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THE HUMAN CAPITAL EFFECT ON PRODUCTIVITY AND AGRICULTURAL FRONTIER EXPANSION IN BRAZIL

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Abstract

Agricultural production expansion is an important strategy to encourage structural changes and lead to economic development. However, the increase in the agricultural production can occur in two different ways: through productivity - intensive margin - and through area expansion - extensive margin. Human capital can enhance production both ways, but its effects remain little explored in the literature. This paper aims to investigate the effect of human capital on the increase in agricultural productivity and on the expansion of the agricultural frontiers in Brazil. The results indicate that human capital has a positive effect on these albeit with varying intensities and significant heterogeneities. Human capital affects agricultural productivity more in agricultural frontier regions where there is often a shortage of skilled labor. However, human capital does not affect the expansion of agricultural area in consolidated agricultural regions of the country.

KEYWORDS

Agricultural Productivity, Frontier Expansion, Human Capital, Education

JEL CLASSIFICATION

O13, O15, Q1, Q12, E24

1. Introduction

Growth in agricultural production is one of the most efficient ways to promote poverty reduction. However, one of the main issues in underdeveloped countries is related to human capital (i.e. skilled labor), where it is usually low and poorly dispersed, especially in the agriculture sector. Human capital is an important driver of economic development as the accumulation of knowledge and skills increases agricultural productivity and income, reducing poverty and promoting a change in the economic structure (Schultz 1956, 1960, 1980; Banerjee and Duflo 2007; Duo, Kremer, and Robinson 2008, 2011).

Expansion of agricultural production is seen as an important strategy that leads to structural changes and increased welfare (Byerlee, Janvry, and Sadoulet 2009; Bustos, Caprettini, and Ponticelli 2016). Agriculture is strategic for food security (Hubbard and Hubbard 2013; Capone et al. 2014), reduces the rural exodus and provides resources for low-income families, especially in family farming (Berchin et al. 2019). In addition, the modernization of agriculture generates technical progress and benefits, such as reduced costs and increased productivity (Foster and Rosenzweig 2004; Vieira Filho and Silveira 2016). In fact, the Brazilian regions with the greatest growth in agricultural production and modernization have obtained great economic and social gains in the recent decades (Weinhold and Reis 2008; Tritsch and Le Tourneau 2016; Braganca 2018).

The increase in agricultural production can occur in two different ways: (i) through increases in productivity - intensive margin - or (ii) with the expansion of agricultural area - extensive margin. Increases in productivity are related, to a large extent, to the adoption of technology and the skilled labor employed in agricultural production. On the other hand, the expansion of agricultural areas mostly occurs with the addition of newly deforested areas (Foster and Rosenzweig 2004; Babcock 2015).

According to FAO data (2020), agricultural productivity (tons/ha.) between 2000 and 2018 increased worldwide and this increase was greater in the countries of the Americas, especially in South America. Brazil is one of the few countries of the world that registered increases in land use on both margins (Babcock, 2015). In the Brazilian Amazon and Cerrado regions, this has occurred largely through deforestation putting increased pressure on forest areas. Therefore, understanding the dynamics of agricultural productivity and the advance of the agricultural frontier can help to understand agricultural production and also, its environmental impacts (Bento de Souza Ferreira Filho, Ribera, and Horridge 2015; Assunção, Gandour, and Rocha 2015).

One of the factors that impact agricultural productivity is human capital. This has a direct impact on productivity and indirectly facilitates the adoption of technology and in the institutional improvement (Hanushek and Woessmann 2008). Human capital assists in the learning, application and technical knowledge dissemination. It also affects the farmer's ability to adjust new technologies to particular conditions, such as changes in demand, area restrictions and environmental issues (Djomo and Sikod 2012; Gollin, Lagakos, and Waugh 2013). The complementarity between education and technology makes the expected return on adoption higher for more educated economic agents (Foster and Rosenzweig 2004). Improvement in human capital, through encouraging modernization of the agricultural sector, can also reduce the expansion of agricultural frontiers (Bhattarai and Hammig 2004).

Brazil has experienced an educational expansion in recent decades. This was made possible by the greater availability of primary and secondary education and the availability of teachers, especially between the 1960s and 1980s (Binelli & Menezes, 2019). From the 1990s onwards, there was an expansion of public and private higher education, with funding programs for students from private institutions, in addition to the increase in the number of public and private universities and university professors in general, especially after the year 2000 (Binelli & Menezes, 2019). Given this, the question arises: is educational expansion impacting the increase in agricultural production? In other words, has the increase in human capital, experienced in recent decades, had a positive effect on agricultural productivity and on the expansion of agricultural frontiers in Brazil?

The main goal of this paper is to investigate the effect of human capital on the increase in agricultural productivity and on the expansion of agricultural frontiers in Brazil. This is due to the importance of agricultural production in social and economic development, as it ensures food and nutritional security in developing countries (Capone et al. 2014). In addition, agricultural production impacts the environmental, social and structural changes in the economy (Bustos, Caprettini, and Ponticelli 2016). Therefore, it is important to assess the possible implications of human capital on the agricultural sector in Brazil.

The article is structured in four sections, including this introduction. In the second section, there is the theoretical and empirical framework, while in the third, the empirical strategy and the database are detailed. The results and their analysis are in the fourth section, followed by the final remarks.

2. Theoretical framework

The presence of market and government failures are common in developing countries and they include informational asymmetries, restrictions on access to credit and ill-defined property rights. In addition, the mean population has a low level of human capital, which makes it difficult for them to obtain and process information. The low level of skills often results in not optimal decisions (Greenstone and Jack 2015). Institutional improvement can positively impact productivity, mainly in the definitions of agricultural property rights. Institutional advance can increase incentives to invest in physical and human capital and reduce uncertainties and transaction costs. This scenario creates incentives for the efficient use of productive resources impacting agricultural production and productivity. Institutional improvement defines whether the agricultural expansion occurs by the intensive or extensive margin (Barbier and Burgess 2001; Otsuki, Hardie, and Reis 2002; Faria and Almeida 2016). Human capital investment, which also reflects the quality of institutions, can act to reduce environmental degradation and improve the sustainability of agricultural production (Salahodjaev 2016). However, resource-rich countries typically lack incentives to build strong institutions. Therefore, the lack of institutions creates conditions for corrupt behavior and reduces the expected return on investment in human capital (Gylfason 2001).

In fact, Igliori (2006) found evidence that the human capital level is negatively correlated with the agricultural area expansion and positively with productivity. According to Barbier and Burgess (2001), the advance of agricultural frontiers in developing countries reflect the structural features of the agricultural sector, such as by low adoption of technology, low level physical and human capital and weak institutions. Another point that affects agricultural production is foreign trade. Access to the international market impacts relative prices, which may create incentives for the area and/or agricultural productivity expansion. These results depend on the characteristics of the sector and institutions in the country (Assunção, Gandour, and Rocha 2015; Faria and Almeida 2016). Since the 2000s, the Brazilian agricultural sector has significantly increased its international presence, which are reflected in the expansion of its productivity, through investment in technology and capital, and in the planted area (Faria and Almeida 2016). The size of the population and the scale of economic activity are also important in explaining agricultural production as they increase demand for agricultural products and forest resources (Cropper and Griffths 1994; Igliori 2006).

Human capital is important for agricultural production, especially because it increases its productivity. In general, it allows the individual to increase their capacity to receive, decode and understand information (Nelson and Phelps 1966). Education increases people’s ability to perceive new types of problems and, consequently, find ways to solve them (Schultz 1975). However, there are two possible distinct effects of human capital on agricultural production: i) worker effect; ii) allocative effect. According to Welch (1970), the first effect shows that schooled workers are better able to use resources more efficiently. The second effect refers to their ability to acquire and decode information about the input's costs and characteristics. Although the positive impact of human capital on agricultural production is often evidenced in the literature, the topic is still the subject of extensive research that attempts to clarify the transmission channels through which human capital can improve agricultural productivity (Headey, Alauddin, and Rao 2010; O'Gorman and Pandey 2010; Peterman et al. 2011; Gollin, Lagakos, and Waugh 2013; Cao and Birchenall 2013; Menon, van der Meulen Rodgers, and Nguyen 2014; Reimers and Klasen 2013; Abro, Alemu, and Hanjra 2014; Bustos, Caprettini, and Ponticelli 2016; Rocha, Ferraz, and Soares 2017; Sabasi and Shumway 2018; Valencia Caicedo 2018).

According to Asadullah and Rahman (2009), education allows the economic agent to make better use of the information available and, consequently, allocate his resources more efficiently, becoming better managers. On the other hand, Asfaw and Admassie (2004) claim that more educated farmers are not only able to use the information available more efficiently, but also have better access to the required information. Lockheed, Jamison, and Lau (1980) argue that educated farmers pay and receive better prices for their inputs and outputs. These results indicate that education can be a public policy to overcome the information asymmetries prevalent in the agricultural market in general. Reimers and Klasen (2013) argue that farmers with higher levels of human capital are more likely to adopt new technologies or products. Thus, these farmers have better access to information related to their work environment and the ability to distinguish between promising and non-promising innovations.

According to Foster and Rosenzweig (2004), the adoption and diffusion of technology has complementarities with human capital, mainly in the agricultural sector. Workers with a higher education are more likely to adopt new technologies, especially if they are complex and with uncertain returns. In general, educated farmers usually have: (i) a higher level of income and wealth and lower budget constraints for the acquisition of new technologies; (ii) greater access to information and; (iii) a high capacity to process and decode new information, making learning more efficient and faster.

3. Empirical Design

3.1. Identification Strategy

We estimate by ordinary least squares (OLS) the following basic model in order to capture the human capital effect on the increase in agricultural productivity and on the expansion of agricultural frontiers in Brazilian municipalities in a cross-section data:

$$Y_{i,2017} = \beta HumanCapital_{i,2017} + \varepsilon_{i,2017} \qquad i = 1,\ldots,5080 \qquad (1)$$

where $Y_{i,2017}$ represents maize productivity, soybeans and livestock, as well as the expansion of agricultural areas for each municipality i in the year 2017. We estimate one regression for each dependent variable. $HumanCapital_{i,2017}$ is the human capital proxy and $\varepsilon_{i,2017}$ is the error term. The choice of these crops to represent agricultural productivity is due to the fact that soybeans and maize are the ones that have the highest Gross Production Value (GPV) in the country. For livestock, we use cattle ranching that occupies the first position of the GPV of livestock.

However, due to the recurring endogeneity problem in papers that measure the impact of human capital, ($E(\varepsilon|x) \neq 0 \rightarrow Cov(\varepsilon|x) \neq 0$ - explanatory variable correlated with the regression error term), we need a method that overcomes this problem. The basic hypothesis for the consistency of OLS estimators is that the error term cannot be correlated with the explanatory variables otherwise they will be biased and inconsistent. To overcome this issue, we used the instrumental variables (VI) approach to treat endogeneity (Greene, 2008). In other words, we explored an exogenous source of variation to instrumentalize human capital. Technically, it is necessary to have valid and relevant instruments, that is, not correlated with the endogenous regressors and at the same time orthogonal to the error term (Greene 2008). Therefore, we used the number of schools that existed in the year of birth of the representative farmer (average year of birth of farmer) in the municipality. The supply of schools in the period is correlated with the average schooling of a farmer and it is exogenous to the other components of the regression. Thus, the first stage, estimated in a reduced form, is:

$$HumanCapital_{i,2017} = \gamma Schools_{i,2017-t} + u_{i,2017} \qquad i = 1,\ldots,5080 \qquad (2)$$

where $HumanCapital_{i,2017}$ is the human capital for which we used the average schooling (years of study of the farmer) as a proxy, commonly adopted in economics literature, as in Hanushek and Woessmann (2008), for each municipality. To constructed this variable, we considered farmers education and that each level of education has a corresponding number of years of study (see appendix A1). Then, we used the farmer average schooling at the municipality level. $Schools_{i,2017-t}$ is the number of primary state schools[1] that existed in the year of birth of the representative farmer (average year of birth of farmer), i.e. in year t. This variable aims to capture the fact that the supply of schools has an effect on the student's subsequent schooling, an identification strategy similar to that used by Teixeira and Menezes-Filho (2012) and Binelli and Menezes-Filho (2019); $u_{i,2017}$ is the error term.

We need to consider the possibility of weak instruments to use the instrumental variables method otherwise two major problems in two-stage estimation (2SLS) may occur: selection bias and minimum standard error. We used the Wooldridge test to test the

[1] We used the number of primary schools in the state as an instrument due to the lack of information at the municipal level for Brazil in the period.

validity of the instrument. We use a rule of thumb as an F statistic over 10 to shows that instruments are not weak. We estimate the second stage to capture the human capital impact on productivity (intensive margin) and the expansion of agricultural areas (extensive margin), considering the following specification:

$$Y_{i,2017} = \beta \widehat{HumanCapital}_{i,2017} + \delta Tec_{i,2017} + \theta Controls_{i,2017} + \varepsilon_{i,2017} \qquad (3)$$
$$i = 1, \ldots, 5080$$

where $Y_{i,2017}$ is the soybeans, maize, livestock and the agricultural frontier expansion; $HumanCapital_i$ is the variable human capital (exogenous), for each municipality; $Tec_{i,2017}$ is an agricultural technology index; $Controls_{i,2017}$ are control variables that capture state, institutional, socioeconomic and geographic features that may be correlated with the instrument and the error term, which would invalidate identification strategy; ε_i is the error term.

It is worth mentioning that we created a technology index to control for possible complementarities of technology and human capital in the agricultural sector (Foster and Rosenzweig, 2004). In addition, technology adoption could be confounded with human capital, what would compromise our exclusion restriction, biasing the results. We construct the agricultural technology index with Principal Component Analysis (PCA), which summarized twelve technology variables identified as important in the literature (Souza et al. 2019). The index seeks to represent the multi-dimensional character of the technological modernization of Brazilian agriculture, especially with regard to the use of inputs, machinery and modern practices, extracted from the 2017 agricultural census. These are: (1) tractors; (2) Seed drill; (3) fertilizers; (4) harvesters; (5) technical assistance; (6) irrigation; (7) fertilizing; (8) soil preparation; (9) electrical energy; (10) lime; (11) pesticides; (12) food supplementation. The technology index also reduces multi-collinearity problems between agricultural variables.

We considered per capita income, population density, proportion of individuals living in rural areas and inequality to control structural characteristics. These variables seek to capture local demand for agricultural goods, agglomeration effects, the size of the labor market and social inequality. We used variations in rainfall, temperature, altitude, soil quality and forest remnants as geographic controls, since crops and agricultural frontiers are sensitive to these features, encouraging or curbing it. We considered *proxies* for property rights, trade opening, access to rural credit and land tenure as institutional controls. We used the agricultural settlements controlled by squatters as property right. We constructed the trade opening variable considering the sum between exports and imports as a proportion of GDP in the municipality $[(X + M)/GDP]$. The access to rural credit variable consists of the proportion of farms that have obtained some type of credit from financial institutions. The land structure variable is represented by the average area of a farm in the municipality.

In order to check the robustness of the results, we estimated the model using an equation systems method (3SLS)[2] which controls possible correlations between equation errors. In general, agricultural productivity and expansion of frontiers have important interconnections.

As a heterogeneity test, we re-estimate our main results for two distinct groups: (i) agricultural frontier; (ii) and non-agricultural frontier. We considering the years 2006 and 2016, a decade prior to the year used in this paper. This is to verify whether the dynamics vary depending on the local characteristics in land use changes. Agricultural frontier regions are expected to present significant institutional and structural differences in their economic scales, labor market and infrastructure, which can heterogeneously impact the

[2] To verify the model endogeneity, we used Sargan's C statistic.

trends of the variables. It is worth mentioning that we estimate all the models using heteroskedasticity-robust standard errors, therefore, minimizing potential heteroscedasticity in the estimations.

3.2. Database

The main data sources are they are the 2017 agricultural census and the 2010 demographic census, both carried out by *Instituto Brasileiro de Geografia e Estatística (IBGE).* The first is conducted through direct interviews with the owners of farms while the second considers the entire population of the country, and both are available at the municipal level. For the instrument, we used the IBGE 20th century statistics that include data on the number of primary schools per state from 1908 to 2000. Table 1 presents the description, source and expected results for the database.

[Table 1]

The proxy used for the expansion of agricultural frontiers is the municipal area increase destined for agricultural production. The information was obtained from the Annual Coverage and Land Use Mapping Project (Mapbiomas). The number of municipalities included in the sample is 5,080 (we excluded those without data for agriculture).

3.3. Descriptive Statistics

In our identification strategy the variations in the farmer's human capital and availability of schools in their years of birth play an important role. These descriptive statistics are presented in Table 2.

[Table 2]

The average education of farmers, the human capital proxy, is 8.04 years of study, corresponding to a complete primary education. In addition, 16% of municipalities have the lowest education levels in the sample, 4% have the EJA (Youth and Adult Education), 62% have primary education, 15% have high school and 6% have higher education. In summary, it is worth noting that the majority of workers hired in the Brazilian agricultural sector do not have much formal education or have incomplete elementary education. This demonstrates the low level of education prevalent in Brazilian rural areas (Bernardelli et al. 2020).

On the other hand, the average number of primary schools per state in the period from 1935 to 1975 was 7146 schools, with the state of São Paulo having the largest number (21,798 units in 1975) and the Roraima state the fewest (45 units in 1963). According to Binelli and Menezes-Filho (2019), the expansion of Brazilian education in recent decades reflects the increase in the number of primary schools, mainly between 1936 and 1980, which increased the availability and quality of education, positively impacting the educational choices of individuals. Finally, it is worth noting that we did not find any extreme correlation values that could compromise the model estimates and / or inferences.

4. Results and Discussion

The causal effects of human capital on agricultural productivity and on the agricultural frontier expansion can be seen in Tables 3, 4, 5 and 6. The tables present the productivity of maize, soybeans and cattle and, finally the expansion of agricultural areas. First, we estimate the regressions with ordinary least squares (OLS), which we compare with the estimates that consider the endogeneity between human capital and the various agricultural production dimensions. We estimate columns from (1) to (6) in two stages with the number of state primary schools in the year of birth as an instrument for the current schooling of farmers.

In addition, institutional, socioeconomic and geographical controls were gradually included to check the robustness of the results. Column 7 aims to test the robustness of the coefficients for human capital, adopting an alternative method estimated by 3SLS. This considers the possible endogeneity between the dependent variables, estimating the equations in a system of equations. In the OLS estimates, a positive and statistically positive correlation was found between human capital and all dependent variables. However, the Wooldridge endogeneity test for robust standard errors confirmed the endogeneity of human capital, a fact that makes the coefficients biased. Therefore, we further consider the IV results as the benchmark in the following analyses.

The results of first-stage regression are shown in Table 3. It showed that all variables are significant at the 1% levels. As expected, the number of primary state schools that existed in the year of birth of the representative farmer have had a significant and positive impact on the current schooling of farmers. These results do not change significantly with the addition of control variables and are similar to those of Teixeira and Menezes-Filho (2012) and Binelli and Menezes-Filho (2019).

[Table 3]

Table 4 presents the results for maize productivity. It is important to note that, after estimating in two stages using an instrumental variable, the estimation is no longer endogenous. The rule of thumb of the F-statistic above 10 shows that the instrument is not weak. In addition, human capital changes only slightly after the introduction of additional controls (State, Institutional, Socioeconomic and Geographic) and remains statistically significant, reinforcing the robustness of the results. Finally, due to the log-log specification of the model, we can interpret the coefficient as elasticity, that is, an increase of 1 % in human capital (measured by average farmers schooling) causes a 2.59 % increase in maize productivity (ton/he).

[Table 4]

It is worth noting that in column (6), which introduces the technology variable in order to measure how much maize productivity is correlated with the technological level of farmers, the magnitude of the human capital parameter does not change significantly. Therefore, this implies that technology adoption and human capital are not confounded, which reinforces our exclusion restriction hypotheses that our instrument only impacts the outcome variable through human capital. Despite this, the technological variable has a positive relationship with maize productivity, with a 1% increase in the technology index being correlated to an increase of 0.57% in maize productivity. Finally, to check the robustness of our results, we re-estimated the model IV (6) using a 3SLS approach to further eliminate any endogeneity and autocorrelation between the equations that could bias the estimates. In the results for the 3SLS, there was a reduction in the magnitude of the coefficients, however, the variables remained statistically significant at 1 %, not changing the relationship between human capital and maize productivity.

We used the same identification strategy for soybean productivity (Table 5), which considered the endogeneity of human capital. Among the results, we highlight that human capital is no longer endogenous and the coefficient remained statistically significant despite the reduction in magnitude. In addition, the magnitude of the coefficient is relevant from an economic point of view, with an increase of 1 % in human capital (measured by the average farmer's schooling) causing a 7.97 % increase in soybean productivity (tonne/ha.). The technological index (IV (6)), on the other hand, does not change the impact of human capital, further reinforcing the robustness of our results. Soybean productivity is significantly correlated with the adoption of modern technologies, with a 1 % increase in the technological level being related to a growth of 4.70 % in productivity. To check the robustness of the estimates, we re-estimated the model IV (6) using 3SLS. In short, the impact of human capital was reduced to 4.98 %, indicating that to assess the role of education in soybean productivity it is necessary to consider its relationship with the agricultural sector.

[Table 5]

Soybean production is more sensitive to soil/climate factors and this requires greater technology when compared, for example, to maize (Kukal and Irmak, 2018; Battisti et al. 2017; Joris et al.2013). Therefore, both the farmers' average education level and the agricultural farmers' technological level tend to have greater effects for crops that use more technology, such as soybeans (Valencia Caicedo, 2019; Mariyono, 2019; Canales, Bergtold and Williams, 2018).

However, this does not imply that planting and harvesting maize crop makes less intensive use of human capital or technology. According to Bustos, Caprettini and Ponticelli (2016) technological advances in soybean cultivation have increased the productivity of farms through the implementation of a second maize crop (soybean and maize rotation). In some cases, the second crop benefits from the investments made in the first crop, such as fertilization and soil preparation - variables included in the technology index -, which leads to a reduction in the direct impact of the technological level on the productivity of the maize.

The results for cattle productivity are presented in Table 6. Although the impact of human capital lowers with the inclusion of control variables, the coefficients remain statistically significant at 1 %, indicating that an increase of 1 % in human capital causes an increase of 2.85 % in cattle productivity (head per hectare of pasture). It is worth noting that although the result hardly changes with the inclusion of the technology index, the technological level is negatively correlated with cattle productivity, with a 1% increase being related to a fall of 0.66 % in productivity. Finally, the results estimated with 3SLS present only a slight reduction in the impact of human capital, confirming the robustness of results. In fact, a positive effect of human capital on livestock productivity is expected, since more educated individuals are able to adopt better practices due to their greater management skills which, in the end, translate into larger herds and higher productivity.

[Table 6]

A positive effect of human capital on livestock productivity was expected. More educated rural producers are able to adopt new better practices related to livestock production, especially regarding animal nutrition, and are able to acquire skills more quickly. Ultimately, this translates into ever-larger herds, better detection and treatment of sick animals and, consequently, higher yields. Similar results were reported in Davis et al. (2012) for East Africa where education increased livestock productivity.

Finally, Table 7 presents the results for the agricultural area expansion - extensive margin. We found that human capital is no longer endogenous and that its coefficient changed as additional controls were included. Despite this, it is important to note that the coefficients remained significant and increased their relative size. On the other hand, the technological index is not correlated with the agricultural frontier expansion or with human capital, supporting our approach. We also confirmed the robustness of the results with the system of equations estimated by 3SLS, despite the reduction in the impact of human capital. In short, the 1 % increase in human capital leads to a 0.06 % increase in the expansion of the agricultural area.

[Table 7]

The empirical evidence is in line with the literature that seeks to understand the importance of human capital for agricultural productivity. Human capital is a central element of economic development allowing structural changes and increases in productivity. On the other hand, it also creates incentives to advance agricultural frontiers, which, in turn, is the main driver of deforestation in tropical forests (Assunção, Gandour, and Rocha 2015; Bustos, Caprettini, and Ponticelli 2016; Rocha, Ferraz, and Soares 2017; Bragança 2018).

Although human capital has positive impacts on agricultural productivity, these benefits can induce significant environmental damage, evidencing the rebound effect. In other words, more productive agriculture is likely to be more profitable and could lead to an expansion of cultivated areas. The magnitude of this rebound effect depends on the price elasticity of demand in the short term. Although demand for staple crops for human consumption is relatively inelastic, the global demand for certain commodities, such as meat, is elastic (Lambin and Meyfroidt, 2011; Angelsen, 2010; Angelsen and Kaimowitz, 2001).

However, it is important to note that this damage can be minimized by strengthening institutions that guarantee compliance with environmental legislation. In the long term, the magnitude of the rebound effect depends on the impact of technological progress on economic and population growth (Lambin and Meyfroidt, 2011).

4.1. Heterogeneity test

To better exploit this opportunity cost, we replicated the identification strategy for two distinct groups, dividing the sample into municipalities with agricultural frontiers and municipalities with consolidated agricultural areas. To differentiate agricultural frontiers from consolidated areas, we considered the agricultural area expansion (or retraction) at the municipality level the in the previous decade, 2006-2016. Then, we classified a municipality as frontier if it has presented an expansion in his arable area; otherwise, we considered as a consolidate area. The results are described in Tables 8 and 9.

Table 9 presents the t-test for differences in the parameters of the regressions for agricultural frontiers and non-agricultural frontiers. In general, the null hypothesis that the parameters are the same for each group is rejected. Therefore, human capital has varying casual effects on agricultural productivity and on expansion. These effects depend on whether municipalities are located in consolidated agricultural areas or in agricultural frontier regions. In general, we found that productivity and the advance of the agricultural frontier have significant heterogeneities after considering local changes in land use. In particular, the impact of human capital is greater for maize in frontier regions, with a 1% increase in schooling causing a growth of 3.10% in its productivity, against 1.64% in other regions.

[Table 8]

The impact on soybean productivity, in turn, presents an even more heterogeneous relationship; with frontier regions increasing 21.48% for each 1% increase in schooling against a non-statistically significant result for non-frontier regions. Finally, the impact of human capital on cattle productivity is 3.93 % in frontier regions versus 1.17 % for other regions, similar to maize. Thus, the results confirm the importance of human capital for agricultural productivity, especially in agriculture frontier regions where its impact is greatest due to a scarcity effect. In addition, the impact is greater for complex and capital-intensive agricultural activities, which employ a higher level of machinery and technology, such as soybeans and, to lower levels, such as maize. Human capital presented a causal relationship with the advance of the agricultural areas in frontier regions, but not in consolidated ones. A 1% increase in the average schooling of farmers in frontier regions leads to an expansion of approximately 0.26% in the agricultural area, which, in most cases, is equivalent to deforestation.

[Table 9]

We can therefore conclude that in non-frontier regions, human capital positively impacts production via productivity - intensive margin, but not the expansion of the area - extensive margin. On the other hand, human capital had a significant impact both on the expansion of area and productivity in agricultural frontier regions. Beyond the rebound effect, the scarcity of skilled labor in agricultural frontier regions, associated with a greater demand for skilled labor in capital and technology intensive activities, such as soybeans, may have created the conditions that explain the results.

5. Conclusions

Understanding the causes of the advance of agricultural production is important due to the growing world demand for food and agricultural raw materials. This is even more relevant in the Brazilian case, which is a major world producer and has a wide margin for productive expansion. Within this context, the quality of the labor input has become increasingly important in agricultural production, especially due to the capital-biased technological advances. For this reason, this article sought to investigate the human capital effect on soybean, maize and cattle productivity, and on the expansion of agricultural areas.

To achieve this, we used an identification strategy based on an instrumental variable to correct the presence of endogeneity in a two-stage estimation because human capital has an endogenous relationship with agricultural production. As an instrument, we used the number of state primary schools existing in the year of birth of the representative farmer in all Brazilian municipalities. In general, it is expected that a greater supply of schools in the past impacts the level of average schooling and that it does not affect the current expansion in the agricultural production except through the channel of human capital. Then, in order to check the robustness of the results, we estimated the models with the 3SLS method.

The results show that human capital has a positive impact on the productivity of soybeans, maize and livestock, although with different intensities, and in the expansion of agricultural areas. The technology index, in turn, has a positive correlation with the productivity of soybeans and maize but a negative relationship with livestock. We also confirmed the robustness of the results using the 3SLS method. In summary, the empirical evidence is in line with the literature that claims that human capital is a relevant input in agricultural production.

Therefore, we can conclude based on the empirical evidence that human capital has a positive impact on agricultural production. However, it is possible that there are relevant negative externalities (through the rebound effect) in this relationship due to important interconnections with Brazilian deforestation. If, on the one hand, the increase in agricultural productivity can encourage investment and the intensification of agriculture production, discouraging an increase in the expansion of areas, it can also create incentives for deforestation due to the growth in expected returns from agriculture. In addition, agricultural frontier expansion itself is ultimately conditioned by forest clearings, especially in Brazil. In this context, we highlight the central role that the strengthening of environmental institutions can play by creating the right incentives for farmers, especially in agricultural frontier regions.

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Table 1: Description, source and expected results for the database at municipal level

Type	Variables	Description	Source
Dependent	Maize (ton/he.)	Production in tons (1st and 2nd harvest) per hectare.	IBGE
	Soybeans (tone/he.)	Production in tonnes (1st and 2nd harvest) per hectare.	IBGE
	Cattle (head/he.)	Number of heads per hectare of pasture.	IBGE
	Agriculture Frontier (he.)	Agriculture Frontier Expansion in hectares (he).	Mapbiomas
Explanatory	Human Capital	Farmer years of study	IBGE
	Technology Index	Technological level of agricultural farm.	IBGE
Instrument	Schools	Number of primary schools in the state when the individual was born.	IBGE
State Controls	States	Dummy variables representing states	-
Institutional Controls	Trade Opening	Trade opening index.	IPEA
	Property Right	Squatter-controlled settlements.	IBGE
	Insecurity in Property Right	Number of landless workers.	IBGE
	Land Structure	Average area of agricultural farms	IBGE
	Rural Credit	Proportion with access to the credit market.	IBGE
Socioeconomic Controls	Demographic density	Total number of inhabitants per km2	IBGE
	Rural Population	Proportion of the population living in rural areas.	IBGE
	per capita GDP	Economic scale.	IBGE
	Inequality	Gini Index	IBGE
Geographic Controls	Rainfall	Average Rainfall	IPEA
	Temperature	Average Temperature	IPEA
	Altitude	Average Altitude	IPEA
	Forest	Proportion of forest area	Mapbiomas
	Soil	Soil quality	Embrapa

Table 2: Descriptive Statistics (n = 5080)

Variables	Mean	Standard Dev.	Min.	Max.
Maize	3810.77	2832.66	7.00	12400.00
Soybean	1441.80	1657.51	0.00	4800.00
Cattle	2.33	23.25	0.00	1628.93
Agricultural Frontier	-0.01	0.05	-0.68	0.21
Human Capital	8.05	1.39	2.59	12.43
Technology Index	0.08	0.07	0.00	1.00
Schools	7146.69	4561.86	45.00	21798.00
Trade Opening	0.04	0.15	0.00	3.36
Property Right	18.38	55.92	0.00	797.00
Insecurity in Property Right	14.19	63.44	0.00	1073.00
Land Structure	98.51	203.06	0.68	5949.06
Rural Credit	17.76	12.32	0.00	75.45
Demographic Density	58.77	171.74	0.15	4386.67
Rural Population	0.37	0.22	0.00	0.94
Inequality	0.49	0.07	0.28	0.80
Per capita GDP	21850.74	20538.16	3285.03	344847.20
Pluviometry Index	1640.00	782.06	0.00	4357.11
Temperature	22.78	3.05	14.38	28.04
Altitude	421.82	292.32	0.00	1505.00
Forest	0.43	0.28	0.01	1.00
Soil	0.37	0.24	0.00	1.00

Table 3: Results of first-stage regression analysis

Variables	OLS	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)
Schools	0.061***	0.142***	0.111***	0.073***	0.057***	0.057***
	(0.002)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Constant	1.543***	0.852***	0.933***	0.816***	1.262***	1,272***
	(0.025)	(0.053)	(0.044)	(0.051)	(0.107)	-0,108
State	No	Yes	Yes	Yes	Yes	Yes
Institutions	No	No	Yes	Yes	Yes	Yes
Socioeconomics	No	No	No	Yes	Yes	Yes
Geographic	No	No	No	No	Yes	Yes
Observations	5080	5080	5080	5080	5080	5080
R^2	0.0942	0.4466	0.5485	0.6449	0.6817	0.6824
F test	444.13	233.21	246.64	303.06	283.12	280,47

Note: * p < 0; 1; ** p < 0; 05; *** p < 0; 01. Robust standard errors.

Table 4: Results for maize productivity

Variables	OLS	IV (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	3SLS
Human Capital	4.46***	4.92***	4.58***	4.63***	4.27***	2.59***	2.58***	2.47***
	(0.07)	(0.22)	(0.18)	(0.25)	(0.40)	(0.52)	(0.51)	(0.36)
Technology Index							0.57***	0.56***
							(0.2)	(0.17)
State	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Institutions	No	No	No	Yes	Yes	Yes	Yes	Yes
Socioeconomics	No	No	No	No	Yes	Yes	Yes	Yes
Geographic	No	No	No	No	No	Yes	Yes	Yes
Observations	5080	5080	5080	5080	5080	5080	5080	5080
R^2	0.42							
Endog. test	5.35*							
F test		444.13	563.89	497.68	275.09	197.38	198.68	
Chi2 test								11132.07

Note: * p < 0; 1; ** p < 0; 05; *** p < 0; 01. Robust standard errors.

Table 5: Results for soybean productivity

Variables	OLS	IV (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	3SLS
Human Capital	10.72***	7.24***	14.24	12.97***	13.66***	8.10***	7.97***	4.98***
	(0.26)	(0.89)	(0.68)	(0.88)	(1.39)	(1.74)	(1.73)	(1.34)
Technology Index							4.70***	4.47***
							(0.61)	(0.64)
State	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Institutions	No	No	No	Yes	Yes	Yes	Yes	Yes
Socioeconomics	No	No	No	No	Yes	Yes	Yes	Yes
Geographic	No	No	No	No	No	Yes	Yes	Yes
Observations	5080	5080	5080	5080	5080	5080	5080	5080
R^2	0.24							
Endog. test	17.71**							
F test		444.13	563.89	497.68	275.09	197.38	198.68	
Chi2 test								6483.20

Note: * p < 0; 1; ** p < 0; 05; *** p < 0; 01. Robust standard errors.

Table 6: Results for Cattle productivity

Variables	OLS	IV (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	3SLS
Human Capital	0.99***	2.17***	1.95***	2.35***	2.10***	2.85***	2.67***	2.16***
	(0.04)	(0.15)	(0.14)	(0.16)	(0.25)	(0.39)	(0.39)	(0.24)
Technology Index							-0.66***	-0.56***
							(0.13)	(0.11)
State	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Institutions	No	No	No	Yes	Yes	Yes	Yes	Yes
Socioeconomics	No	No	No	No	Yes	Yes	Yes	Yes
Geographic	No	No	No	No	No	Yes	Yes	Yes
Observations	5080	5080	5080	5080	5080	5080	5080	5080
R^2	0.07							
Endog. test	4.10*							
F test		444.13	563.89	497.68	275.09	197.38	198.68	
Chi2 test								4973.54

Note: * p < 0; 1; ** p < 0; 05; *** p < 0; 01. Robust standard errors

Table 7: Results for Agricultural Frontier Expansion

Variables	OLS	IV (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	3SLS
Human Capital	0.04***	-0.37***	0.03***	0.02*	0.04*	0.08***	0.08***	0.06***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.02)
Technology Index							0.00	0.00
							(0.01)	(0.01)
State	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Institutions	No	No	No	Yes	Yes	Yes	Yes	Yes
Socioeconomics	No	No	No	No	Yes	Yes	Yes	Yes
Geographic	No	No	No	No	No	Yes	Yes	Yes
Observations	5080	5080	5080	5080	5080	5080	5080	5080
R^2	0.02							
Endog. test	71.87*							
F test		444.13	563.89	497.68	275.09	197.38	198.68	
Chi2 test								1476.83

Note: * p < 0; 1; ** p < 0; 05; *** p < 0; 01. Robust standard errors.

Table 8: Results for maize, soybeans and cattle productivity and agricultural frontier expansion - (agricultural frontier)

Variables	Maize		Soybeans		Cattle		Frontier Expansion	
	IV (6)	3SLS	IV (6)	3SLS	IV (6)	3SLS	IV (6)	3SLS
Human Capital	3.03**	3.10***	23.30***	21.48***	5.04***	3.93***	0.33***	0.26***
	(1.29)	(1.00)	(5.27)	(4.07)	(0.39)	(0.76)	(0.09)	(0.66)
Technology Index	-0.56***	-0.55***	4.70***	4.11***	-0.54**	-0.63***	0.01	0.01
	(0.34)	(0.17)	(0.61)	(1.22)	(0.26)	(0.23)	(0.01)	(0.01)
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institutions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	2291	2291	2291	2291	2291	2291	2291	2291
F test	28.47		28.47		28.47		28.46	
Chi2 test		3325.55		1655.02		1127.89		476.75

Note: * p < 0; 1; ** p < 0; 05; *** p < 0; 01. Robust standard errors.

Table 9: Results for maize, soybeans and cattle productivity and expansion of agricultural frontiers - (non-agricultural frontier)

Variables	Maize		Soybeans		Cattle		Frontier Expansion	
	IV (6)	3SLS	IV (6)	3SLS	IV (6)	3SLS	IV (6)	3SLS
Human Capital	1.45***	1.64***	0.83	-0.98	1.73***	1.17***	-0.01	0.00
	(0.48)	(1.12)	(1.84)	(1.34)	(0.31)	(0.24)	(0.03)	(0.02)
Technology Index	0.57***	0.56***	4.36***	4.15***	-0.63***	-0.70***	-0.02	-0.01
	(0.16)	(0.21)	(0.77)	(0.91)	(0.14)	(0.13)	(0.01)	(0.01)
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institutions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	2789	2789	2789	2789	2789	2789	2789	2789
F test	153.40		153.40		153.40		153.40	
Chi2 test		6248.81		3540.81		3325.54		713.87
Test t for equality of parameter (agricultural frontier vs. non-agricultural frontier) $H_0 : \beta_1 = \beta_2$								
$Prob.$	0,95							
t_*	$\pm 1,96$							
Human Capital								
t_0	32,19	38,37	112,07	145,04	223,06	95,45	99,29	10,35
Technology Index								
t_0	-87,35	-171,59	14,65	-0,86	9,10	8,00	78,84	52,56

Note: * p < 0; 1; ** p < 0; 05; *** p < 0; 01. Robust standard errors.

Appendix

Table A1: Definitions used to construct the human capital variable

Education level	Farmers years of study
Never attended school	0
Literacy of youth and adults (AJA)	4
Youth and adult education and supplementary elementary or primary education (EJA)	4
Youth and adult education and supplementary secondary or high school education (EJA)	4
Literacy class (CA)	8
Former primary (elementary)	8
Former junior high school (middle 1st cycle)	8
Regular elementary school or 1st grade	8
Ancient scientistc, classic, etc. (medium 2nd cycle)	11
Regular high school or 2nd grade	11
High school or high school technician	11
Higher education	14
Master's or PhD degree	14