=\omega\,(1-\mu)^{\varepsilon}\left(\frac{P_{k,t+1}}{P_{a,t+1}}\right)^{1-\varepsilon}\frac{E_{t+1}}{P_{k,t+1}}+(1-\omega)\,(1-\mu)^{\varepsilon}\left(\frac{P_{a,t+1}}{P_{k,t+1}}\right)^{\varepsilon}\overline{c}N_t, \tag{22}$$

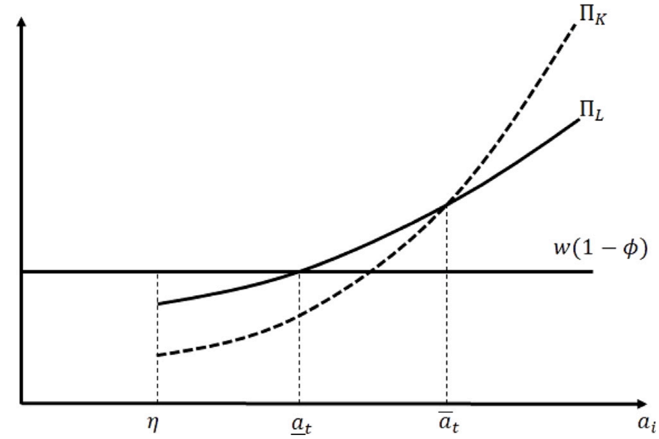

Fig. 5. Income profile of individuals. Note: This figure shows that the profits of farmers are increasing in abilities. It also shows that for farmers with $a^i \in [\eta, \underline{a}_t]$ the non-agricultural wage is larger than profits in agriculture, for $a^i \in [\underline{a}_t, \overline{a}_t]$ profits are larger in labor-intensive agriculture, and for $a^i \in [\overline{a}_t, \infty]$ profits are larger in capital-intensive agriculture.

$$C_{m,t+1} = (1-\omega)\, E_{t+1} - (1-\omega)\, P_{a,t+1}\overline{c} N_t, \tag{23}$$

where $P_{a,t+1}$ is the price of the agricultural good. In Appendix A, it is shown to be equal to

$$P_{a,t+1} = \left[\mu^{\varepsilon} P_{n,t+1}^{1-\varepsilon} + (1-\mu)^{\varepsilon} P_{k,t+1}^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}. \tag{24}$$

Definition 1. Given an initial level of capital, K_0, and a path of $\{A_{m,t}, A_{k,t}, A_{n,t}, N_t, L_t\}_{t=0}^{\infty}$, an equilibrium in this economy is a path of ability thresholds $\{\underline{a}_t, \overline{a}_t\}_{t=0}^{\infty}$ that satisfies (12) and (13), a path of aggregate demands of land $\{L_{n,t}, L_{k,t}\}_{t=0}^{\infty}$ that satisfies (14), a path of aggregate demands of capital $\{K_{n,t}, K_{k,t}, K_{m,t}\}_{t=0}^{\infty}$ that satisfies (15) and (16), a path of aggregate consumption demands $\{C_{n,t}, C_{k,t}, C_{m,t}\}_{t=0}^{\infty}$ that satisfies (21), (22) and (23), a path of sectoral outputs $\{Y_{n,t}, Y_{k,t}, Y_{m,t}\}_{t=0}^{\infty}$ that satisfies (4) and (18), a path of aggregate consumption expenditure and capital $\{E_t, K_t\}_{t=0}^{\infty}$ that satisfies (17) and (20), and a path of prices $\{P_{a,t}, R_t, P_{n,t}, P_{k,t}, x_t\}_{t=0}^{\infty}$ that satisfies (24), and market clearing conditions for labor-intensive agriculture, $C_{n,t} = Y_{n,t}$, for capital-intensive agriculture, $C_{k,t} = Y_{k,t}$, for non-agricultural products, $Y_{m,t} = C_{m,t} + K_{t+1}$, and for land holdings $L_t = L_{n,t} + L_{k,t}$.

At this point, we discuss some remarks on the equilibrium. First, capital is obtained from the market clearing condition in the non-agricultural sector and, since capital fully depreciates after one period, it is equal to $K_{t+1} = Y_{m,t} - C_{m,t}$.

Second, since capital and land are perfectly substitute assets, the price of land is not required in the definition of equilibrium. In fact, this price is obtained from arbitrage. To see this, we define the price of land as P_t. Since the income of young individuals is used to purchase land and capital, aggregate income of the young is equal to $P_t L_t + K_{t+1}$. The old consume the return from these assets. Therefore, aggregate consumption expenditures can be written as $E_{t+1} = \left(P_{t+1} + x_{t+1}\right) L_t + R_{t+1} K_{t+1}$. Non-arbitrage between the two assets implies equal return in period $t+1$, that is $R_{t+1} = \left(P_{t+1} + x_{t+1}\right)/P_t$. Using this condition and the aggregate consumption expenditure equation, we obtain the price of land as $P_t = (E_{t+1}/R_{t+1} - K_{t+1})/L_t$.

Third, the novelty in this paper is the process of structural change within agriculture. Therefore, it is important to clarify what drives this process in equilibrium. To this end, we combine Eqs. (21) and (22) with the market clearing conditions for labor and capital-intensive agriculture to obtain the sectoral composition of agricultural production

$$\frac{P_{n,t} Y_{n,t}}{P_{k,t} Y_{k,t}} = \left(\frac{\mu}{1-\mu}\right)^{\varepsilon} \left(\frac{P_{n,t}}{P_{k,t}}\right)^{1-\varepsilon}.$$

Combining the equation above with expressions (14), (15) and (18), we obtain the sectoral composition of both land and capital in agriculture, which are, respectively:

$$\frac{L_{n,t}}{L_{k,t}} = \frac{\beta_n}{\beta_k} \left(\frac{\mu}{1-\mu}\right)^{\varepsilon} \left(\frac{P_{n,t}}{P_{k,t}}\right)^{1-\varepsilon}, \qquad \frac{K_{n,t}}{K_{k,t}} = \frac{\alpha_n}{\alpha_k} \left(\frac{\mu}{1-\mu}\right)^{\varepsilon} \left(\frac{P_{n,t}}{P_{k,t}}\right)^{1-\varepsilon}. \tag{25}$$

Finally, in the supplementary appendix, we obtain that the fraction of farmers in capital-intensive agriculture, n_k, is

$$n_k = \left[1 + \left(\frac{\mu}{1-\mu}\right)^{\varepsilon} \left(\frac{P_{n,t}}{P_{k,t}}\right)^{1-\varepsilon} \left(\frac{\lambda\left(1-\beta_n-\alpha_n\right)-1}{\lambda\left(1-\beta_k-\alpha_k\right)-1}\right)\right]^{\frac{\lambda(1-\beta_n-\alpha_n)}{1-\lambda(1-\beta_n-\alpha_n)}}.$$

These equations show that the sectoral composition of agriculture depends on the term $\left(P_{n,t}/P_{k,t}\right)^{1-\varepsilon}$. If this term decreases, then the value of production, capital and land shift towards the capital-intensive agricultural sector and the fraction of farmers in capital-intensive agriculture increases. The value of the elasticity of substitution between the agricultural goods, ε, is crucial. In fact, when $\varepsilon = 1$, sectoral composition within agriculture remains constant even under the presence of biased technological progress. Therefore, if $\varepsilon = 1$, there is no reallocation of production factors towards capital-intensive agriculture.

Finally, when population, land and the sectoral TFPs converge to a constant value, the long run equilibrium is a steady state in which the sectoral composition and the variables characterizing the equilibrium are constant. In the numerical analysis of the following section, we study the process of structural change along the transition to this steady state.

5. Quantitative analysis

The goal of this section is to quantify the effect of structural change within agriculture on relative productivity. We perform two different analyzes. First, we quantify this effect for Brazil during the period 1960–2018. In Section 5.1, we calibrate the model assuming that the equilibrium is in a transition driven by permanent shocks in sectoral TFPs, and by the increase in the amount of land and in the total number of workers in the economy. In Section 5.2, we show that along this transition the productivity of agriculture relative to non-agriculture increases. We quantify the effect of structural change within agriculture by comparing the calibrated economy with a counterfactual economy in which the elasticity of substitution between the two agricultural goods is unitary and, as a consequence, there is no structural change within agriculture.

Second, in Section 5.3 we quantify the effect of agricultural composition on relative productivity in a cross-section of economies. In the simulation, we assume that these economies are in the steady state. We also assume that all cross-country differences are generated by differences in sectoral TFPs, which are calibrated to match observed differences in GDP per worker, in the fraction of workers in agriculture, and in the fraction of land used in capital-intensive agriculture. We show that the model generates cross-country differences in sectoral productivities that are consistent with observed data. Finally, we compare these results with those of a counterfactual economy in which the elasticity of substitution between agricultural goods equals one to quantify the effect of differences in agricultural composition on relative productivity.

5.1. Calibration

We distinguish between two sets of parameters. The first set consists of capital and land–output elasticities in each sector that are calibrated using data for the US. The remaining parameters are calibrated using data for Brazil. In particular, we match the process of structural change, both between broad sectors and within agriculture, observed in this

Table 5
Calibration.

Parameter	Value	Target	Data
Technology			
α_m	0.33	Capital income share in non-agriculture[a]	0.33
β_n	0.03	Relative land–output ratio between the two agricultural sectors[b]	0.15
β_k	0.22	Land income share in agriculture[a]	0.18
α_k	0.42	Relative capital–output ratio between the two agricultural sectors[b]	0.313
α_n	0.13	Capital income share in agriculture[a]	0.36
Preferences			
$\bar{c}$	0.04682	Employment share in agriculture in Brazil in 1960[c]	59%
ω	0.0146	Employment share in agriculture in Brazil in 2018[d]	12%
μ	0.5255	Fraction of land in labor-intensive agriculture in Brazil in 1961[e]	30%
ε	12.9	Fraction of land in labor-intensive agriculture in Brazil in 2018[e]	8.2%
Abilities			
λ	8.3	Fraction of farms smaller than 10 ha. in Brazil in 1960[f]	44.8%
η	1	Normalization	-.-
Taxes			
τ	0.32	Relative cap. intensity btw. agr. and non-agr. in Brazil, avg. 1995–2009[g]	0.545
ϕ	0.832	Relative nom. prod. btw. agr. and non-agr. in Brazil, avg. 2000–2018[d]	35.2%
Exogenous processes			
$A_{m,1960}$	1	Normalization.	-.-
$A_{n,1960}$	0.1912	Price of agriculture relative to non-agriculture in 1965	1
$A_{k,1960}$	0.2734	Relative real. prod. btw. agr. and non-agr. in Brazil in 1960 [c]	7.9%
$A_{m,2020}$	1.38	Annual growth of GDP per worker between 1960–2018[h]	1.7%
$A_{n,2020}$	0.6883	Relative price of agriculture relative to non-agriculture in 2019[i]	0.327
$A_{k,2020}$	1.5855	Fraction of farms smaller than 10 ha. in Brazil in 2017[f]	50.1%
N_{1960}	1	Normalization	-.-
N_{2020}	4.01	Increase in the number of workers in Brazil between 1960 and 2018[h]	4.01
L_{1960}	5.074	Average farm size in Brazil in 1960 (hectares)[f]	8.6
L_{2020}	5.9	Average farm size in Brazil in 2017 (hectares)[f]	12.5

Note:
[1] The model is calibrated to fit the values in the data exactly.
[2] Relative productivity in agriculture and non-agriculture is measured at 2015 constant prices. Relative land–output (capital–output) between the two agricultural sectors is land–output (capital–output) ratio in labor-intensive agriculture divided by the same ratio in capital-intensive agriculture. Relative capital intensity is the ratio between capital intensity in agriculture and in non-agriculture.
[3] All exogenous processes increase gradually from 1960 to 2020 and remain constant after year 2020.
Source:
[a] Valentinyi and Herrendorf (2008).
[b] 2012 US Census of Agriculture.
[c] GGDC 10-Sector Database.
[d] GGDC/UNU-WIDER Economic Transformation Database.
[e] Calculated from FAO.
[f] IBGE, Agricultural Census of Brazil for 1960 and 2017.
[g] World Input–Output Database 2012.
[h] Penn World Table 10.0.
[i] Calculated from World Development Indicators.

country during the period 1960–2018. We also match the change in the distribution of farm sizes, the growth of real GDP per worker, and the decline of prices in agriculture observed during this period. The calibration matches all the targets in the data, specified below, exactly. The parameter values and the targets of the calibration are summarized in Table 5. The calibration strategy is as follows.

First, we assume that capital and land–output elasticities for Brazil are the same as for the US and, hence, we set their values using data for the US. The value of α_m is obtained from the capital income share in the non-agricultural sector as reported by Valentinyi and Herrendorf (2008). The technological parameters of the agricultural sector, α_n, α_k, β_n and β_k, are set jointly to match the following four targets of the US economy: (i) capital–output ratio of labor-intensive agriculture relative to capital–output ratio of capital-intensive agriculture, which gives us $\alpha_n/\alpha_k = 0.313$; (ii) land–output ratio of labor-intensive agriculture relative to land–output ratio of capital-intensive agriculture, which gives us $\beta_n/\beta_k = 0.15$; (iii) capital income share in agriculture, which gives us $\left(\alpha_n P_n Y_n + \alpha_k P_k Y_k\right) / \left(P_k Y_k + P_n Y_n\right) = 0.36$; and (iv) land income share in agriculture, which gives us $\left(\beta_n P_n Y_n + \beta_k P_k Y_k\right) / \left(P_k Y_k + P_n Y_n\right) = 0.18$. The capital–output ratio and the land–output ratio of the two agricultural sectors are obtained from the US Census of Agriculture in 2012, while capital and land income shares in agriculture are obtained from Valentinyi and Herrendorf (2008).

Second, preference parameters μ and ε are set to match the fraction of harvested land in labor-intensive agriculture in 1961 and 2018, while preference parameters $\bar{c}$ and ω are set to match the values of the share of employment in agriculture in 1960 and 2018. Therefore, preference parameters are jointly calibrated to explain the process of structural change in Brazil. Note that the calibrated value of ε is larger than one, which implies that the two agricultural sectors are imperfect substitutes.

Third, sectoral TFPs are assumed to grow at a constant rate during the period 1960–2020 and remain at a constant value after that. Table 5 reports the values of sectoral TFPs in 1960 and 2020. The initial value of TFP in labor-intensive agriculture, $A_{n,t}$, is set to match the value of the agricultural price index in 1965, whereas the initial value of TFP in capital-intensive agriculture, $A_{k,t}$, is set such that productivity in agriculture relative to non-agriculture in 1960, measured at constant prices, is 7.9%.[7] The initial value of the sectoral TFP in non-agriculture, $A_{m,t}$, is normalized to 1. We set the path of $A_{n,t}$ to match the decline in the price index of agriculture observed in Brazil during 1965–2019, which is obtained from the World Development Indicators database of the World Bank. The path of $A_{m,t}$ is set to match the growth rate of real

[7] The base year in the data is 2015 and in the simulation is 2020.

GDP per worker observed in Brazil during 1960–2018 of 1.7%, obtained using data from the Penn World Table 10.0. As explained below, we set the path of $A_{k,t}$ to match the farm size distribution in Brazil.

Fourth, we set jointly the parameter λ of the Pareto distribution, the path of $A_{k,t}$, and the path of agricultural land, L_t, to match the change in the distribution of farm sizes observed in Brazil between 1960 and 2017. More specifically, we match (i) the 1.45-fold increase in average farm size from 8.6 hectares in 1960 to 12.5 hectares in 2017, and (ii) the percentage of small farms in agriculture in both 1960 and 2017 which are, respectively, 44.8% and 50.1%. We compute average farm sizes using data from the IBGE Agricultural Census of Brazil for years 1960, 1970, 1975, 1980, 1985, 1996, 2006, and 2017. A small farm is defined as a farm with less than 10 hectares. To calculate averages, we consider only cultivated land, which includes land in permanent and temporal crops. We exclude land used for other purposes or non-cultivated land.[8]

Fifth, the number of workers, N_t, is set to match the 4.01-fold increase in the number of persons engaged in Brazil during the period 1960–2018, as reported in the Penn World Table 10.0.

Sixth, the tax τ is set to match, jointly with the sectoral factor income shares, the relative capital intensity between agriculture and non-agriculture, which is given by

$$\frac{R_t\left(K_{k,t}+K_{n,t}\right)}{P_{k,t}Y_{k,t}+P_{n,t}Y_{n,t}} \Big/ \frac{R_t K_{m,t}}{Y_{m,t}} = (1-\tau)\left(\frac{\alpha_k}{\alpha_m}\frac{P_{k,t}Y_{k,t}}{P_{k,t}Y_{k,t}+P_{n,t}Y_{n,t}} + \frac{\alpha_n}{\alpha_m}\frac{P_{n,t}Y_{n,t}}{P_{k,t}Y_{k,t}+P_{n,t}Y_{n,t}}\right). \tag{26}$$

Since the sectoral factor income shares are set using data for the US, we must set $\tau = 0.32$ to match the average value of relative capital intensity in Brazil during the period 1995–2009. Note that τ, calibrated in this way, reduces relative capital intensity between agriculture and non-agriculture. If $\tau = 0$, the value of relative capital intensity would be close to the US level, which is much larger than in Brazil. However, this parameter has no effect on relative capital intensity between labor and capital-intensive agriculture, which is determined by α_n/α_k. This relative capital intensity remains constant at the level of the US. This is a caveat of our calibration, since the value of this relative capital intensity influences the effect of structural change within agriculture on relative productivity.

Finally, using data from the GGDC/UNU-WIDER Economic Transformation Database, we obtain that the average value during the period 2000–2018 of relative productivity between agriculture and non-agriculture in Brazil is 35%, when productivities are measured at current prices. We set the tax ϕ to match this value.

In the following subsection, we use this calibration to measure the effect of structural change within agriculture on relative productivity in Brazil.

5.2. Structural change and labor productivity

Fig. 6 compares the time path of the main variables implied by the simulation of the calibrated economy with actual data. Taking into account that each period is 20 years, the simulation is reported for the period 1960–2020 and matches the data for Brazil during 1960–2018.

The first two panels in Fig. 6 show the process of structural change between broad sectors and within agriculture. Panel (a) shows the decline in the fraction of employment in agriculture. In the model, this decline is mainly driven by income growth and an income effect due to a minimum requirement of agricultural consumption. The model is calibrated to match the fall in agricultural employment of 47 percentage points.

In Panel (b), we show the process of structural change within agriculture in terms of land shares.[9] Although the simulation is unable to explain the large drop of the fraction of land in labor-intensive agriculture during the sixties and early seventies, it matches the reduction of 21.8 percentage points observed during the entire period. This process of structural change is driven by the change in the relative price between the two agricultural sectors. The accumulation of capital, associated with economic development, benefits the capital-intensive agricultural sector more and, as a consequence, the price of labor-intensive crops relative to capital-intensive crops increases. This relative price increase generates a process of structural change from labor to capital-intensive agriculture when these sectors are imperfect substitutes; that is, when the elasticity of substitution is larger than one. In fact, to match the observed change in land shares, the calibrated value of the elasticity is greater than one.

As shown in Panel (c), data on capital intensity in agriculture relative to non-agriculture is available for the period 1995–2009. Although the data spans for only 14 years, it shows a clearly increasing path. In the simulation, while the average value of relative capital intensity is targeted, the increase in relative capital intensity is not. This increase is entirely driven by structural change within agriculture. Too see this, we can use Eq. (26), where relative capital intensity between agriculture and non-agriculture is expressed as the weighted average of relative capital intensities between each agricultural sector and non-agriculture, with weights being the fraction of value added in each agricultural sector. Given that technologies are Cobb–Douglas, the relative capital intensity between each agricultural sector and non-agriculture are constant and equal to α_k/α_m and α_n/α_m. Therefore, the increase in the capital intensity of aggregate agriculture relative to non-agriculture is driven entirely by the increase in the fraction of agricultural value added generated in the capital-intensive sector.

Notice that the novelty of our calibration is to use μ and ε to match changes in the sectoral composition in agriculture. Instead, the technological change literature, and Chen (2020) in particular, utilizes technological parameters to match a technological adoption curve. In Chen (2020), there is a single agricultural product and the share of farmers producing with the more capital-intensive technology increases as the technology becomes less expensive. Our contribution to this literature is to relate the rise in capital intensity to observed changes in the composition of the agricultural sector.

The average farm size increases as a result of the reduction in agricultural employment and the increase in cultivated land. This is shown in Panel (d), where we decompose the average farm size in average size of small and large farms. As we can observe, the rise in average farm size is driven by the rise in average size of large farms. As before, small farms are defined as those with less than 10 hectares. In the data, the average size of small farms slightly declines, while the average size of large farms shows a 1.86-fold increase between 1960 and 2017. The simulation matches these very different patterns and, in particular, explains the considerable increase in the average size of large farms. Notice that we target the average farm size, not the average farm size of small and large farms. In the simulation of the calibrated economy, the average size of large farms increases because this segment of farms includes all capital-intensive farms, which are the ones benefiting the most from economic development in Brazil.

In panel (e), we show the relative price of agriculture, which is a target of our calibration. The data shows a clearly decreasing trend, despite large initial fluctuations. The simulation matches the reduction in this relative price. In the calibrated economy, this decline results from an increase in the productivity of agriculture relative to non-agriculture.

[8] In Brazil, there are large differences between cultivated and total land. The latter also includes forestry, pastures and other land such as lakes, degraded land, idle land, and land unsuitable for exploitation. During 1960–2018, cultivated land grew faster than total land.

[9] The process of structural change within agriculture could also be illustrated in terms of the fraction of farmers or the fraction of value added in each agricultural sector. We use land shares due to data availability.

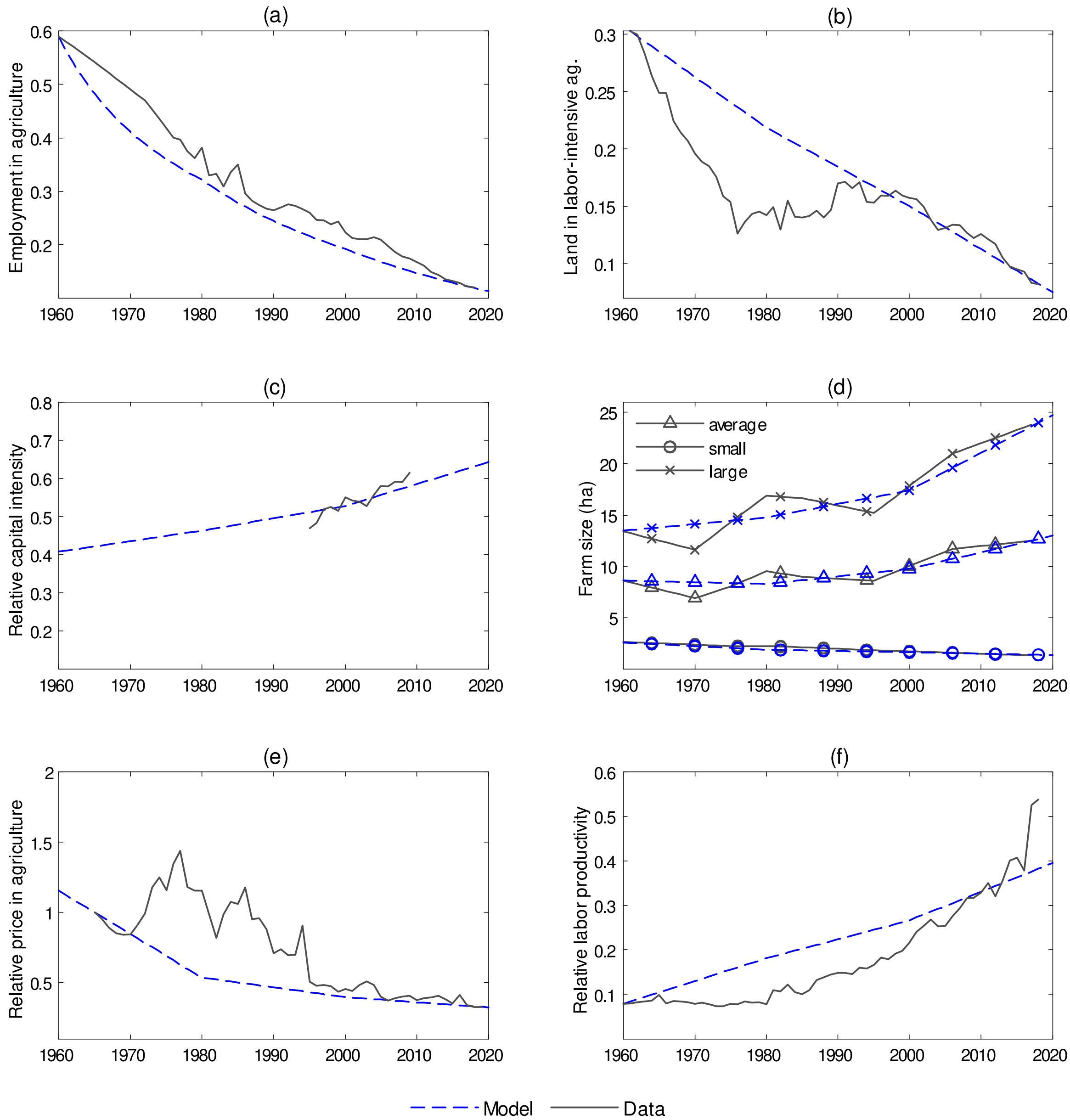

Fig. 6. Quantitative results. Note: [1] This figure compares the results of the benchmark simulation with the data for Brazil. Continuous lines indicate data, dashed lines indicate model simulation. In Panel (d) lines with crosses show average size of large farms, triangles show average farm size of all farms, and circles show average size of small farms. [2] The fraction of employment in agriculture is obtained from GGDC 10-Sector Database (1960–2011) and GGDC/UNU-WIDER Economic Transformation Database (2012–2018). The fraction of land in labor-intensive agriculture is computed from FAO. Capital intensity in agriculture relative to non-agriculture is obtained from the World Input–Output Database 2012. The average farm size and the average size of small and large farms is elaborated from the IBGE Agricultural Census of Brazil for years 1960, 1970, 1975, 1980, 1985, 1996, 2006, and 2017. To compute averages we consider only cultivated farmland, which includes land in permanent and temporal crops. We exclude land used for other purposes or non-cultivated. The price of agriculture relative to non-agriculture is calculated from World Development Indicators. Agricultural productivity relative to non-agricultural productivity at 2015 constant prices is obtained from GGDC 10-Sector Database (1960–2011) and GGDC/UNU-WIDER Economic Transformation Database (2012–2018).

Panel (f) in Fig. 6 shows the increase of agricultural labor productivity relative to non-agricultural labor productivity. Note that the increase of this ratio is not a target of the calibration. It increases from 7.9% to 53.8% in the data and from 7.9% to 38.3% in the simulation, during the period 1960–2018. Therefore, our model explains 66.2% of the observed increase in relative productivity. This increase is the result of the combination of different mechanisms: an increase in TFP that is larger in the agricultural sectors, selection, the increase in average farm size and the increase of agricultural capital intensity relative to non-agricultural capital intensity. On the one hand, the reduction in the number of farmers implies that the farmers who remain in agriculture have higher abilities and manage more land. As in Lagakos and Waugh (2013) and Adamopoulos and Restuccia (2014) both effects increase productivity in agriculture. On the other hand, the increase in productivity is also explained by the increase in capital intensity that, in our model, results entirely from the process of structural change within agriculture. In the following subsection, we measure the importance of this mechanism.

5.2.1. *The role of structural change within agriculture*

To measure the effect of structural change within agriculture on relative productivity, in Fig. 7 we compare the calibrated economy with a counterfactual economy in which the elasticity of substitution is set to one. In the counterfactual, we set $\bar{c} = 0.0533$ and $\mu = 0.761$ to match the initial sectoral composition, given by the fraction of employment in agriculture (59%) and by the fraction of harvested land in labor-intensive agriculture (30%). Therefore, the parameters $\bar{c}$ and μ are set so

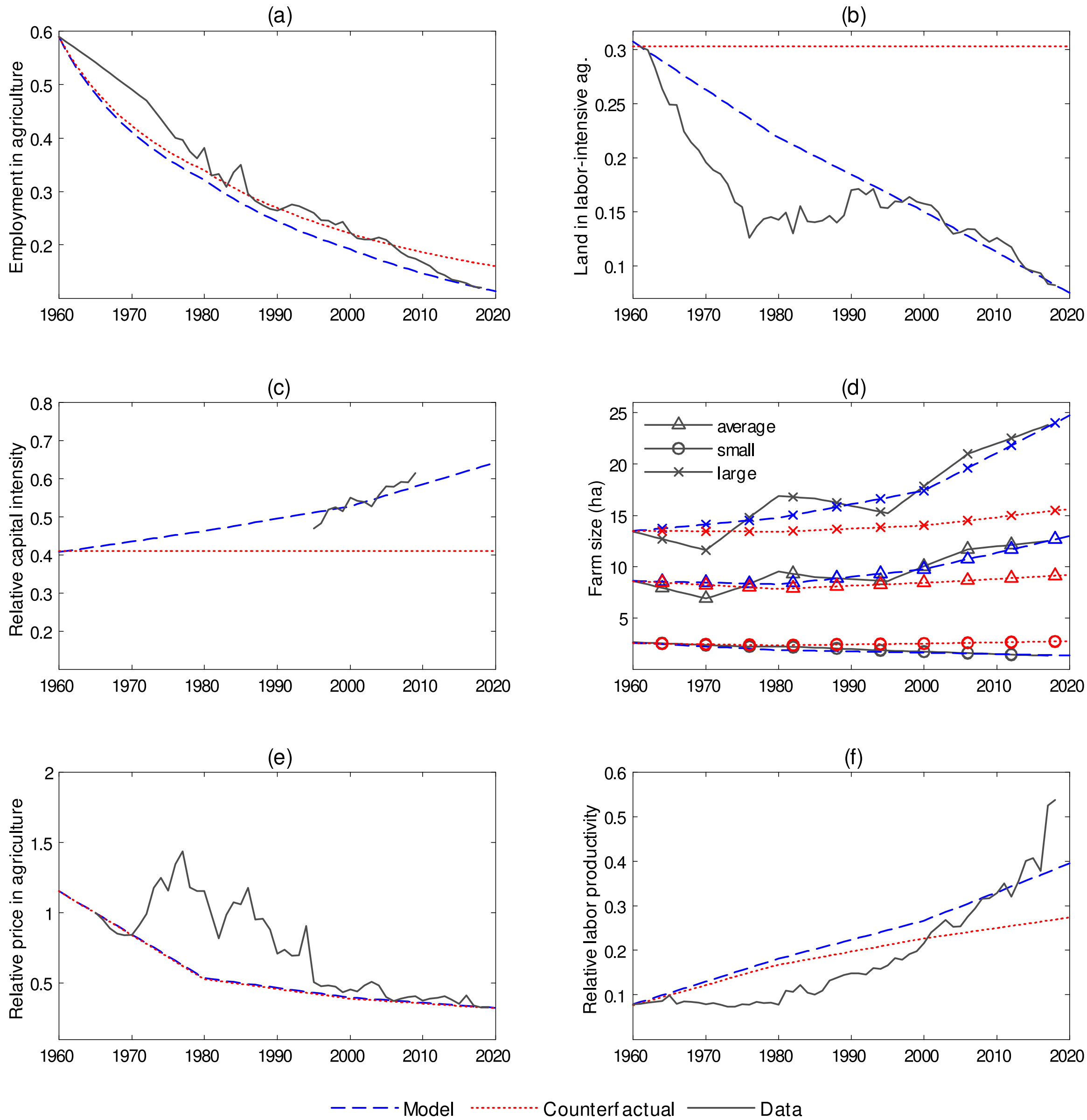

Fig. 7. Counterfactual simulation. Note: This figure compares the results of the counterfactual simulation with the benchmark simulation and the data for Brazil. Continuous lines indicate data, dashed lines indicate model simulation, and dotted lines indicate counterfactual simulation. In Panel (d) lines with crosses show average size of large farms, triangles show average farm size of all farms, and circles show average size of small farms. Data sources are the same as in Fig. 6.

that the two economies are initially identical, with the same initial sectoral composition, relative capital intensity and farm size distribution, and all differences along the transition are due to different processes of structural change that result from different elasticities of substitution. More precisely, in both economies, the price of labor-intensive crops relative to capital-intensive crops increases. However, as shown in (25), while the relative price increase reduces the fraction of harvested land in labor-intensive agriculture under imperfect substitution, it has no effect on sectoral composition when the elasticity of substitution is equal to one. These different patterns are illustrated in Panel (b) of Fig. 7.

The process of structural change within agriculture determines the dynamics of relative capital intensity in Panel (c). It remains constant in the absence of structural change within agriculture and it increases in the benchmark economy as farmers move to the capital-intensive sector. Obviously, these different dynamics of capital intensity affect agricultural labor productivity negatively in the counterfactual economy. As a consequence, the reduction in the number of farmers and the increase in the average farm size are limited in the counterfactual economy, as shown in Panels (a) and (d) of Fig. 7. Note also that the counterfactual economy generates only a small increase in the average size of large farms and does not explain the reduction in the average size of small farms. The failure of the counterfactual economy to explain the change in the distribution of farms is a consequence of the absence of structural change within agriculture.

Since average farm size and relative capital intensity are negatively affected by the absence of structural change in the counterfactual economy, the increase in relative productivity is smaller than in the benchmark economy. In fact, relative productivity in the counterfactual economy increases from 7.9% to 26.9% only. This counterfactual economy without structural change explains only 41.4% of the observed increase in relative productivity in the data. Since the benchmark economy explains 66.2%, we conclude that structural change in the agricultural sector accounts for 24.8% of the observed increase in relative productivity of Brazil during the period 1960–2018.

Table 6
Cross-country quantitative results.

	Targeted moments			Non-targeted moments		
	Y/N	L_k/L	N_a/N	Y_a/N_a	Y_m/N_m	$\frac{Y_a/N_a}{Y_m/N_m}$
Data	16.0	0.83/0.67	0.06/0.82	27.3	3.87	7.05
Benchmark	16.0	0.83/0.67	0.06/0.82	22.9	3.61	6.36
Counterfactual	13.1	0.67/0.67	0.26/0.82	15.9	3.59	4.42

Note:
[1] Data on GDP per worker (Y/N), labor productivity in agriculture (Y_a/N_a), labor productivity in non-agriculture (Y_m/N_m) and agricultural productivity relative to non-agricultural productivity ($Y_a/N_a/Y_m/N_m$) is obtained from Restuccia et al. (2008) and is PPP-adjusted. Data on agricultural employment (N_a/N) is obtained from Restuccia et al. (2008) and the fraction of land in capital-intensive agriculture (L_k/L) is calculated from FAO. All data refers to the year 1985. In the simulation, we use prices of the high-income country to value the sectoral outputs of each country.
[2] For Y/N, Y_a/N_a, Y_m/N_m and $Y_a/N_a/Y_m/N_m$ we compute the ratio between the median value of the 25% richest countries and the median value of the 25% poorest countries of the world income distribution. For L_k/L and N_a/N we report both rich and poor country median values. Median values are computed to minimize the effect of outliers.

5.2.2. Nominal labor productivity

In the previous subsection, we have analyzed relative productivity measured at constant prices. More precisely, relative productivity is defined as the ratio between agricultural labor productivity and non-agricultural labor productivity when these productivities are valued at constant prices.[10] Alternatively, other authors have studied the agricultural productivity gap, as defined by Gollin et al. (2014a). This gap is defined as the ratio of nominal productivity in agriculture relative to nominal productivity in non-agriculture. That is, output is measured at current prices.

Structural change within agriculture also contributes to explain the change in the ratio of productivities when valued at current prices. To see this, we use data from the GGDC/UNU-WIDER Economic Transformation Database and find that the ratio of nominal productivities between agriculture and non-agriculture increases by 31 percentage points in Brazil during the period 1990–2018, for which data is available. In the calibrated economy, this ratio increases by 8 percentage points during the same period. In contrast, in the counterfactual economy with an elasticity equal to one, this ratio is constant. Therefore, the increase in nominal relative productivity of 8 percentage points generated in the simulation is explained entirely by structural change within the agricultural sector. We conclude that structural change within agriculture contributes to explain the increase in both nominal and real relative productivity.

5.3. Cross-country labor productivity differences

In this section, we ask how much of the difference in relative productivity observed across countries can be explained by differences in agricultural composition. The cross-country data is summarized in the first row of Table 6.[11] As shown in the table, the difference in real GDP per worker between countries in the top and bottom quartiles of the world income distribution is 16-fold. While employment in agriculture is only 6% of total employment in advanced countries, it is 82% in low-income countries. Regarding productivity, Table 6 shows that countries in the top quartile are 27.3 times more productive in agriculture than countries in the bottom quartile. In non-agriculture, the difference in productivity between high and low-income countries is only 3.87-fold. As a result, there is a 7.05-fold difference in the agricultural productivity relative to non-agricultural productivity ratio between high and low-income countries. These facts have been documented by Caselli (2005) and Restuccia et al. (2008). The novelty reported here is that countries in the top quartile of the world income distribution allocate more land to capital-intensive agriculture compared to countries in the bottom. That is, while 83% of total harvested land is allocated to capital-intensive agriculture in high-income countries, only 67% of harvested land is allocated to this sector in low-income countries.

The second row in Table 6 shows how much of the difference in relative productivity across countries can be explained by the model. To do this, we assume countries are in the steady state and we set sectoral TFPs, A_m, A_k and A_n, to match differences in real GDP per worker, agricultural employment and land in capital-intensive agriculture between countries in the top and bottom quartile of the world income distribution.[12] All other parameters are set as in the benchmark calibration for Brazil and the exogenous variables L_t and N_t are set at their 1960 values for Brazil. That is, we calibrate cross-country moments using only the sectoral TFPs. For the country in the top quartile, we set A_m, A_k and A_n so that GDP per worker equals the median value of countries in the top quartile, employment in agriculture is 6% of total employment and land in capital-intensive agriculture is 83%, as in the data. Then, for the country in the bottom quartile, we reduce A_m, A_k and A_n to match that real GDP per worker is one-sixteenth of that in high-income countries, employment in agriculture is 82% and land in capital-intensive agriculture is 67%. More specifically, for countries in the top quartile we set $A_m = 1.487$, $A_k = 1.6485$ and $A_n = 1.7189$ and for countries in the bottom quartile we set $A_m = 0.6320$, $A_k = 0.2885$ and $A_n = 0.1591$. Notice that we match 100% of the difference in real GDP per worker, agricultural employment and land in capital-intensive agriculture between rich and poor countries observed in the data. With this calibration, we can analyze moments not directly targeted such as relative productivity.

The benchmark model generates a 6.36-fold difference between rich and poor countries in agricultural productivity relative to non-agricultural productivity, compared to a 7.05-fold difference in the data. That is, it accounts for 90.2% of differences observed in the data, which gives a sense of the good fit of the model. The model generates roughly the same non-agricultural productivity difference between rich and poor countries, 3.61 in the model and 3.87 in the data. It also accounts for a large fraction of the difference in agricultural productivity between rich and poor countries, 22.9 in the model and 27.3 in the data.

How much of the cross-country difference in agricultural productivity relative to non-agricultural productivity is explained by agricultural composition? To answer this, we compare the results of the benchmark model with a counterfactual simulation with unitary elasticity of substitution between capital and labor-intensive agricultural products. In the counterfactual simulation, we set $\varepsilon = 1$ to keep the composition of agriculture constant and we set $\bar{c} = 0.06492$ and $\mu = 0.778$ so that the fraction of land in capital-intensive agriculture is fixed at 67%, as in the bottom quartile, and the fraction of employment in agriculture in poor countries is 82%. To keep comparability, the differences in sectoral TFPs across countries are the same in both the benchmark and the counterfactual simulation. Results are shown in the third row of Table 6.

The main result of this exercise is that, in the counterfactual simulation, cross-country differences in sectoral TFPs have no effect on

[10] We make comparisons of real output, that is, we value sectoral production along the transition using constant prices. Other authors have also used real sectoral output to compare sectoral productivity across countries. For instance, Restuccia et al. (2008) and Lagakos and Waugh (2013) use the same international prices to value the sectoral outputs of each country.

[11] For each variable, we report the ratio between the median country in the top quartile of the world income distribution and the median country in the bottom quartile. Results hold if instead we compare top and bottom quintiles or deciles.

[12] Data on sectoral productivities and GDP per worker is from Restuccia et al. (2008). In these data, the same international prices are used to value the sectoral outputs of each country. To compare the result from the model with these data, we use prices of the high-income country to value the sectoral outputs of each country.

Table 7
Quantitative results by quartiles.

Quartiles	Targeted moments								
	Y/N			L_k/L			N_a/N		
	Data	Model	$\varepsilon=1$	Data	Model	$\varepsilon=1$	Data	Model	$\varepsilon=1$
4	16.0	16.0	13.1	0.83	0.83	0.67	0.06	0.06	0.26
3	6.6	6.6	5.0	0.75	0.75	0.67	0.28	0.28	0.46
2	3.0	3.0	2.2	0.70	0.70	0.67	0.53	0.53	0.67
1	1.00	1.00	1.00	0.67	0.67	0.67	0.82	0.82	0.82
Quartiles	Non-targeted moments								
	Y_a/N_a			Y_m/N_m			$(Y_a/N_a)/(Y_m/N_m)$		
	Data	Model	$\varepsilon=1$	Data	Model	$\varepsilon=1$	Data	Model	$\varepsilon=1$
4	27.3	22.9	15.9	3.87	3.61	3.59	7.05	6.36	4.42
3	5.41	3.25	2.86	2.06	1.89	1.89	2.62	1.72	1.52
2	2.68	1.60	1.52	1.51	1.26	1.26	1.78	1.27	1.21
1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Note: This table shows cross-country quantitative results by quartile of the world income distribution. For Y/N, Y_a/N_a, Y_m/N_m and $Y_a/N_a/Y_m/N_m$ we compute the ratio between the median value of countries in each quartile relative to the median value of countries in the first quartile. For L_k/L and N_a/N we report median values for each quartile. Median values are computed to minimize the effect of outliers. Data sources are the same as in Table 6.

agricultural composition and, consequently, the counterfactual economy is less effective than the benchmark economy in explaining relative productivity differences. Table 6 shows that the counterfactual simulation, which excludes changes in the sectoral composition of agriculture, generates a 4.42-fold gap in agricultural productivity relative to non-agricultural productivity between rich and poor countries. Since the benchmark model explains 90.2% (6.36/7.05) of the relative productivity differences observed in the data and the counterfactual model explains 62.7% (4.42/7.05), we conclude that agricultural composition accounts for 27.5% of cross-country differences in relative productivity.

Table 6 also shows cross-country differences in agricultural and non-agricultural productivity. The counterfactual simulation generates a 3.59-fold difference in non-agricultural productivity between rich and poor countries, a value similar to that of the benchmark simulation. However, the counterfactual model generates a much lower gap in agricultural productivity between rich and poor countries. While the benchmark model generates a 22.9-fold productivity gap in agriculture, in the model with $\varepsilon = 1$ this gap is only 15.9-fold. This shows that the mechanism in this model is driving agricultural productivity differences between the rich and the poor.

The results in Table 6 hold for other quartiles of the world income distribution, as shown in Table 7. The data shows that, as expected, employment in agriculture declines with income in each quartile. More interestingly, in the data, the fraction of land in capital-intensive agriculture increases with income, with countries in the first, second, third and fourth quartile allocating, respectively, 67%, 70%, 75% and 83% of land to this sector. To simulate the benchmark model, as before, we set sectoral TFPs to match real GDP per worker, employment and land composition in each quartile. More precisely, in the third quartile we set $A_m = 0.974$, $A_k = 0.5121$ and $A_n = 0.3767$, and in the second quartile we set $A_m = 0.745$, $A_k = 0.3631$ and $A_n = 0.2249$ (for quartiles one and four, sectoral TFPs are the same as before).

Table 7 shows that the benchmark model explains the increase in agricultural productivity relative to non-agricultural productivity observed in the data, as countries move to higher income quartiles. Moreover, for each quartile, the benchmark model explains more of the relative productivity gap between rich and poor countries than the counterfactual model with fixed agricultural composition. For example, for countries in the third quartile, the gap in relative productivity compared to countries in the bottom quartile is 2.62-fold in the data, 1.72-fold in the benchmark simulation and only 1.52-fold in the counterfactual. For countries in the second quartile, the gap is 1.78-fold in the data, 1.27 in the benchmark model and 1.21-fold in the counterfactual. Clearly, differences in L_k/L are larger across countries when they are further apart in the distribution of income. For this reason, the performance of our mechanism is better for countries further apart in the distribution. However, we can conclude that our mechanism is still able to explain part of the relative productivity differences observed in each quartile.

Finally, in this section, we generate cross-country differences in the model by introducing differences in sectoral TFPs only. Alternatively, we could introduce differences in the parameter λ that governs the shape of the distribution function. This parameter affects the distribution of abilities and, hence, affects the farm size distribution. In particular, a higher value of λ increases the fraction of individuals with low agricultural abilities, which increases the number of small farms. As a consequence, employment in agriculture increases, the average farm size declines and agricultural composition shifts towards labor-intensive agriculture. The shift towards the labor-intensive sector reduces capital intensity of agriculture relative to non-agriculture. The change in the distribution of abilities combined with the reduction in average farm size and in relative capital intensity results in a reduction of agricultural productivity relative to non-agricultural productivity. The effect of an increase in λ is, therefore, similar to that of lower sectoral productivities, both of them impoverish the economy. By combining differences in λ and in sectoral TFPs, we could carry out more specific cross-country analysis such as the comparison of the relative productivity among economies with similar level of development but different distribution of farm sizes.

6. Concluding remarks

Differences in labor productivity between developed and developing countries are substantially larger in agriculture than in non-agriculture. Since agricultural employment is large in developing countries, the development literature has concluded that explaining these large differences in agricultural productivity is central to understand cross-country income differences. We contribute to this literature by showing that the composition of agriculture can explain a significant part of low agricultural productivity relative to non-agricultural productivity in developing countries.

We use data from the US Census of Agriculture and FAO to group agricultural products into two agricultural sectors that differ in capital intensity. Using this data, we calibrate a model and show that, as the economy develops and capital becomes abundant, the price of labor-intensive agriculture relative to capital-intensive agriculture increases. When the agricultural goods produced in both agricultural sectors are imperfect substitutes in preferences, this change in relative prices, along with economic development, drives a process of structural change that implies: (i) a reduction in the number of farmers; (ii) an increase in the average farm size; (iii) a decrease in the fraction of harvested land used in the labor-intensive sector; and (iv) an increase in the capital intensity of the agricultural sector relative to the non-agricultural sector. Since farms are larger and the agricultural sector is more capital intensive, productivity in agriculture increases relative to non-agriculture. We show that these development patterns, implied by our model, are consistent with time series evidence for Brazil, and with a cross-country sample that includes developing and developed countries.

In order to quantify how much of the increase in relative productivity is explained by structural change within the agricultural sector, we conducted counterfactual simulations in which the elasticity of substitution between the two agricultural goods is unitary and, hence, there is no structural change in the agricultural sector. We conclude that changes in the sectoral composition of agriculture explain 24.8% of the observed increase in the relative productivity of Brazil in the period 1960–2018 and 27.5% of the observed differences in relative productivity across countries. Therefore, structural change within agriculture explains roughly a quarter of the increase in relative productivity both across countries and over time.

We conclude this paper by discussing two avenues for future work. First, this model can be used to study how misallocation associated to taxes or regulations affect relative labor productivity. From the development literature, we know that taxes that produce a direct wedge between income in agriculture and non-agriculture affect relative labor productivity. In this model, taxes could also affect relative labor productivity by altering the composition of agriculture, even if they do not generate a wedge between income in agriculture and non-agriculture. Regarding regulations, a policy that limits the mobility of individuals out of agriculture could shift agricultural composition towards the labor-intensive sector and reduce the relative labor productivity. Therefore, this model offers a benchmark to study how misallocations of factors across agricultural sectors could have a negative impact on relative labor productivity. Second, throughout this paper, we maintain that the force that drives the process of structural change within agriculture is the change in domestic consumption of agricultural goods. However, we acknowledge that exports of agricultural products could be another potential source of structural change in some countries. This suggests that the introduction of trade could be an interesting extension.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

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Appendix A. Consumers' problem

The consumer chooses c_n^i, c_k^i and c_m^i to maximize (1) subject to (2) and (3). We break down this problem into two steps. First, consumers choose c_n^i and c_k^i to maximize (2) subject to

$$E_{a,t+1}^i = P_{n,t+1}c_{n,t+1}^i + P_{k,t+1}c_{k,t+1}^i,$$

where $E_{a,t+1}^i$ is the agricultural expenditure of individual i. Maximization implies

$$c_{n,t+1}^i = \mu^\varepsilon \left(\frac{P_{n,t+1}}{P_{a,t+1}}\right)^{1-\varepsilon} \frac{E_{a,t+1}^i}{P_{n,t+1}}, \tag{27}$$

$$c_{k,t+1}^i = (1-\mu)^\varepsilon \left(\frac{P_{k,t+1}}{P_{a,t+1}}\right)^{1-\varepsilon} \frac{E_{a,t+1}^i}{P_{k,t+1}}, \tag{28}$$

where $P_{a,t+1}$ is the price of the agricultural good and is equal to

$$P_{a,t+1} = \left[\mu^\varepsilon P_{n,t+1}^{1-\varepsilon} + (1-\mu)^\varepsilon P_{k,t+1}^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}.$$

Note that this price satisfies

$$P_{a,t+1}c_{a,t+1}^i \equiv E_{a,t+1}^i = P_{n,t+1}c_{n,t+1}^i + P_{k,t+1}c_{k,t+1}^i.$$

Second, consumers choose c_a^i and c_m^i by maximizing (1) subject to $E_{t+1}^i = c_{m,t+1}^i + P_{a,t+1}c_{a,t+1}^i$.

Maximization implies

$$c_{m,t+1}^i = (1-\omega)E_{t+1}^i - (1-\omega)P_{a,t+1}\bar{c}, \tag{29}$$

and

$$P_{a,t+1}c_{a,t+1}^i = \omega E_{t+1}^i + (1-\omega)P_{a,t+1}\bar{c}.$$

Combining this last equation with (27) and (28), we obtain

$$c_{n,t+1}^i = \omega\mu^\varepsilon \left(\frac{P_{n,t+1}}{P_{a,t+1}}\right)^{1-\varepsilon} \frac{E_{t+1}^i}{P_{n,t+1}} + (1-\omega)\mu^\varepsilon \left(\frac{P_{n,t+1}}{P_{a,t+1}}\right)^{-\varepsilon}\bar{c}, \tag{30}$$

$$c_{k,t+1}^i = \omega(1-\mu)^\varepsilon \left(\frac{P_{k,t+1}}{P_{a,t+1}}\right)^{1-\varepsilon} \frac{E_{t+1}^i}{P_{k,t+1}} + (1-\omega)(1-\mu)^\varepsilon \left(\frac{P_{k,t+1}}{P_{a,t+1}}\right)^{-\varepsilon}\bar{c}. \tag{31}$$

Eqs. (29)–(31) determine the individuals' consumption demands.

Appendix B. Factors' demands and aggregate production

To obtain Eqs. (14) and (15), we take into account that land in labor-intensive agriculture is given by $L_{n,t} = N_t \int_{\underline{a}_t}^{\bar{a}_t} L_{n,t}^i f(a^i)\, da^i$ and in capital-intensive agriculture it is given by $L_{k,t} = N_t \int_{\bar{a}_t}^{\infty} L_{k,t}^i f(a^i)\, da^i$. Similarly, capital in labor-intensive agriculture is given by $K_{n,t} = N_t \int_{\underline{a}_t}^{\bar{a}_t} K_{n,t}^i f(a^i)\, da^i$ and in capital-intensive agriculture it is given by $K_{k,t} = N_t \int_{\bar{a}_t}^{\infty} K_{k,t}^i f(a^i)\, da^i$. Using these equations, (8), (9) and the distribution of abilities, we obtain

$$L_{s,t} = N_t \left[\left(\frac{\alpha_s}{R_t}\right)^{\alpha_s} \left(\frac{\beta_s}{x_t}\right)^{1-\alpha_s} (1-\tau)P_{s,t}A_{s,t}\right]^{\frac{1}{1-\beta_s-\alpha_s}} \Delta_{s,t}$$

$$K_{s,t} = N_t \left[\left(\frac{\alpha_s}{R_t}\right)^{1-\beta_s} \left(\frac{\beta_s}{x_t}\right)^{\beta_s} (1-\tau)P_{s,t}A_{s,t}\right]^{\frac{1}{1-\beta_s-\alpha_s}} \Delta_{s,t}$$

for $s = \{k, n\}$, where

$$\Delta_{n,t} = \int_{\underline{a}_t}^{\bar{a}_t} (a^i)^{\frac{1}{1-\beta_n-\alpha_n}} f(a^i)\, da^i = \lambda\eta^\lambda \left(\frac{(\underline{a}_t)^{\frac{1}{1-\beta_n-\alpha_n}-\lambda} - (\bar{a}_t)^{\frac{1}{1-\beta_n-\alpha_n}-\lambda}}{\lambda - \frac{1}{1-\beta_n-\alpha_n}}\right),$$

and

$$\Delta_{k,t} = \int_{\bar{a}_t}^{\infty} (a^i)^{\frac{1}{1-\beta_k-\alpha_k}} f(a^i)\, da^i = \int_{\bar{a}_t}^{\infty} \lambda\eta^\lambda (a^i)^{\frac{1}{1-\beta_k-\alpha_k}-(1+\lambda)}\, da^i.$$

Note that only if $\lambda > \frac{1}{1-\beta_k-\alpha_k}$ then $\Delta_{k,t}$ is finite and equal to

$$\Delta_{k,t} = \lambda\eta^\lambda \left(\frac{(\bar{a}_t)^{\frac{1}{1-\beta_k-\alpha_k}-\lambda}}{\lambda - \frac{1}{1-\beta_k-\alpha_k}}\right).$$

The inequality $\lambda > \frac{1}{1-\beta_k-\alpha_k}$ implies that $\Delta_{k,t} > 0$. It also implies that $\lambda > \frac{1}{1-\beta_n-\alpha_n}$ and, hence, $\Delta_{n,t}$ is also positive when $\bar{a}_t > \underline{a}_t$. Therefore, we assume that $\lambda > \frac{1}{1-\beta_k-\alpha_k}$.

To obtain Eq. (18), we take into account that output in labor-intensive agriculture is given by $Y_{n,t} = N_t \int_{\underline{a}_t}^{\bar{a}_t} Y_{n,t}^i f(a^i)\, da^i$, whereas output in capital-intensive agriculture is given by $Y_{k,t} = N_t \int_{\bar{a}_t}^{\infty} Y_{k,t}^i f(a^i)\, da^i$. Using these equations and (10), we obtain (18).

Appendix C. Aggregate consumption expenditures

We use (7) and (19) to obtain aggregate consumption expenditure as

$$E_{t+1} = R_{t+1}N_t \left\{ \begin{array}{c} \int_{\eta}^{\underline{a}_t} (1-\phi)\, w_t f(a^i)\, da^i \\ + \int_{\underline{a}_t}^{\bar{a}_t} \left[(1-\tau)P_{n,t}y_{n,t}^i - x_t L_{n,t}^i - R_t K_{n,t}^i\right] f(a^i)\, da^i \\ + \int_{\bar{a}_t}^{\infty} \left[(1-\tau)P_{k,t}y_{k,t}^i - x_t L_{k,t}^i - R_t K_{k,t}^i\right] f(a^i)\, da^i \\ + \int_{\eta}^{\infty} T_t^i f(a^i)\, da^i \end{array} \right\}.$$

We assume that tax revenues are returned to individuals as a transfer and the government budget constraint is balanced in each period, hence,

$$\int_{\eta}^{\infty} N_t T_t^i f\left(a^i\right) da^i = \left(\int_{\eta}^{\underline{a}_t} \phi w_t f\left(a^i\right) da^i + \int_{\underline{a}_t}^{\overline{a}_t} \tau P_{n,t} y_{n,t}^i f\left(a^i\right) da^i + \int_{\overline{a}_t}^{\infty} \tau P_{k,t} y_{k,t}^i f\left(a^i\right) da^i \right) N_t.$$

We use the government budget constraint to obtain

$$E_{t+1} = R_{t+1} N_t \left\{ \begin{array}{c} \int_{\eta}^{\underline{a}_t} w_t f\left(a^i\right) da^i + \int_{\underline{a}_t}^{\overline{a}_t} \left[P_{n,t} y_{n,t}^i - x_t L_{n,t}^i \right. \\ \left. - R_t K_{n,t}^i \right] f\left(a^i\right) da^i \\ + \int_{\overline{a}_t}^{\infty} \left[P_{k,t} y_{k,t}^i - x_t L_{k,t}^i - R_t K_{k,t}^i \right] f\left(a^i\right) da^i \end{array} \right\},$$

and using (8)–(10) we get

$$E_{t+1} = R_{t+1} N_t \left\{ \begin{array}{c} w_t \int_{\eta}^{\underline{a}_t} f\left(a^i\right) da^i + \left[1 - (1-\tau)\beta_n - (1-\tau)\alpha_n \right] P_{n,t} \\ \times \int_{\underline{a}_t}^{\overline{a}_t} y_{n,t}^i f\left(a^i\right) da^i \\ + \left[1 - (1-\tau)\beta_k - (1-\tau)\alpha_k \right] P_{k,t} \\ \times \int_{\overline{a}_t}^{\infty} y_{k,t}^i f\left(a^i\right) da^i \end{array} \right\}.$$

Using the definition of aggregate output for each agricultural sector, $Y_{n,t} = N_t \int_{\underline{a}_t}^{\overline{a}_t} y_{n,t}^i f\left(a^i\right) da^i$ and $Y_{k,t} = N_t \int_{\overline{a}_t}^{\infty} y_{k,t}^i f\left(a^i\right) da^i$, Eqs. (4) and (5) and $N_{m,t} = N_t \int_{\eta}^{\underline{a}_t} f\left(a^i\right) da^i$, we obtain Eq. (20).

Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2022.102934.

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