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Economic impacts of information access through public policies: impacts of rural extension and internet access on Brazilian agricultural production

Adauto Brasilino Rocha Junior

Thesis presented to obtain the degree of Doctor in Science: Area: Applied Economics

Piracicaba
2021

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DEDICATION

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Epigraph

"Quando te olho com amor, te vejo bela." Autor desconhecido.

CONTENTS

RESUMO

Impactos econômicos do acesso à informação por meio de políticas públicas: impactos da extensão rural e do acesso à internet na produção agrícola brasileira

Nesta tese são analisadas duas problemáticas inseridas no contexto de políticas públicas para a promoção do acesso à informação, e suas implicações sobre a produtividade agrícola. A primeira análise trata do impacto do acesso à assistência técnica e extensão rural (ATER) na produção dos agricultores familiares brasileiros; a segunda consiste na avaliação do impacto de um caso real de política pública proposta para expandir o acesso à internet no campo brasileiro. O modelo primal *Output Distance Function* é a abordagem paramétrica aplicada para modelar a fronteira de possibilidades de produção e o nível de eficiência técnica da agricultura para os municípios brasileiros, e os impactos na produção agrícola devido ao acesso à assistência técnica para os agricultores familiares e à internet para todos os agricultores. Os resultados de ambos os estudos constituem embasamento metodológico para a estimativa de impactos de variáveis que afetam a eficiência técnica e a fronteira de possibilidades de produção por meio de *Output Distance Functions*, e evidências do papel da assistência técnica e do acesso à internet para a produção agrícola brasileira.

Palavras-chave: Assistência técnica; eficiência técnica; agricultura familiar; acesso à internet

ABSTRACT

Economic impacts of information access through public policies: impacts of rural extension and internet access on Brazilian agricultural production

In this dissertation I analyze two policy issues in information access and agricultural productivity. The first one is the impact of the technical assistance and rural extension (TA) access on the production of Brazilian family farmers, and the second one is the impact evaluation of a real case of public policy proposed to expand the internet access in Brazilian countryside. The Output Distance Function is the parametric approach applied to model the production possibilities frontier and the technical efficiency level of the agriculture for Brazilian municipalities, and impacts on agricultural production due to the technical assistance access for family farmers, and internet access for all farmers, are estimated in each paper. The results from both studies constitute methodological background for the estimation of impacts on production from Output Distance Functions, and evidence of the role of technical assistance and internet access for the Brazilian agricultural production.

Keywords: Technical assistance; Technical efficiency; Family farming; Broadband access

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1. ECONOMIC IMPACTS OF INFORMATION ACCESS THROUGH PUBLIC POLICIES: IMPACTS OF RURAL EXTENSION AND INTERNET ACCESS ON BRAZILIAN AGRICULTURAL PRODUCTION

ABSTRACT

In this dissertation I analyze two policy issues in information access and agricultural productivity. The first one is the impact of the technical assistance and rural extension (TA) access on the production of Brazilian family farmers, and the second one is the impact evaluation of a real case of public policy proposed to expand the internet access in Brazilian countryside. The output distance function is the parametric approach applied to model the production possibilities frontier and the technical efficiency level of the agriculture for Brazilian municipalities, and impacts on agricultural production due to the technical assistance access for family farmers, and internet access for all farmers, are estimated in each paper. The results from both studies constitute methodological background for the estimation of impacts on production from Output Distance Functions, and evidence of the role of technical assistance and internet access for the Brazilian agricultural production.

Keywords: Technical assistance; Technical efficiency; Family farming; Broadband access

1.1. Introduction

Information access is essential to promote productivity increase in agriculture. Economically rational farmers maximize their utility by allocating their inputs to produce different agricultural goods given the market prices and the available technologies. The economic result from such behavior is directly related to the information access, given that the set of options farmers consider when making decisions is directly affected by their knowledge about the existing set of possibilities. Also, since farmers allocate inputs to produce a set of outputs given the available technology, the information about how to use correctly that technology will determine how close the farm will be in respect to the Production Possibilities Frontier (PPF) affecting, due to that, the technical efficiency.

From the discussed above, one can expect those policies to promote access to information play a role in agricultural production, by leading to shifts at the PPF and at the efficiency level of farmers. In productivity literature, in the scope of information access, rural extension and internet access have been considered drivers of productivity change. Rural extension is widely recognized by diffusing technologies and increasing efficiency (Birkhaeuser et. al, 1991; Freitas et. al, 2018) affecting, by consequence, farm income, what has been identified through several studies controlling for selection bias in different countries (Egziabher et. Al, 2013; Baiyegunhi et al., 2019; Rocha Junior et al., 2020). By the other side, the internet access is considered as one of 12 disruptive technologies (Manyika, 2013), and a productive enhancing factor (Pilat, 2005) but its impact is considered ambiguous and can be even negative for countries with high income inequality (Noh and Yoo, 2008).

Considering this context, in this study I analyze two policy issues in information access and their impacts on agricultural production. The first one is the impact of the technical assistance and rural extension (TA) access on the production of Brazilian family farmers, and the second one is the impact evaluation of a real case of public policy proposed to expand the internet access on rural areas.

In recent years, the National Policy of Technical Assistance and Rural Extension has undergone significant changes in its management processes and in the amount of resources allocated by the government, although it is one of the main public policy instruments for the development of Brazilian agriculture. Considering this context, the technical argument concerning the economic importance of technical assistance has the potential to overcome the ideological conflicts inherent to the political environment, helping to build guidelines for economic and social development.

In regard to the public policy to increase internet access, in 2017 just 28% of the Brazilian farmers had access to internet, which is a considerable increase in comparison to the value observed in 2006 (1.46% of the establishments) (IBGE, 2019), but still very low. The need to map and prioritize rural areas that are not or poorly served with broadband connection is decreed by the Decree 9.612 / 2018, in its Art. 9, and I evaluated the impact of a technical plan elaborated through the Technical Cooperation Program PCT BRA/IICA/02/2015 (FEALQ/IICA/MAPA, 2020), whose implementation is proposed to be conducted in 4 annual steps.

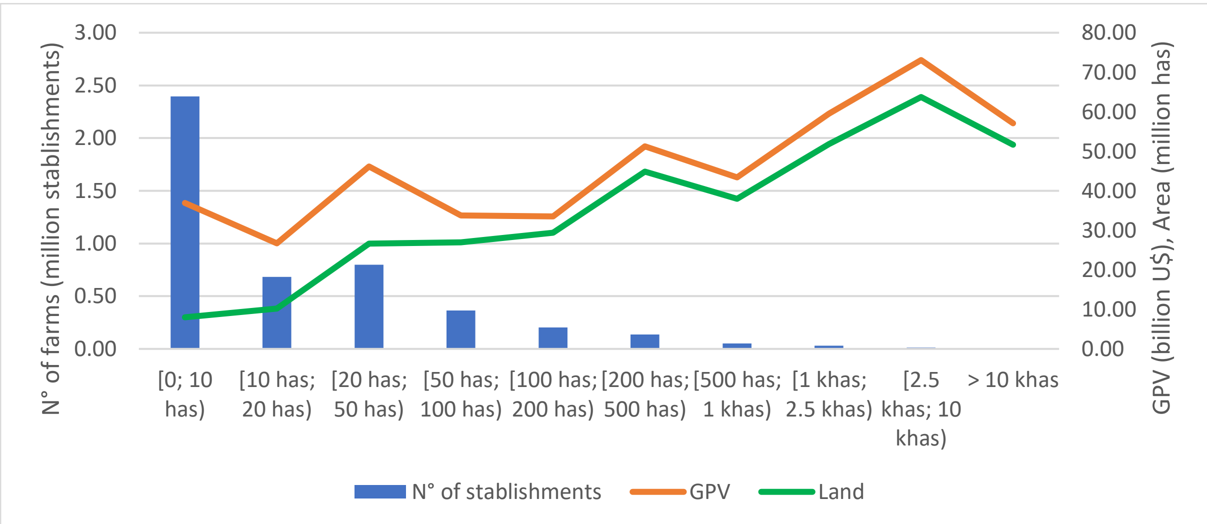
1.1.1. Technical Assistance and rural extension for family farming

Brazil is the fourth largest livestock producer, and the fifth largest agricultural producer of the world. In 2018, the gross production value of livestock was U$85.49 billion, and of agricultural production was U$203.4 billion (FAOSTAT, 2020). Despite that, there are many constraints to be overcome in Brazil, and the main ones are the inequality in land and income distribution (Hoffman, 2009; Machado et. al, 2017), and the restricted infrastructure (Rocha, 2015; de Castro, 2017; Vieira Filho et al., 2019).

Data from the last Brazilian Agricultural Census (Figure 1) shows that farms smaller than 50 has constitute more than 80% of the Brazilian farms, and produce about 24% of the agricultural GPV cultivating less than 13% of the agricultural land. Also, about 82% of those farmers are classified as family farmers (FFs) for policy purposes.

According to the Law 11.326/2006, FF is the rural family entrepreneur who practices activities in rural areas, has an area of up to four fiscal modules, predominantly family labor and income and management of the enterprise linked to his own family (Brasil, 2015).

Figure 1. N° of farms, GPV and land per class of farm size, in Brazil, in 2017



Source: The author, based on IBGE (2019).

According to Wanderley (2013), the term family farming became popular in Brazil with the implementation of the National Program for the Strengthening of Family Farming (Pronaf, in Portuguese) in 1995, whose main objective was to foster the sustainable development of family farming. Although the implementation of Pronaf is a historical milestone in the structuring of institutions that promote TA access for FF, there have been a series of events which led to its emergence and that have characterized the improvement of institutions to support FF since then. According to de Castro (2015), TA services in Brazil started in 1948, when the Association of Credit and Rural Assistance (ACAR) was created in Minas Gerais state, on the recommendation of the American businessman Nelson Rockfeller. According to de Castro (2015):

"[...] ACAR was structured according to the North American model of dissemination of innovations, which basically attributed to the rural extension the mission of providing technical and financial assistance to rural producers to adopt the innovations developed in agricultural research institutes." (de Castro, 2015, p. 50)

According to Oliveira (1999), at the end of the 1950s, ATER services were present in half of the Brazilian states, completely covering the Southeast and South regions, and expanding to Northeast and Midwest regions. Caporal (1998) points out that, in 1956, the Brazilian Association of Credit and Rural Assistance (Abcar) - a private entity- brought together all the ACARs according to a centralized and vertical model of orientation.

Another fundamental institutional milestone was the implementation of Law No. 4,504 of November 30, 1964, known as the "Land Statute", which formally established the legal foundations that permit the agrarian reform, providing the legal bases for the formulation of agricultural policies and promotion of colonization processes (Brasil, 2016). The result of this milestone was the expansion of agricultural borders, encouraged by the State through subsidized rural credit (Brasil, 2016).

Because the institutions of TA were growing, the Brazilian government started to provide financial support in exchange for support to its rural development project. This process provided conditions for the second major institutional framework of TA in Brazil (Castro, 2015), which was the constitution, through Law No. 5,851 of 12/7/1972, of the National Research and Extension System, initially coordinated by the Brazilian Agricultural Research Company (EMBRAPA), and after 1974, through Law No. 6,126 of 11/6/1974, by the Brazilian Company of Technical Assistance and Rural Extension (EMBRATER) (Bianchini, 2015). After the creation of EMBRATER, which incorporated Abcar, the state units of ACAR were renamed as State Company of Technical Assistance and Rural Extension (Emater), which were subordinated to its control (CASTRO, 2015). Thus, Ematers succeeded the State Associations of Credit and Rural Assistance (ACARs) and EMBRATER the Brazilian Association of Credit and Rural Assistance (ABCAR).

From the enactment of the 1988 Constitution, there was an organizational rearrangement characterized by polarization around the defense of the interests of business farmers and family farmers. With regard to business farmers, there was an alliance around the National Confederation of Agriculture (CNA), the Ruralist Democratic Union (UDR) and the Brazilian Agribusiness Association (ABAG) (Bianchini, 2015). In regard to family farmers, there was strengthening of the National Confederation of Agricultural Workers (CONTAG), and were created by new organizations such as the Landless Rural Workers Movement (MST), the Campesina Road and the National Department of Rural Workers of CUT (DNTR) that would give rise to the Federation of Family Farming Workers (FETRAF) (Bianchini, 2015).

Since the 1990s, problems with rural credit have arisen due to the disarticulation between credit interest and agricultural price changes, resulting in predominance of working capital and decrease in resources applied (Rezende, 2001). In 1994, mobilizations organized by family farmers, known as "Grito da Terra Brasil", gave origin to the Program for the Valorization of Small Rural Production (PROVAPE), and then, in 1995, the National Program for Strengthening Family Farming (PRONAF) (Bianchini, 2015). An important result of this process is the elaboration of Resolution 2101 of August 24, 1994, which establishes the rural credit standards of PROVAPE, characterizing small rural producers as those who managed establishments with: area of up to 4 MF, 80% of gross income from agriculture and lack of permanent employees (BRASIL, 1994).

PRONAF is recognized as one of the most remarkable events for the Brazilian rural environment, as it represents the recognition and legitimation by the State of the specific demands from such social category (Schneider, Mattei & Cazella, 2004). However, although the criteria of Resolution 2101 of August 1994 characterized this public, which had been on the margins of agricultural public policies, the classification of family farmers has evolved considerably since then, going to incorporate specificities of this public, which were detailed mainly based on the publication "Novo Retrato da Agricultura Familiar- O Brasil Redescoberto". According to Bianchini (2015), based on this publication and also on other studies about production systems included in publications of the Food and Agriculture Organization (FAO) in partnership with the National Institute of Colonization and Agrarian Reform (INCRA), it was possible to stratify family farming by income, defining farmers in rural poverty, in transition and capitalization, which gave rise to the classification between types A, B, C, D and E. This classification considers other criteria such as number of employees and origin of the community (quilombola remnants, indigenous, settled and etc.). This stratification is relevant because it allows, in addition to the political recognition of the class, the understanding of the heterogeneity inherent to family farming, which helps in the formulation of more focused public policies.

Another fundamental institutional milestone for the economic development of FF in Brazil was the creation of the Ministry of Agrarian Development (MDA), since, through MP 2,216-37 of August 31, 2001, the Ministry of Agriculture, Livestock and Supply (MAPA) transferred to MDA the attributions related to promoting the sustainable development of family farming, through the Secretariat of Family Farming and Agrarian Reform and the Secretariat of the National Council for Sustainable Rural Development. According to Bianchini (2015), the transfer of PRONAF to the MDA allowed its consolidation and the beginning of public support to settlements of Agrarian Reform (Group A), to farmers classified below the Poverty Line (Group B), to farmers in the transition (Group C), in the beginning of capitalization (Group D) and, from the 2004-05 crop year, to family farmers located in the Expanded Breeding Level (Group E).

This transfer of competences, in context of valorization in respect to the socio-environmental dimension of the development process, determined the need for a new TA policy, enabling the creation of the National Policy for Technical Assistance and Rural Extension - PNATER, whose coordination was attributed to the Department of Technical Assistance and Rural Extension - Dater of SAF/MDA, established by Decree No. 5,033, of April 5, 2004 (MDA, 2004). PNATER arose from the transfer, to SEAF, of the responsibility for coordinating ATER activities, through Decree No. 4,739 of June 13, 2003, and was characterized as a participatory policy, in conjunction with various spheres of the federal government, and based on dialogue with governments and state institutions, segments of civil society, leaders of organizations representing family farmers and social movements committed to this issue (MDA, 2004).

Through a team coordinated by MAPA and composed by managers from EMBRAPA, the National Council of State Agricultural Research Systems (CONEPA) and the National Confederation of Agriculture (CNA), a proposal was made for the creation of a national TA framework, which led to dialogue between SEAF, DATER and Embrapa's Technology Transfer Department (DTT). From those negotiations, the National Agency for Technical Assistance and Rural Extension (ANATER) was established as an autonomous social service organization, created through Bill No. 5740/2013, with the purpose of managing the public resources allocated to TA, through the articulation of the National System of Technical Assistance and Rural Extension with the National Agricultural Research System coordinated by Embrapa (Thomson, Bergamasco & Borsato, 2017; Bianchini, 2015).

The creation of ANATER followed the creation of the last two major institutional milestones important for public performance in TA for FF, which were the creation of PRONATER in 2005 and the operationalization of the Brazilian System of Technical Assistance and Rural Extension (SIBRATER) in 2006. This set of efforts resulted in the current versions of PNATER, PRONATER and the decentralized management model of the current SIBRATER, which assists the strengthening of a national TA network with social movements, state entities of TA, NGOs, associations and cooperatives of family farmers and Universities (Thomson, Bergamasco & Borsato, 2017).

Although the institutional structuring highlights a long process of political recognition for family farming, mainly through the promotion of access to subsidized rural credit and technical assistance, the current context is uncertain regarding the fate of Brazilian current TA institutions, especially after the extinction of the MDA in 2016. This scenario makes even more relevant the impact analysis proposed in this project.

1.1.2. Relevance of internet access and a plan to expand its access in rural areas

The so-called "Agriculture 4.0" has been the target of research and development for startups in the agricultural sector. Agriculture 4.0 or "Agro 4.0" is a term inherited from "Industry 4.0", innovation that started in the German automotive industry and is currently employed in various segments of the industry, which consists of the complete automation of production processes (VDMA VERLAG, 2016; Masshurá et al., 2014).

Agro 4.0 is part of the Internet of Things (IoT), which consists in machines, vehicles, appliances, smartphones, computers, residences and other physical structures connecting to the internet and sharing data about their functioning, receiving instructions and acting according to the information received. Seen as the inevitable path of agriculture, Agro 4.0 would come with the promise of a major paradigm shift in agricultural production, since it would introduce the element predictability in an activity that, unlike industry, has always been subject to weather and other constraints (Rose and Chilvers, 2018).

Through Agro 4.0, technologies such as sensor networks, machine-to-machine (M2M) communication, connectivity between mobile devices, cloud computing, methods and analytical solutions to process large volumes of data (bigdata) and construction of systems to support decision-making in crop management are employed with the objective of raising productivity rates, promoting the efficient use of agricultural inputs and pesticides, reducing labor costs and labor hard work, improving the safety of rural workers, and reducing impacts on the environment (Massruhá and Leite, 2014). Beyond that, even for smaller farmers who have no conditions to implement more capitalized technologies, internet access can increase the knowledge about existing technologies, providing a broader set of options to allocate their inputs in a more productive way.

In this context, the study that gave rise to the public policy analyzed in this thesis results from a demand from the Ministry of Agriculture Livestock and Supply (MAPA) to spatially analyze the availability of connectivity (internet access) in rural areas, aiming to expand the access to technological innovations and promote the integration of the various institutions that act to foster rural development.[1]

[1] Project Technical Cooperation IICA/BRA/02/2015 - "International Technical Cooperation Project for the Regionalization of Brazilian Agribusiness Development and Cooperativism Policies";

The analysis of the legal background and instruments[2] shows the legal framework and other measures adopted by the federal government, such as stimulating private sector investments via tax exemptions and reducing tax burdens, the structuring of ANATEL to act as regulatory agent and the Brazilian Communications Company (Telebrás) as responsible for the implementation of the telecommunications infrastructure, as well as the construction of the Geostationary Satellite of Defense and Communications (SGDC) and its launch in 2017, were not enough to address broadband supply gaps, especially in rural areas.

From the finding of a great demand for information due to the broadband supply gaps in Brazilian countryside, FEALQ/IICA/MAPA (2020) tested several spatially explicit mathematical models for mapping areas with no signal (broadband coverage). In this context, two different approaches to the problem were adopted: the COST231-Hata model and the ITM model. The COST231-Hata model is an extension of the Okumura-Hata model, the most used for commercial applications (Molisch, 2011). It belongs to a class of models whose calculation is elaborated in order to incorporate factors as the height antennas and the location of the transmission, divided for the application into three categories: i) dense urban spaces; (ii) suburban spaces or smaller cities; and iii) open areas.

The model implementation used for FEALQ/IICA/MAPA (2020) to estimate the internet coverage and its increase was based on the SignalServer software (Farrant, 2019), with a small modification in the calculation of distances to include the variation of antenna height from the terrain. This was done to allow further comparison with the third model used, ITWOM, whose implementation was done through the same software. The COST231-Hata model is an advance over the Friis formula by incorporating the height of antennas and the transmission location. However, the incorporation of relief in the distance between antennas is not a sophisticated way to include this important factor in the calculation and extrapolations of the application range can have unpredictable consequences for the results from such model.

ITM is an acronym for the words Irregular Terrain Model and its formulation is also known as Longley-Rice, which includes a more realistic interpretation about the influence of terrain on wave transmission and propagation. Thus, the ITM model produces a very detailed calculation, which incorporates both: electromagnetic theory and statistical analyses to take into account the irregularity of the terrain, the surface refractivity and climatic influence on the path of rays between antennas (Parsons, 2000).

The analyses on the connection in the rural environment through spatial modeling revealed that the more robust ITM model presents a more realistic response in relation to previous models, showing that the expansion of broadband connection especially in the North and Midwest regions is extremely necessary.

Having filled this knowledge gap about the areas with highest demand for coverage, FEALQ/IICA/MAPA (2020) explored the target farmers, which were characterized in profiles, so that it was possible to propose regionalized strategies for the expansion of connectivity. The final document consisted in a proposal for installation of 20,795 antennas for internet transmission, being 5,604 antennas installed in existing towers with idle capacity, and 15,191 antennas in new towers. It was calculated the percentage increase in rural areas with satisfactory internet signal due to the installation of 25% of the proposed antennas per year, along 4 years, for each Brazilian municipality. This data was used to model the economic impact of that policy at the agricultural GPV.

[2] such as the General Law of Telecommunications Actions – LGT (Law nº 9.472/1997), the Fund of Universalization of Telecommunications Services – FUST (Law nº 9.998/2000), the National Broadband Program – PNBL (Decree nº 7.175 of May 2010), the Smart Brazil Program (Decree nº 8.776 of May 2016), the Internet for All Program and the Decree No. 9,612/2018, which replaces the PNBL and the Intelligent Brazil Program.

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2. DOES THE TECHNICAL ASSISTANCE IMPACT PRODUCTIVITY OF BRAZILIAN FAMILY FARMERS?

ABSTRACT

In this study two different approaches are used to assess the impact of technical assistance and rural extension (TA) on family farming production in Brazilian municipalities. The first one is Data Envelopment Analysis (DEA), a non-parametric approach that we use to estimate output-oriented efficiency. A fractional logistic model is used to regress this measure on technical assistance from different sources, education and internet access. The second approach is the estimation of a Cobb Douglas Stochastic Output Distance Function (SODF) with TA as efficiency and frontier changing variable. Both models are estimate using municipality level data from the Brazilian Agricultural Census of 2017. We found that TA impacts positively the productive efficiency and technology of family farmers, and by consequence, the agricultural gross production value (GPV). We also find that impacts differ across TA sources, all sources affected efficiency, and the public TA and TA from technicians hired directly for farmers are the ones presenting statistically significative impact on production. Finally, this study represents a contribution to the Brazilian family farm literature, considering that there are few economic impact evaluations of technical assistance for Brazilian family farmers.

Keywords: Technical assistance; Technical efficiency; Family farming; Productivity

2.1. Introduction

Brazilian agriculture is historically inserted in a context of social and economic conflicts. The main consequence of this process is that inequality in the Brazilian rural area has become a chronic problem, for which institutional measures have been adopted in the relatively recent period. Due to this history, the current Brazilian rural scenario is marked by high land concentration due to the coexistence of large farmers producing commodities, whose production is directed mainly to the export and to supply agroindustry; and small farms that constitute the so-called family farming (FF)[3], generally diversified, whose productive matrix is constituted mainly by basic food products directed to the local markets. This configuration is observed in a brief analysis of the Brazilian agricultural census of 2017, which shows that the productive matrix has not changed since 2006 (IBGE, 2019).

The size of the territory occupied by FF in Brazil, which cultivated 80,9 million of hectares in 2017, and the number of family farmers, which exceeded 3.89 million in the same year (IBGE, 2019), show the economic and social importance of the activity. Despites the economic and social relevance of FF production, there are innumerable constraints to its development in Brazil, such as the difficulty in building social capital and promoting market access, which prevent family farmers from valuing the attributes of their location and accessing more specialized markets (Abramovay, 1998). Thus, policies to access rural credit and the public provision of technical assistance and rural extension (TA) are important for the development of family farming and food security.

The Brazilian Constitution of 1988 and, in parallel, the rural trade union movement, supported the formulation of public policies directed to decrease inequality (Hampf, 2013). Given this context, in 1996 the National

[3]In the resolutions of Law no. 11,326 / 2006 and the updates given by Decree no. 9.064 / 2017, AF is the rural family entrepreneur who practices activities in the rural area, has an area of up to four fiscal modules, predominantly family labor and own family income and management of the enterprise (BRAZIL, 2015).

Program for Strengthening of the Family Farming (PRONAF) was established, whose main objectives are promoting access to rural credit and encouraging technical assistance access for this public (Dias, 2008). However, despite the importance of PRONAF in meeting the demand for credit, other recurring demands were not sufficiently met, such as the access to technical assistance and specific rural extension (TA) (de Castro & Pereira, 2017).

Although the institutional structuring process shows a long way by which family farming has been politically recognized, the current context is uncertain about the current TA institutions fate in Brazil, especially after the MDA's extinction in 2016. The public provision of TA plays relevant role for family farmers given they constitute the poorest category of farmers, facing barriers to access markets (Abramovay, 1998). They also present the lowest levels of per capita income and education (IBGE, 2019), factors which are determinants to access TA (Rocha Junior et al., 2019).

Considering the relevance of public policies to promote access to technical assistance for FF, the objective of this paper is to analyze the impact of receiving technical assistance on the technical efficiency of family farming in Brazil, taking into account the possibility that there are differences among the impact of different TA sources. This study underlies relevant discussions to decision making by policy makers, allowing more rationality in managing this relevant dimension of the Brazilian government agenda.

Two methodological approaches, Data Envelopment Analysis and Stochastic Output Distance Function are applied to analyze the impacts of technical assistance under different assumptions, and I derived production elasticities in respect to the TA access, showing how much extra output family farmers can produce due to increases in TA coverage. Those results are important to support discussions of systemic implications for TA actions directed to family farming.

In recent years, the National Policy of Technical Assistance and Rural Extension has undergone significant changes in its management processes and in the amount of resource allocated by the government, although it is one of the main public policy instruments for the development of Brazilian agriculture. Considering this context, the technical argument concerning the economic importance of technical assistance has the potential to overcome the ideological conflicts inherent to the political environment, helping to build guidelines for economic and social development.

2.2. Methodology

2.2.1. Measuring efficiency and frontier changing effects in output space

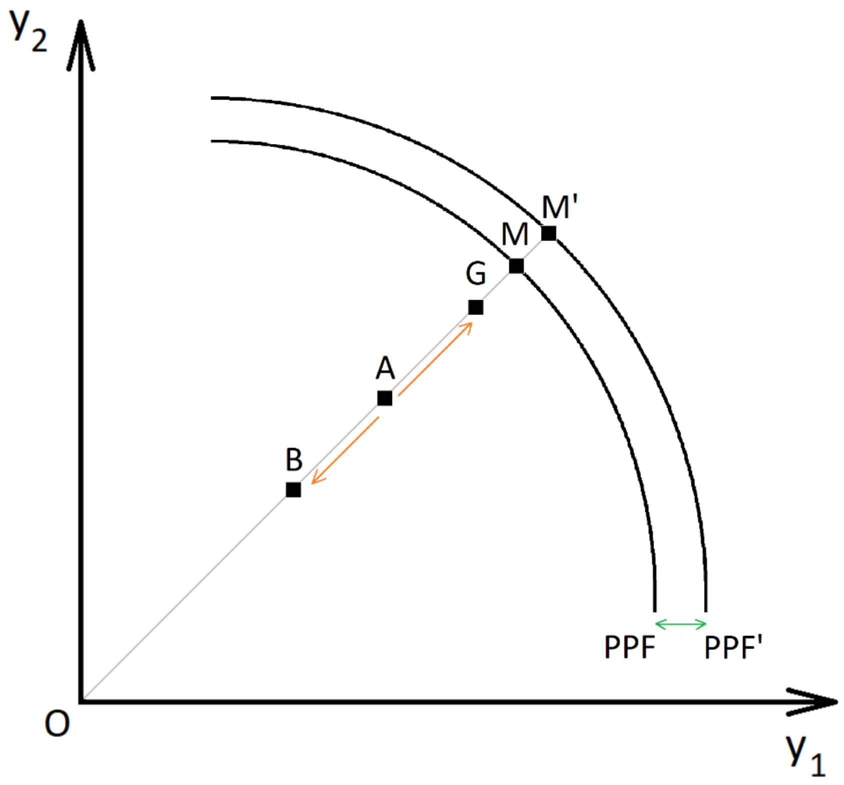
The departure point to evaluate the impact of technical assistance at technical efficiency in this paper is the Farrell's (1957) seminal paper on efficiency measurement, which led to the development of several approaches to efficiency and productivity analysis. Beside the presence of inefficiency, we also consider that access to information can affect the amount of output produced given the inputs vector. Family farmers use their land, labor, capital, energy, Fuels, lubricants and chemical inputs to produce crops, livestock and other products.

Graphically, it is possible to define a production possibilities frontier (PPF), for each observation, considering the amount of input used, the soil quality and relief, as well the infrastructure and other exogenous factor which can promote conditions for the adoption of more or less productive technologies. This structure is illustrated at Figure (Figure 2).

In this paper the impact of the TA is represented by a radial movement of the outputs vector due to the better/worst use of the technology (Figure 2). Considering an observation with output oriented technical efficiency $OE_A = \overline{OA}/\overline{OM}$, the TA can increase its output-oriented efficiency moving it from A to G, providing a new level of

OE given by $OE_G = OE_A + \Delta OE = \overline{OG}/\overline{OM}$. Optionally, if the TA access results in less output level for the same amount of input used, because misinformation or any other reason, the resulting movement is from A to B, resulting in a worse level of output-oriented efficiency given by $OE_G = OE_A + \Delta OE = \overline{OB}/\overline{OM}$. Besides that, the TA access can promote the access to more/less productive technologies, shifting the PPF from M to M' (or vice versa).

Figure 2. Production possibility frontier with output oriented technical inefficiency



Source: the author.

In this paper I model the TA impact on the production level through two different approaches: Data Envelopment Analysis (DEA) and Stochastic Output Distance Function (SODF). While using the DEA model measure just the impact of TA at the output oriented technical efficiency, using SODF the impact of TA access as a frontier changing variable is also modelled, allowing a more complete understanding about its effects on production.

At the past literature there are seminal papers discussing different ways to construct the PPF. Basically, those papers compare parametric and non-parametric ways to define frontiers. Some examples are: Coelli (1995), who discussed about different frontier techniques and their limitations and strengths; Sharma et al. (1997), examining the productive efficiency of a sample of swine producers in Hawaii by estimating a stochastic frontier production function and the constant returns to scale (CRS) and variable returns to scale (VRS) output-oriented DEA models; and other researchers like Førsund, Lovell, and Schmidt (1980); Bauer (1990); Bjurek, Hjalmarsson, and Førsund (1990); Seiford and Thrall (1990); Battese (1992); Bravo-Ureta and Pinheiro (1993); and Fried, Lovell, and Schmidt (1993).

Basically, the main difference between DEA and Stochastic frontiers is that the DEA is more flexible because it does not impose a functional form to the frontier. According to Cooper and Tone (1997), DEA can be described as 'data-oriented', because the resulting frontier is a piece-wise linear technology, whose construction and its evaluations and inferences come directly from observed data. Another important advantage is that it allows us to work with multiple inputs and outputs. In the other hand, because the non-parametric nature of this approach, the DEA does not accommodate stochastic noise, then this approach is very sensitive to outliers.

In respect to the stochastic frontier, the main strength is that it accommodates stochastic noise, which is useful, although it is necessary to impose a functional form for the frontier. Multiple inputs and outputs can be also modelled through this framework, as summarized by Kumbhakar and Lovell (2000). Besides of that, even imposing a functional form to the frontier, I parametrize that in the present paper by allowing for variable elasticities according to the soil quality and relief index. I also allow that technical assistance, access to information and the education shift the production possibilities frontier due to their effects at the technical choice.

Considering the multiple input and output nature of the Brazilian family farm production, at the present paper we apply those two approaches to analyze the impact of technical assistance. The DEA, a non-parametric approach, is applied combined with an econometric second step to evaluate the impact of TA from different sources at the estimated output-oriented efficiency. The parametric approach applied is a Stochastic Cobb-Douglas Output Distance Function in which TA is a frontier/efficiency changing variable. Comparing the results obtained from such analysis, it is analyzed, under different assumptions, the hypothesis that TA affects output-oriented efficiency, and that there are differences among the impact from different TA sources.

2.2.2. Data Envelopment analysis with multiple input-outputs

In this paper the output-oriented efficiency is modelled using DEA by assuming a linear piecewise technology presenting convexity, free disposability, and variable returns to scale, due to its less restrictive assumption about the technology properties. We follow Fare, Grosskopf and Lovell (1994) and use the *dea* function of the software Rstudio 3.1.6 to solve, for each observation of the sample, the following linear programming

$$F_o(x^j, y^j | V, S) = \max_{\theta^F, z} \theta^F$$

$$s.t. \theta^F y^j \leq z\boldsymbol{M}$$

$$z\boldsymbol{N} \leq x^j$$

$$z \in R_+^j$$

$$\sum_{j=1}^{J} z_j = 1$$

Where $\boldsymbol{M}$ is the set of observed outputs and $\boldsymbol{N}$ is the set of inputs at the sample, y_i is the vector of outputs and x_i the vector of inputs for observation i, z is the is the convex combination wheighting vector, and θ^F is a measure of inefficiency, that can be converted to the Output Oriented Efficiency (OOE) through the expression

$$OOE_i = \frac{1}{\theta_i^F} = \frac{y_i}{y_{MAX,i}} \qquad (1)$$

Where y_i is the observed production for observation i, and $y_{MAX,i}$ is the maximum output observation i can produce given the vector of inputs. To analyze the impact of technical assistance access as an efficiency changing variable, we follow Ramalho, Ramalho and Henriques (2010), who argue that the traditional linear or tobit approaches to second-stage DEA analysis do not constitute a reasonable data-generating process for DEA scores. Alternatively, they recommend the use of fractional regression models because, under the assumption that DEA scores can be treated as descriptive measures of the relative performance of units in the sample, it is the most natural way to model them. Thereby, we use the OOE estimated in (1) as the dependent variable in a Fractional logit model

$$ln\left(\frac{OOE_i}{1 - OOE_i}\right) = \boldsymbol{z_i\beta} + \varepsilon_i \qquad (2)$$

Where $\boldsymbol{z_i}$ is the vector of efficiency changing variables for observation i, $\boldsymbol{\beta}$ is the vector of parameters related to $\boldsymbol{z_i}$, and ε_i is a random noise. This model was estimated using the *glm* command in the software Stata 15. Using $\boldsymbol{\beta}$, it is possible to derive the semi elasticity of y_i in respect to $\boldsymbol{z_i}$. Deriving (1) in respect to $z_{j,i}$

$$\theta = \frac{\boldsymbol{y_i}}{\boldsymbol{y_{MAX}}} \rightarrow \frac{\boldsymbol{d}OOE_i}{dz_{j,i}} = \frac{1}{y_{MAX}}\frac{dy_i}{dz_{j,i}} \rightarrow \frac{\left(\frac{dy_i}{dz_{j,i}}\right)}{y_i} = \frac{\left(\frac{\boldsymbol{d}OOE_i}{dz_{j,i}}\right)}{OOE_i} \rightarrow \frac{dlny_i}{dz_{j,i}} = \frac{dlnOOE_{i_i}}{dz_{j,i}} \tag{3}$$

Differentiating (2) in respect to $z_{j,i}$

$$\frac{d}{dz_{j,i}}\left[ln\left(\frac{OOE_i}{1-OOE_i}\right)\right] = \frac{d}{dz_{j,i}}\boldsymbol{z_i\beta} + \frac{d}{dz_{j,i}}\varepsilon_i \rightarrow \frac{dlnOOE_i}{dz_{j,i}} - \frac{dln(1-OOE_i)}{dz_{j,i}} = \beta_j \rightarrow$$

$$\frac{dlnOOE_i}{dz_{j,i}} - \frac{1}{(1-OOE_i)}\left(-\frac{dOOE_i}{dz_{j,i}}\right) = \beta_j \rightarrow \frac{dlnOOE_i}{dz_{j,i}} = \beta_j(1-OOE_i) \tag{4}$$

Replacing (3) on (4), we have

$$\frac{dlny_i}{dz_{j,i}} = \beta_j(1-OOE_i) \tag{5}$$

Which gives the percentage increase at the observed production due to an increase in the efficiency changing variable.

2.2.3. Stochastic Cobb Douglas Output Distance Function (SFA)

Because the diversification within farms, inherent to the Brazilian family farming, it is not possible to disaggregate some inputs among different activities. Considering that, I model the production parametrically using the transformation function

$$F(\mathbf{y}.\mathbf{OE^{-1}}, \mathbf{x}) = 0 \tag{6}$$

Where $\boldsymbol{y}$ is a vector containing M outputs produced using the vector $\boldsymbol{x}$ constituted by J inputs. The term $\boldsymbol{OE^{-1}}$ is included to represent the output oriented technical inefficiency at the production of $\boldsymbol{y}$, where $0 \leq OE \leq 1$ is a scalar that shows the proportion of the potential output produced due to technical inefficiency. As mentioned above, the hypothesis analyzed in this paper is that TA access can increase the production level, what can be measured as an impact at the output-oriented efficiency OE and at the technology. In the literature, for multiple inputs and outputs the transformation function given by (6) is represented through a distance function

$$\mathrm{D_0(y,x)} = \min_{\theta}\left\{\theta \middle| \left(\frac{\mathrm{Y}}{\theta}\right) \in \mathrm{P(X)}\right\} \tag{7}$$

where $P(x)$ is a vector of output feasible given the input set X. Considering the homogeneity of degree 1 for $D_0(y,x)$ in the outputs, the following is true

$$\frac{\mathrm{D_0(y,x)}}{\mathrm{y_1}} = \mathrm{f}\left(z_1, \dots, z_J, \mathrm{x_1}, \dots, \mathrm{x_J}, \frac{\mathrm{y_2}}{\mathrm{y_1}}, \dots, \frac{\mathrm{y_m}}{\mathrm{y_1}}\right) = \mathrm{f}(\mathbf{z}, \mathbf{x}, \tilde{\mathbf{y}}) \tag{8}$$

Where $\boldsymbol{z}$ is the vector of frontier changing variables, $\boldsymbol{x}$ is the vector of inputs and $\tilde{\mathbf{y}}$ is a vector of outputs ratios in respect with y_1. I assume a Cobb Douglas specification for $f(\boldsymbol{x}, \tilde{\boldsymbol{y}})$ and impose that both inputs and outputs sets are separable in the short run[4], and that, under revenue maximizing behavior, the outputs ratios are exogenous in respect to y_1 (Coelli, 2000). Then, taking the logarithmic in both sides of equation (8),

$$\ln D_{0,i}(y,x) - \ln y_{1,i} = \gamma_i + \sum_{n=1}^{N} \gamma_n z_{n_i} + \sum_{j=1}^{J} \beta_{j,i} \ln x_{j,i} + \sum_{m=2}^{M} \alpha_{m,i} \ln \tilde{y}_{m,i}$$

Where $\beta_{j,i}$ and $\alpha_{m,i}$ are observation specific parameters, determined by the soil quality and relief index of municipality i $(Aptitude_i)$, as following

$\beta_{j,i} = \beta_0 + \beta_1 Aptitude_i$

$\alpha_{m,i} = \alpha_0 + \alpha_1 Aptitude_i$

$\gamma_i = \gamma_0 + \gamma_1 Aptitude_i$

Allowing inefficiency, $0 \leq D_0(y,x) \leq 1$, it can be moved to the right-hand side, a two-sided noise term v_i is added, and it gives us the Stochastic Cobb Douglas Output Distance Function (SFA)

$$-\ln y_{1i} = \gamma_i + \sum_{n=1}^{N} \gamma_n z_{n_i} + \sum_{j=1}^{J} \beta_{j,i} x_{ji} + \sum_{m=2}^{M} \alpha_{m,i} \tilde{y}_{mi} + v_i - \ln D_{0,i}(y,x) \tag{9}$$

denoting $ln\ D_{0,i}(y,x) = -u_i$, the following system can be estimated using the maximum likelihood estimator for stochastic cost function[5]

$$-\ln y_{1i} = \sum_{n=1}^{N} \gamma_n z_{n_i} + \sum_{j=1}^{J} \beta_{j,i} x_{ji} + \sum_{m=2}^{M} \alpha_{m,i} \tilde{y}_{mi} + \epsilon_i$$, where

$\epsilon_i = v_i + u_i$

$v_i \sim i.i.d.\ N^+(0, \sigma^2_{v,i})$

$u_i \sim i.i.d.\ N^+(\mu_u, \sigma^2_{u,i})$,

Given that $D_o(\boldsymbol{y},\boldsymbol{x})$ is decreasing in each input level, increasing in each output level and concave in $\boldsymbol{y}$, the expected signal of each $\alpha_{m,i}$ is positive, and the expected signal of each $\beta_{j,i}$ is negative. Beyond that, because we impose a Cobb-Douglas functional form and impose homogeneity of degree 1 in outputs, the parameter $\alpha_{m,i}$ gives the elasticity of the output distance in respect to $y_{m,i}$, which is, under profit maximizing behavior, equivalent to its marginal cost (Fulginiti, 2010) or shadow revenue (Feng and Serletis, 2010); and $\beta_{j,i}$ gives the elasticity of the output distance in respect to x_{ji}, which is equivalent to the negative of its marginal revenue product (Fulginiti, 2010) or its shadow cost (Feng and Serletis, 2010).

The specific interest of this paper is to analyze the impact of the technical assistance, as an efficiency and frontier changing variable, at the output produced. To do that, we impose a Half-Normal distribution to the u_i term ($u_i \sim i.i.d.N^+(0, \sigma^2_{u,i})$), and parametrize the heteroscedasticity of u_i and v_i, $\sigma^2_{u,i}$ and $\sigma^2_{v,i}$, as being an exponential function of $\mathbf{z}$, in according to Caudill and Ford (1993), Caudill, Ford, and Gropper (1995), and Hadri (1999). It allows us to evaluate the impact of the technical assistance at the efficiency level.

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[4] Separability is not a strong assumption here because it is a cross sectional analysis and there is no activity-specific input in the inputs vector.

[5] This mathematical formulation gives rise to a positive skewness, which is consistent to the stochastic cost function Maximum likelihood estimator of Kumbhakar, Wang and Horncastle (2015).

Besides the economic application of allowing us to include efficiency changing variables, it is important to notice that analogous to the case of a traditional SFA model summarized by Kumbhakar and Lovell (2000), ignoring the heteroscedasticity of v_i causes downward-bias at the intercept parameter of the SODF and its variance, and ignoring the heteroscedasticity of u_i gives biased estimates of the SODF parameters as well as the estimates of technical efficiency.

Based on Kumbhakar, Wang & Horncastle (2015), one can use the standard stochastic cost function approach to estimate this model. The maximum likelihood problem, estimated using the command *sfmodel* written by Kumbhakar, Wang & Horncastle (2015) for the software Stata 15, is constituted by

$$L_i = -ln\left(\frac{1}{2}\right) - \frac{1}{2}ln\left(\sigma_{v,i}^2 + \sigma_{u,i}^2\right) + ln\,\phi\left(\frac{\epsilon_i}{\sqrt{\sigma_{v,i}^2 + \sigma_{u,i}^2}}\right) + ln\,\phi\left(\frac{\mu_{*i}}{\sigma_{*i}}\right), \tag{10}$$

$$\sigma_{u,i}^2 = exp\ (z'_{u,i}w_u) \tag{11}$$

$$\sigma_{v,i}^2 = exp\ (z'_{v,i}w_v) \tag{12}$$

$$\mu_{*i} = -\frac{\sigma_{u,i}^2\epsilon_i}{\sigma_{v,i}^2 + \sigma_{u,i}^2} \tag{13}$$

$$\sigma_{*i}^2 = -\frac{\sigma_{v,i}^2\sigma_{u,i}^2}{\sigma_{v,i}^2 + \sigma_{u,i}^2} \tag{14}$$

By estimating the equations (10), (11), (12), (13) and (14) in one step, we avoid the bias due to a mis-specification of the model estimated at the first step in a two-step approach, according to mentioned by Kumbhakar, Wang & Horncastle (2015). Following Jondrow et al. (1982), it is possible to get point estimates of u_i from the expected value of u_i conditional on the composed error ϵ_i, which gives us

$$E(u_i|\epsilon_i) = \frac{\sigma_*\phi\left(\frac{\mu_{*i}}{\sigma_{*i}}\right)}{\phi\left(\frac{\mu_{*i}}{\sigma_{*i}}\right)} + \mu_{*i} \rightarrow E(u_i) = \sigma\left(\frac{\phi(0)}{\phi(0)}\right) = exp\left[\frac{1}{2}\ln\left(\frac{2}{\pi}\right) + \left(z'_{v,i}w_v\right)\right] \tag{15}$$

$$E[exp\ (-u_i)|\epsilon_i) = exp\left(-\mu_{*i} + \frac{1}{2}\sigma_{*i}^2\right)\frac{\phi\left(\frac{\mu_{*i}}{\sigma_{*i}} - \sigma_{*i}\right)}{\phi\left(\frac{\mu_{*i}}{\sigma_{*i}}\right)} \tag{16}$$

The marginal effect of the kth variable of $z_{u,i}$ on $E[u_i]$ is computed as

$$\frac{dE(u_i)}{dz[k]} = \frac{w[k]\sigma_{u,i}}{2}\left[\frac{\phi(0)}{\phi(0)}\right] = w[k]\sigma_{u,i}\phi(0) \tag{17}$$

Considering that the marginal effect of a change in z_i would cause a change in $y_{m,i}$ because it affects both, the production possibilities frontier (directly related to $y_{MAX,i}$) and the efficiency level (θ_i), differenciating the expression for the Output Distance function in respect to z_i, we have

$$\frac{d}{dz_i}lnD_O(.) = \frac{d}{dz_i}\propto_0 + \frac{d}{dz_i}\sum_{j=1}^{J}\beta_{j,i}lnx_{j,i} + \frac{d}{dz_i}\sum_{m=1}^{4}\alpha_{m,i}lny_{m,i} + \frac{d}{dz_i}\sum_{n=1}^{N}\gamma_n z_{n_i} + \frac{d}{dz_i}\epsilon_{i,t} \tag{18}$$

Supposing the change in the efficiency/frontier changing variables affects $y_{m,i}$ by affecting the technology and the technical efficiency, given that production is measured, in this paper, as gross production value (BRL$), and from the homogeneity of degree 1 in outputs, one has the semi elasticity of the agricultural gross production value for the municipality i, $\boldsymbol{y_i}$, given by

$$\frac{dln\boldsymbol{y_i}}{dz_i} = \frac{d}{dz_i}lnD_O(.) - \frac{d}{dz_i}\sum_{n=1}^{N}\gamma_n z_{n_i} = -(w[k]\sigma_{u,i}\phi(0) + \gamma_n) \tag{19}$$

From (19), we have the impact of technical assistance access being given by its effect at the inefficiency level $\left(\mathrm{w}[\mathrm{k}]\sigma_{\mathrm{u,i}}\phi(0)\right)$, and its effect at the production possibilities frontier (γ_n).

2.2.4. Data

To estimate the DEA and the SFA models it was used cross sectional data from the 2017 Brazilian Agricultural Census, in municipality level. The main advantage of using municipality level data is that it minimizes the effect of possible measurement errors, which is common in farmer level data (Silva, Perrin and Fulginiti, 2019). Then, for each observation, the inputs and outputs are measured as their respective aggregated amount observed for the family farming located in municipality i.

Also, the cross-sectional analysis is done because during the last years there were changes in the criteria which define FF. Therefore, the data for family famers available at the 2017 Brazilian Agricultural Census is not comparable to the data available at the 2006 Brazilian Agricultural Census.

Considering the productivity matrix of Brazilian family farmers, and because we use cross sectional data, the outputs were measured in gross production value and disaggregated among animal production, permanent crops, temporary crops, ant other activities. The inputs are labor, measured in expenditures with salary paid to employees and to family members; land, measured in total cultivated land; capital, measured in number of tractors; energy, measured in expenditure with energy; fuel and lubricants, measured in expenditures with fuel and lubricants; and other inputs, which includes expenditures with chemical inputs, fertilizers, feed and medicines for animal production. Both inputs and outputs were obtained from the 2017 Brazilian agricultural census (IBGE, 2019). A summary of the variables is presented in Table 1.

Table 1. Summary statistics of the variables included in the frontier

Variable	Description	Mean	Standard deviation
Animal production	GPV measured in 1.000 R$ of 2017	8,875	14,257
Permanent crops	GPV measured in 1.000 R$ of 2017	2,230	8,143
Temporary crops	GPV measured in 1.000 R$ of 2017	5,796	13,209
Other productions	GPV measured in 1.000 R$ of 2017	2,348	7,114
Land	Cultivated land, measured in hectares	13,820	21,670
Energy	Expenditure with energy in 1.000 R$ of 2017	742	899
Fuel and lubricants	Expenditure with fuel and lubricants in 1.000 R$ of 2017	925	1,230
Other inputs	Expenditure with fertilizers, seeds, pesticides, medicine, salt and feed to animal production in 1.000 R$ of 2017	5,046	9,810
Capital	Number of tractors in 2017	95	195
Labor	Salary paid to employees and family members in 1.000 R$ of 2017	1,206	1,628

Source: The author, based on IBGE (2019)

The efficiency and frontier changing variables included in the model are presented in Table 2. The share of FF receiving TA from each source was obtained from the 2017 Brazilian agricultural census (IBGE, 2019), and the Aptitude was obtained from Sparovek et al. (2015). 4 different model were estimated using the same set of inputs and outputs, but different specifications for the efficiency (and also frontier, for SFA) changing variables, increasing the disaggregation of TA sources along the models:

Model 1: were included the variables internet access, no education, higher education, and TA access.

Model 2: Similar to Model 1 but the TA access was decomposed into public TA, prived TA (the sum of own TA and prived company TA), and others TA sources.

Model 3: Similar to Model 1 but the TA access was decomposed into public TA, prived TA (the sum of own TA and prived company TA), TA from cooperatives, TA from integrator companies and others.

Model 4: were included the variables aptitude, public TA, own TA, prived company TA, TA from cooperatives, TA from integrator companies, and others.

The models were specified taking into account the desirable level of TA variables disaggregation.

Table 2. Summary statistics of the efficiency changing variables

Variable	Description	Mean	Standard deviation
Total TA	Percentage of FF area covered by TA	29.09%	25.49 p.p.
Government TA	Percentage of FF area covered by TA from the government	9.47%	14.20 p.p.
Own TA	Percentage of FF area covered by Own TA (consulting technician hired by the farmer)	7.28%	11.46 p.p.
Cooperative TA	Percentage of FF area covered by TA from cooperatives	7.78%	17.15 p.p.
Integrator company TA	Percentage of FF area covered by TA from integrator companies (technicians from companies which buy the production from the farmer)	2.39%	8.39 p.p.
Prived company TA	Percentage of FF area covered by TA from prived companies (prived company hired by the farmer)	0.44%	3.09 p.p.
NGO's TA	Percentage of FF area covered by TA from Non Governamental Organizations	0.07%	1.00 p.p.
S System TA	Percentage of FF area covered by TA from the S System (9 institution of professionals stablished by the Brazilian Constitution)	0.06%	0.76 p.p.
Other sources of TA	Percentage of FF area covered by TA from other sources	0.73%	3.36 p.p.
Aptitude	Index relating soil quality and relief, varying between 0(worst)-1(better) (Sparovek et al., 2015)	0.300	0.139
No education	Percentage of household heads that had never received formal education from school	13.92%	12.17 p.p.
Higher education	Percentage of household heads that had concluded technical degree, undergraduation or graduation courses.	6.66%	6.69 p.p.
Internet access	Percentage of households in which there was internet access.	39.31%	23.41 p.p.

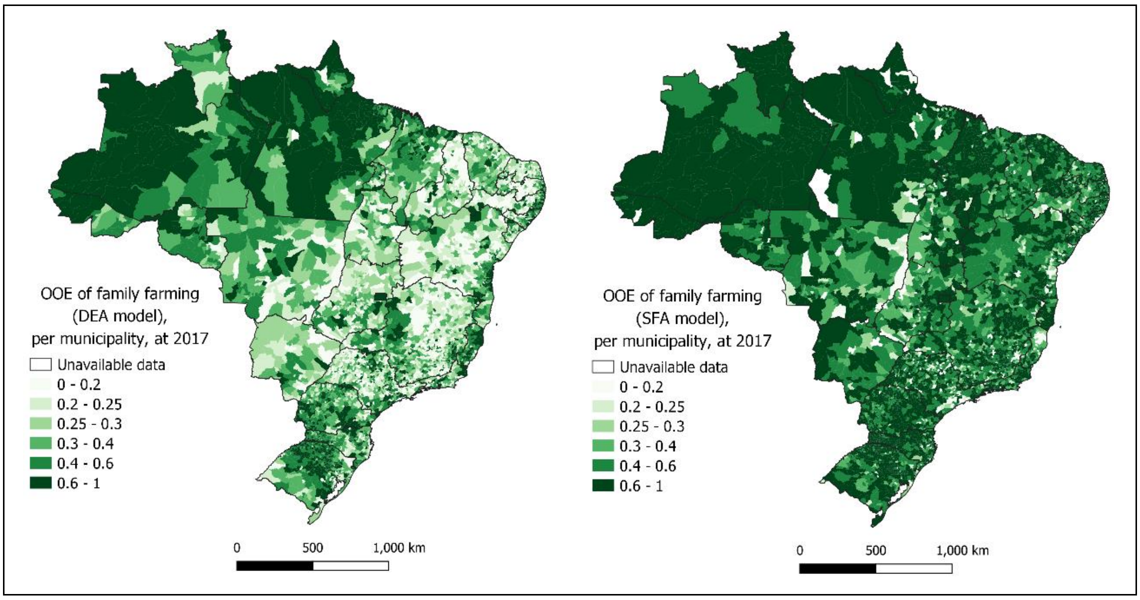
Source: The author, based on IBGE (2019)

As a result of the productive diversification inherent to the Brazilian family farming, the diversity of strategies to enable access to TA and rural credit is also observed. The three main sources of TA in the country, in number of establishments attended in both, 2006 and 2017, were the government, cooperatives, and integrating companies. In 2017, only 18.2% of family farmers in Brazil received some type of technical guidance, and 43.4% of the establishments accessed public TA, 25.7% received technical guidance from cooperatives, 16% from integrator companies, and the others from other sources (IBGE, 2019). What the data allows to infer, therefore, is that there is a predominance of public action in TA for family farming, highlighting a very characteristic aspect of family farming, which is the high dependence on public provision of technical assistance, and collective forms of association as an alternative source of information access.

2.3. Results and discussion

As discussed before, the efficiency scores from DEA and SODF are estimated under different assumptions in terms of how the PPF is defined. Maps presenting the efficiency scores from both models are presented in Figure 3.

Figure 3. Output oriented technical efficiency of the family farming for Brazilian municipalities in 2017



Source: The author, according to the estimated model.

One can observe that there is similar spatial distribution of the efficiency scores between DEA and SFA. The Spearman test shows a significant correlation of 0.30 between efficiencies estimated from those two models, which means that although the difference between frontiers affected the efficiency estimates, there is a spatial distribution pattern of those values.

The SFA efficiency scores are higher than the observed for the DEA due to the effect of its stochastic nature, which allows for random noise, that is labeled as inefficiency at the DEA model. Nevertheless, despite the differences in respect to the methodology by which the PPF is modeled, the observed spatial pattern of higher efficiency scores at Brazilian South and North regions, as well at the Northwest of the Minas Gerais state, and municipalities in Goiás and Mato Grosso do Sul state, show consistency between both estimates.

The presence of high levels of efficiency at the Brazilian North region can be related to açaí production, and big participation of extractivism from the Amazon rainforest at the agricultural GPV, leading to higher levels of production with less use of agricultural inputs. It is worth to mention, however, that high efficiency does not mean, necessarily, higher production. As illustrated in Figure 1, in a condition in which the PPF is close to the origin due to small inputs set and/or technology constraints, one can observe high efficiency and low production and productivity.

Given the parametric nature of the SFA, it is important to analyze if the expected properties of a ODF function are observed. The average values for each parameter of the frontier are presented in Table 3.

Table 3. Average value for parameters of the frontier, for each SFA model

	Model 1	Model 2	Model 3	Model 4
Animal production	0.59	0.59	0.60	0.60
Temporary crops	0.08	0.08	0.08	0.08
Permanent crops	0.05	0.05	0.05	0.05
Other productions	0.28	0.27	0.27	0.27
Land	-0.21	-0.16	-0.16	-0.16
Capital	-0.02	-0.03	-0.03	-0.03
Labor	-0.12	-0.12	-0.12	-0.12
Energy	-0.31	-0.31	-0.32	-0.32
Fuel and lubricants	-0.08	-0.09	-0.11	-0.11
Other inputs	-0.26	-0.26	-0.26	-0.26
Scale elasticity*	1.01	0.97	1.00	1.00

Note: the p-values for the parameters for each observation were estimated through the delta method. All parameters are significant for more than 98% of the observations, and were calculated based on a linear combination of parameters significant at 5% significance level.

*Calculated according to Färe and Primont (2012).

As seen in Table 3, the expected properties for an Output Distance Function are verified. The estimated ODF is increasing in outputs and decreasing in inputs. Also, it presents constants returns to scale, a desirable property to stablish duality between ODF, the revenue function, and the indirect output distance function, as discussed by Färe and Primont (2012). Besides that, the parameters showed small variation among the estimated models, which is evidence that the different specifications for exogenous determinants of the efficiency modelled consistently the variance of u_i, providing consistent estimations of the true parameters for the frontier.

The two highest average elasticities of the output distance function in respect to animal production and to other productions (an aggregation of diversified productions as vegetables, flowers, timber, fish and plant extraction) are consistent to the representativeness of those activities, and show the shadow revenues for both are higher than the observed for temporary and for permanent crops. However, it was observed that higher aptitude levels increase the shadow revenue for temporary crops and other productions, while decreased the ones for permanent crops and animal production.

Using the equations (19) and (20), the average impact of each TA source at the production level were estimated. For each variable, we considered a 1 percentage point (1p.p.) increase at the percentage of family farmed land with farmers accessing technical assistance. The results are presented at Table 4.

Table 4. Average impact of 1 p.p. increase in TA access, from different sources, at the agricultural GPV

Variable	DEA Estimated impact	SFA Average impact
Model 1		
TA access	0.57%***	0.26%**
Model 2		
Public TA	0.24%***	0.45%**
Prived TA	0.37%***	0.64%**
Others TA sources	0.84%***	0.03%
Model 3		
Public TA	-0.14%**	0.69%**
Prived TA	-0.04%	0.22%**
Cooperative TA	0.84%***	0.06%**
Integrator company TA	1.27%***	0.90%
Others TA sources	1.22%***	-0.33%
Model 4		
Public TA	-0.14%**	0.67%**
Own TA	-0.16%*	0.34%**
Cooperative TA	0.82%***	0.05%
Integrator company TA	1.24%***	1.05%
Prived company TA	1.11%***	0.05%
Others TA sources	1,22%***	-0.33%

Source: own elaboration using the estimated models.

Note: All parameters used to calculate those impacts are significant at 5% significance level. For the DEA model the impact was estimated at the mean value for the variables included in the model, and its significance is estimated by the delta method. For the SFA model, the significance of the average impact is given by the bootstrap method and considering the shortest 95% confidence interval comparing the normal, the percentile and the bias corrected ones.

One can observe at Table 4 that to the 4 models the TA impact was found affecting the agricultural GPV. At Model 1, one can observe that an increase in 1 p.p. at the TA coverage in Brazilian municipalities increases about 0.57% the agricultural GPV according to the DEA model, and 0.26% according to the SFA model. Gonçalves et al. (2008) found that rural extension access impacted positively the technical efficiency of dairy farms in Minas Gerais State, in Brazil, by analyzing determinants of DEA efficiency estimates in a tobit regression. Helfand and Levine (2004) found positive effect of rural extension at the technical efficiency of firms located in the Mid-West region in 1995/1996. Freitas (2017) identified higher efficiency scores among small farmers accessing rural extension from public and prived sources in comparison to the ones who have not received technical assistance. More recently, Rocha Junior et al. (2020), analyzing the impact of technical assistance access in 2014, controlling for selection bias, found a significant increase of 25% at the monthly income for farmers who accessed TA during the last crop year.

As more the TA sources are disaggregated, it is observed there are different impacts according to the TA source. In Model 4, from the DEA model estimates, it is observed negative impact of the public TA and the own TA. By the other side, just the TA from other sources presented negative impact at the agricultural production according to the SFA analysis. It is worth to discuss that, as mentioned before, the SFA model parametrize the frontier according to the mean aptitude observed for each municipality, as well allowing the TA, education and internet access to shift the PPF, and accounting for exogenous shocks, randomly distributed, at the agricultural production. By the other side, the PPF defined as reference in the DEA model is a linear piecewise technology which does not take into account the territorial heterogeneity. Due to that, the estimated impact of TA through SFA is more credible, despite the DEA estimates can also be credible in the case the TA coverage of the respective source is not strongly correlated to any omitted variable affecting production.

Even presenting differences, the impact of 1 p.p. increase in TA from integrator companies is very similar for Model 4, resulting in average increases of 1.24% and 1.05% in the FF agricultural GPV, for the DEA and the SFA models, respectively. When analyzed the impacts of other sources through the SFA model, it is possible to understand the mechanism by which they affect the production, that is, if TA access is contracting or expanding the PPF of the FF, and if it is increasing or decreasing the efficiency level, which is presented in Figure 4.

Figure 4. Signal of the average impact from determinants of technology, efficiency, and productivity at Model 4.

	Effect on the PPF	**Effect on efficiency**	**Effect on productivity**
Public TA	-	+	+
Own TA	+	+	+
Cooperative TA	-	+	+
Integrator company TA	-	+	+
Prived company TA	-	+	+
Others TA sources	+	-	-

Source: Own elaboration based on the estimated model.

Notes: + means a positive impact; - means a negative impact.

It is observed at Figure 4 that different sources of TA can impact in a different way the agricultural productivity. The only sources of technical assistance expanding the PPF are own TA and other TA sources. Own TA impacts positively both, the PPF and the efficiency, which means it stimulates the use of more productive technologies, and also provides conditions to the better use of the adopted technologies, making farmers getting closer to the PPF. The other TA sources, however, stimulate the use of more productive technologies but bringing family farmers far from their Production Possibilities Frontier. Beside the negative impact of most of TA sources at the PPF, the final effect on the production, given by the interaction between the shift at the frontier and the change at the efficiency, was positive for all TA sources, except by the other sources.

Freitas et al. (2014) found that the effect of TA access on the agricultural production was positive for farmers at the lower efficiency quantiles and negative for more efficient farmers. Freitas (2017), comparing the effects of technical assistance access from public and prived sources among Brazilian farmers with different scales, identified that farmers who received public rural extension presented higher average efficiency levels, while the prived rural extension was related to higher efficiency levels among larger farmers and lower efficiency levels for very small farms.

2.4. Conclusions

This paper represents a contribution to the Brazilian family farming literature, considering there are few economic impact evaluations of the technical assistance to this category of farmers. The output distance function, when estimated as a Stochastic frontier model, provided a microeconometric methodology useful to understand how the TA can affect production due to its effects at the technology and the technical efficiency. We found the integrator companies TA and the public TA presented the highest levels of impact at the family farming agricultural GPV, and the positive impact of most sources of technical assistance results from increasing at the efficiency levels instead expansion of the PPF.

Is it important to take into account, however, that the assumption of radial effect of efficiency changing variables can impose limitations to evaluate the impact of TA for different production activities. We suggest, in this way, the impact evaluation of technical assistance in the context of more homogenous sample, using farm level data, what can provide more insights about the importance of different sources of technical assistance to Brazilian family farmers.

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3. IMPACT OF INTERNET ACCESS ON THE PRODUCTIVITY EVOLUTION OF THE BRAZILIAN AGRICULTURE

ABSTRACT

In this paper the impact of a real public policy to expand internet access in rural areas along 4 years is simulated based on an econometric approach. The methodology is developed based on a parametric Malmquist calculated from parameters estimated for an output distance function, accommodating impacts from increase in internet access at the production possibilities frontier and the technical efficiency. The estimation is performed using pooled data from the Brazilian Agricultural Censuses of 2006 and 2017. I found positive impact from internet access at the agricultural production, and the installation of a new transmission antenna with radial coverage of 40km² between 2006 and 2017 increasing the municipality agricultural GPV between 0.0005% and 51.47%, with an average impact of 0.25%. Finally, the cumulated impact between 2021 and 2026 of the public policy implemented between 2021 and 2024 is estimated by varying in a range between R$39.53 billion, which represents 8.55% of the Brazilian agricultural GPV observed in 2017; and R$52.70 billion, representing 11.40% of the Brazilian agricultural GPV observed in 2017, according to the trend of expansion in the inputs set. We conclude that those results support the discussion around the importance of public actions in stimulating private investments to expanding internet coverage in the countryside as a promising path to promote economic development in Brazilian agriculture.

Keywords: Technical efficiency, Productivity, Broadband access, Crops Production

3.1. Introduction

The idea that communication between individuals can affect the occurrence of knowledge and technology spillovers is widely discussed in the theory of social capital, social networks and technological diffusion. A social network is made up of individuals and the links between them, through which information, financial resources, goods and services flow (Maertens & Barrett, 2012), and internet access is a way to improve information flows, communication and reduce involved costs (Bertschek & Niebel, 2016). Those aspects have motivated several studies regarding the impact of internet access on productivity, most of them analyzing the effect of this aspect on labor productivity.

According to Manyika (2013), the mobile internet was one of the twelve disruptive technologies with a very high potential economic impact. Some evidences of that are: the use of mobile phones improves market outcomes (Bertschekn & Niebel, 2016); there are positive aspects for individual employees, by increasing their efficiency, as well as negative aspects like the infringement on work-life boundaries; increases work satisfaction, but could also create work-life conflicts (Diaz, Chiaburu, Zimmerman, and Boswell, 2012); processing and storage capabilities increase a worker's productivity by 9%, portability increases productivity by nearly 32%, and wireline and wireless connectivity boosts productivity by 14 and 6%, respectively (Maliranta and Rouvinen, 2006).

Although those studies found evidences about the economic impacts of internet access, those impacts can be ambiguous. For example, Noh and Yoo (2008) found that the implied effect of internet adoption in growth is negative for countries with high income inequality, while Pilat (2005) consider that the broadband access is widely considered to be a productivity-enhancing factor. Crandall et al. (2007) estimate benefits of U.S. broadband penetration on sectoral output and employment at the state level, estimating that, for every percentage point increase in broadband penetration within a state, employment increases by 0.2–0.3 percent per year for the private, non-farm economy.

According to Colombo, Croce, and Grilli (2013) it is not necessarily the connection to the internet that matters but what firms do with that. It might make them more productive, because the internet access allows selective access to information, representing a source of information with potential to increase productivity.

Considering the relevance of connectivity in the economic development of agriculture, the Brazilian government has developed a legal framework that aims to support the expansion of the telecommunications infrastructure in the Brazilian rural areas[6]. However, although there was a considerable growth in the number of rural establishments with internet access between 2006 and 2017, which changed from just over 74 thousand to 1.43 million, only 28.19% of the establishments had internet access in 2017 (IBGE, 2019), which shows a big delay of connectivity in the countryside.

In order to measure the relevance of a public policy to increase the internet access in Brazilian rural areas, I analyze the impact of internet access on the evolution of agricultural productivity between 2006 and 2017, decomposing this effect between impact on technological progress and technical efficiency change. Those results are used to estimate the impact of a policy implementation in 4 annual steps.

3.2. Methodology

3.2.1. Deriving effects from frontier and efficiency changing variables at productivity and observed production through a Parametric Malmquist approach

To model agricultural production in Brazilian municipalities an Output Distance Function was estimated. By accommodating multiple outputs and inputs, it does not require the disaggregation of inputs used in different activities, an inherent difficulty in agricultural production[7]. This property minimizes the need of imposing more restrictive assumptions, simplifying the modeling and allowing the estimation of the production possibilities frontier and the level of technical efficiency for each observation.

The departure point is a transformation function given by

$$F(\boldsymbol{y}.\boldsymbol{OE}^{-1}, \boldsymbol{x}, \boldsymbol{t}) = 0 \tag{1}$$

where $\boldsymbol{y}$ is a vector of M *outputs* produced using a vector $\boldsymbol{x}$ constituted by J *inputs*. The term $\boldsymbol{OE}^{-1}$ is included to represent the technical inefficiency in the production of $\boldsymbol{y}$, $0 \leq OE \leq 1$, and OE is a scalar that shows the proportion of the potential production observed due to the presence of inefficiency.

In the Production Economics literature, for multiple inputs and outputs, the transformation function (1) can be represented by a distance function, defined as

$$D_0(y, x) = \min_{\theta} \left\{ \theta \middle| \left(\frac{Y}{\theta} \right) \in P(X) \right\} \tag{2}$$

[6] The Brazilian General Telecommunications Law - LGT (Law No. 9.472 / 1997) (Brasil, 1997) was created to provide the organization of telecommunications services, the creation and operation of a regulatory framework and other institutional aspects, supporting a series of policies developed subsequently with the purpose of expanding the infrastructure of 4G signal transmission in the field.

[7] In agricultural production, even in farm level observations, it is common inputs as tractors or labor are used throughout the same production cycle in different activities.

where $P(x)$ is the production possibilities set given $\boldsymbol{x}$. Imposing homogeneity of degree 1 in outputs, assuming a Cobb Douglas functional form to represent the distance as a function of the inputs and outputs, assuming Hicks neutral technical progress between 2006 and 2017, taking the logarithm on both sides, assuming the existence of a random component of bilateral noise, and calling $ln\ D_0(y,x) = -u_i$, the following system is obtained, estimated by maximum likelihood (Kumbhakar, Wang and Horncastle, 2015).

$$-lny_{GA,i,t} = \sum_{j=1}^{J} \beta_{j,i} lnx_{j,i,t} + \sum_{m=2}^{4} \alpha_{m,i} ln\tilde{y}_{m,i,t} + s_{i,t}(t_{i,t}, \boldsymbol{z_{i,t}}, \Delta\boldsymbol{z}_i) + \epsilon_{i,t} \quad \text{, where}$$

$$\begin{aligned}
&\beta_{j,i} = \beta_{0j} + \beta_{1j} Aptitude_i \\
&\alpha_{m,i} = \alpha_{0m} + \alpha_{1m} Aptitude_i \\
&s_{i,t} = \tau t_{i,t} + \boldsymbol{\gamma} \boldsymbol{z_{i,t}} + \boldsymbol{\eta} \Delta\boldsymbol{z}_i \\
&\epsilon_{i,t} = v_{i,t} + u_{i,t} \\
&v_{i,t} \sim i.i.d. N\left(0, \sigma_v^2(t_{i,t}, \boldsymbol{z_{i,t}}, \Delta\boldsymbol{z}_i)\right) \\
&u_{i,t} \sim i.i.d. N^+\left(\mu_u, \sigma_u^2(t_{i,t}, \boldsymbol{z_{i,t}}, \Delta\boldsymbol{z}_i)\right),
\end{aligned} \tag{3}$$

where $lnx_{j,i,t}$ is the natural logarithmic of input *j* used by municipality *i* at the time *t*; $lny_{GA,i,t}$ is the natural logarithm of the gross production value of large animals in the municipality *i* at time *t*; $ln\tilde{y}_{m,i,t}$ is the natural logarithm of the GPV ratio $\left(\frac{y_{m,i,t}}{y_{GA,i,t}}\right)$ for each of the other production categories (permanent crops, temporary crops, and other activities); $t_{i,t}$ is a binary variable that takes a value of 0 for observations from 2006 and 1 for 2017; $\epsilon_{i,t}$ is a stochastic term composed by $v_{i,t}$, a two-sided random term with mean equal to 0 and variance $\sigma_v^2(t_{i,t}, \boldsymbol{z_{i,t}}, \Delta\boldsymbol{z}_i)$, and $u_{i,t}$, an inefficiency term following a half normal distribution with constant mean and variance $\sigma_u^2(t_{i,t}, \boldsymbol{z_{i,t}}, \Delta\boldsymbol{z}_i)$; and $z_{i,t}$ is a vector of efficiency changing variables, and $\Delta\boldsymbol{z}_i$ is equal to 0 in 2006, and equal to $\boldsymbol{z}_{i,2017} - \boldsymbol{z}_{i,2006}$ in 2017. The term $s_{i,t}$ involves the frontier changing variables, including the dummy variable for time fixed effect $t_{i,t}$, $\boldsymbol{z_{i,t}}$ and $\Delta\boldsymbol{z}_i$, τ is the parameter related to the time fixed effect, and $\boldsymbol{\gamma}$ and $\boldsymbol{\eta}$ are the vector of parameters related, respectively, to $\boldsymbol{z_{i,t}}$ and $\Delta\boldsymbol{z}_i$.

The estimation was performed with pooled data (10,106 observations) obtained from the Agricultural Censuses of 2006 and 2017 (IBGE, 2019), aggregated in municipality level. The inputs used were land, represented by cultivated area; labor, measured in total number of workers; and capital, measured in total number of tractors. As output, the gross production value of livestock, permanent crops, temporary crops, and other productions were used. To control the heteroskedasticity of the inefficiency term, a vector of variables was used, which are the dummy variable for year, the average grain storage capacity by unit of area, and the percentage of farmers who: received technical assistance, completed higher education, accessed energy, had internet access. The variables used are presented in Table 5.

Table 5. Variables included in the model.

Variable		Description
Livestock production	Output	GPV measured in 1.000 R$ of 2017
Permanent crops		GPV measured in 1.000 R$ of 2017
Temporary crops		GPV measured in 1.000 R$ of 2017
Other productions		GPV measured in 1.000 R$ of 2017
Land	Input	Cultivated land, measured in hectares
Capital		Number of tractors in 2017
Labor		Number of employees
Technical assistance	Efficiency/frontier changing variable	Percentage of cultivated area covered by TA
Energy access		Percentage of farmers that have access to energy
Storage capacity		Storage capacity in ton/ha
Undergraduated farmers		Percentage of farmers undergraduated
Internet access		Percentage of farmers that have access to internet
Cooperativism		Percentage of farmers that participate in cooperatives
Aptitude	Elasticity changing variable	Index relating soil quality and relief, varying between 0(worst)-1(better) (Sparovek et al., 2015)

Source: Own elaboration based on data from the 2006 and 2017 Agricultural Censuses (IBGE, 2019).

*Values inflated to R$ of June 2017 using the General Price Index- Intern Demand (IGP-DI).

3.2.2. Using the Output Distance Function parameters to estimate and decompose the Malmquist Parametric Index

Based on the parameters of the system (3), it is possible to estimate a parametric Malmquist index (Fuentes, 2001). It can be decomposed into two dimensions, technical progress and efficiency change, using the expression

$$M_O^{2006}(x^{i,2006}, y^{i,2006}, x^{i,2017}, y^{i,2017}) = \frac{D_O^{2017}(x^{i,2017}, y^{i,2017})}{D_O^{2006}(x^{i,2006}, y^{i,2006})} \cdot \frac{D_O^{2006}(x^{i,2017}, y^{i,2017})}{D_O^{2017}(x^{i,2017}, y^{i,2017})} \quad (4)$$

$$= \Delta TE(x^{i,2006}, y^{i,2006}, x^{i,2017}, y^{i,2017}). \Delta T(x^{i,2017}, y^{i,2017})$$

where M_O^{2006} is the Malmquist index based on the 2006 technology; ΔTE is the change in technical efficiency, measured as the ratio between 2017 and 2006 technical efficiencies; ΔT is the technical progress, measuring the radial shift in the production possibilities frontier; $D_O^{2006}(x^{i,2006}, y^{i,2006})$ is the measure of the estimated distance for the combination of inputs and outputs observed in 2006 based on the frontier of 2006; $D_O^{2006}(x^{i,2017}, y^{i,2017})$ is the estimated distance for the combination of inputs and outputs observed in 2017 based on the frontier of 2006; $D_O^{2017}(x^{i,2006}, y^{i,2006})$ is the measure of the estimated distance for the combination of inputs and outputs observed in 2006 based on the frontier of 2017; and $D_O^{2017}(x^{i,2017}, y^{i,2017})$ is the estimated distance observed in 2017 based on the frontier of 2017.

Whereas the objective of the present study is to evaluate the impact of productivity changing variables in the Brazilian agriculture productivity, as well to understand the participation of those variables at the observed production, the strategy adopted here is to derive this from the M_O^{2006}, ΔTE and ΔT. The log linearized Cobb Douglas ODF, whose parameters are obtained from the estimation of the system (3), is given by

$$lnD_{i,t} = -E\left[u_{i,t}|e\right] = \alpha_0 + \sum_{j=1}^{J} \beta_j lnx_{j,i,t} + \sum_{m=1}^{4} \alpha_m lny_{m,i,t} + s_{i,t}\left(t_{i,t}, \boldsymbol{z_{i,t}}, \Delta \boldsymbol{z}_i\right) + \epsilon_{i,t} \quad (5), \text{ where}$$

$$s_{i,t} = \tau t_{i,t} + \sum_{n=1}^{N} \gamma_n z_{n_{i,t}} + \sum_{n=1}^{N} \eta_n \Delta z_{n_i}$$

Where $\boldsymbol{\gamma}$ and $\boldsymbol{\eta}$ are the vector of parameters related, respectively, to $\boldsymbol{z_{i,t}}$ and $\Delta \boldsymbol{z}_{i,t}$. From (5) it is observed a relevant aspect from the parametrization of the Output Distance Function through the Stochastic Frontier, which plays a role in the derivation developed here: both terms, $E\left[u_{i,t}|e\right]$ and $s_{i,t}\left(t_{i,t}, \boldsymbol{z_{i,t}}, \Delta \boldsymbol{z}_i\right)$, are estimated as a function of the same vector of variables, from the same maximum likelihood problem. $lnD_{i,t} = -E\left[u_{i,t}|e\right]$, and $E\left[u_{i,t}|e\right] = f\left(t_{i,t}, \boldsymbol{z_{i,t}}, \Delta \boldsymbol{z}_i\right)$ is the expectation of the inefficiency term, which is a function of the vector of variables which affect its variance[8]. By the other side, $s_{i,t}\left(t_{i,t}, \boldsymbol{z_{i,t}}, \Delta \boldsymbol{z}_i\right)$ is a PPF related term.

Let z_1 be the variable of interest. Given[9] $z_{1_{i,2017}} = z_{1_{i,2006}} + \Delta z_{1_i}$, differentiating (5) in respect to Δz_{1_i} in 2017[10]

$$-\frac{dE\left[u_{i,2017}\right]}{d\Delta z_{1_i}} = \sum_{j=1}^{J} \beta_j \frac{dlnx_{j,i,2017}}{d\Delta z_{1_i}} + \sum_{m=1}^{4} \alpha_m \frac{dlny_{m,i,2017}}{d\Delta z_{1_i}} + \gamma_1 + \eta_1 \quad (6)$$

$$\sum_{m=1}^{4} \alpha_m \frac{dlny_{m,i,2017}}{d\Delta z_{1_i}} = -\left(\sum_{j=1}^{J} \beta_j \frac{dlnx_{j,i,2017}}{d\Delta z_{1_i}} + \gamma_1 + \eta_1 + \frac{dE\left[u_{i,2017}\right]}{d\Delta z_{1_i}}\right) \quad (7)$$

Assuming $\frac{dlnx_{j,i,2017}}{d\Delta z_{1_i}} = 0$, which means inputs quantities are not affected by changings in productivity changing variables. Given the radial nature of the distance in (2), the homogeneity of degree 1 in outputs and the fact they are measured as GPV, and the assumption of Hicks neutral technical change, the expected impact of a change in Δz_{1_i} is proportional in all outputs, so

$$\frac{dlny_{m,i,2017}}{d\Delta z_{1_i}} = \frac{dlny_{n,i,2017}}{d\Delta z_{1_i}}, \text{ for } m \neq n \text{ and } \sum_{m=1}^{4} \alpha_m = 1, \text{ then} \quad (8)$$

$$\frac{dlnY_{i,2017}}{d\Delta z_{1_i}} = -\left(\gamma_1 + \eta_1 + \frac{dE\left[u_{i,2017}\right]}{d\Delta z_{1_i}}\right) \quad (9)$$

Equation (9) gives the percentage increase in the total gross production value observed for municipality i in 2017 ($Y_{i,2017}$) due to an increase in Δz_1. The term $\gamma_1 + \eta_1$ gives the impact on production due to changes in technology, and $\frac{dE\left[u_{i,2017}\right]}{d\Delta z_{1_i}}$ gives the impact due to $\Delta z_{1_{i,t}}$ effects on the inefficiency term, and is obtained from the estimated parameter for the system (3), as derived by Kumbhakar, Wang and Horncastle (2015).

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[8] Due to its half normal distribution, $E\left[u_{i,t}|\mathrm{e}\right] = f\left(t_{i,t}, \boldsymbol{z_{i,t}}, \Delta \boldsymbol{z}_{i,t}\right)$, as derived by Kumbhakar, Wang and Horncastle (2015).

[9] It is worth to remember that $\Delta \boldsymbol{z}_{i,t}$ is equal to 0 in 2006, and equal to $\boldsymbol{z}_{i,2017} - \boldsymbol{z}_{i,2006}$ in 2017, because the model here is estimated base on 2006 and 2017 data.

[10] Given $z_{1_{i,2017}} = z_{1_{i,2006}} + \Delta z_{1_i}$, $z_{1_{i,2006}}$ is not affected by a change in Δz_{1_i}.

One can observe that while γ_1 is related to a level change in z_1, η_1 gives the additional effect due to Δz_1 dynamic. For example, a change in internet coverage, in a given municipality, from 10% to 40% of the farmed area leads to a shift in the production possibilities frontier. It is possible, however, that the speed by what the increasing happened also affects the productivity change. In this sense, by including the 30 p.p. change observed from t to $t+11$ as an additional variable Δz_1, this dynamic effect can be estimated. It is worth to mention, however, that the presence of this dynamic effect can be tested by comparing models with restricted parameters ($H_0: \sum_{n=1}^{N} \eta_n = 0$).

The impact of Δz_i on the Malmquist index is given by

$$M_O^{2006}(x^{i,2006}, y^{i,2006}, x^{i,2017}, y^{i,2017}) = \frac{D_O^{2006}(x^{i,2017}, y^{i,2017})}{D_O^{2006}(x^{i,2006}, y^{i,2006})}$$

$$\frac{dM_{O,i}^{2006}(x,y)}{d\Delta z_{1_i}} = \frac{dD_O^{2006}(x^{i,2017}, y^{i,2017})}{d\Delta z_{1_i}} \frac{1}{D_O^{2006}(x^{i,2006}, y^{i,2006})} \tag{10}$$

From (7) and (9)

$$lnD_O^{2006}(x^{i,2017}, y^{i,2017}) = \alpha_0 + \sum_{j=1}^{J} \beta_j lnx_{j,i,2017} + \sum_{m=1}^{4} \alpha_m lny_{m,i,2017} + \sum_{n=1}^{N} \gamma_n z_{n_{i,2006}} + \epsilon_{i,t} \tag{11}$$

$$\frac{dD_O^{2006}(x^{i,2017}, y^{i,2017})}{d\Delta z_{1_i}} = \frac{d\, e^{lnD_O^{2006}(x^{i,2017}, y^{i,2017})}}{d\Delta z_{1_i}}$$

$$\frac{dD_O^{2006}(x^{i,2017}, y^{i,2017})}{d\Delta z_{1_i}} = \frac{dlnD_O^{2006}(x^{i,2017}, y^{i,2017})}{d\Delta z_{1_i}} . D_O^{2006}(x^{i,2017}, y^{i,2017})$$

$$\frac{dD_O^{2006}(x^{i,2017}, y^{i,2017})}{d\Delta z_{1_i}} = \left(\sum_{m=1}^{4} \alpha_m \frac{dlny_{m,i,t}}{d\Delta z_{1_i}}\right) . D_O^{2006}(x^{i,2017}, y^{i,2017})$$

$$\frac{dD_O^{2006}(x^{i,2017}, y^{i,2017})}{d\Delta z_{1_i}} = -\left(\gamma_1 + \eta_1 + \frac{dE[u_{i,2017}]}{d\Delta z_{1_i}}\right) . D_O^{2006}(x^{i,2017}, y^{i,2017}) \tag{12}$$

Replacing (12) in (10)

$$\frac{dM_{O,i}^{2006}(x,y)}{d\Delta z_{1_i}} = -\left(\gamma_1 + \eta_1 + \frac{dE[u_{i,2017}]}{d\Delta z_{1_i}}\right) . M_{O,i}^{2006}(x,y) \tag{13}$$

From (6), and using (12)

$$\frac{d\Delta TE(.)}{d\Delta z_{1_i}} = \left(-\frac{dE[u_{i,2017}]}{d\Delta z_{1_i}}\right) \frac{D_O^{2017}(x^{i,2017}, y^{i,2017})}{D_O^{2006}(x^{i,2006}, y^{i,2006})} \tag{14}$$

$$\frac{d\Delta T(.)}{d\Delta z_{1_i}} = -\left(\gamma_1 + \eta_1 + \frac{dE[u_{i,2017}]}{d\Delta z_{1_i}}\right) . \Delta T(.) + \left(\frac{dE[u_{i,2017}]}{d\Delta z_{1_i}}\right) \Delta T(.)$$

$$\frac{d\Delta T(.)}{d\Delta z_{1_i}} = -(\gamma_1 + \eta_1) \Delta T(.) \tag{15}$$

Finally, expression (9) gives the percentage impact of Δz_1 on the observed gross production value of 2017, (13) gives its impact on the Malmquist Index, (14) gives the impact on efficiency change and (15) the impact on technical change.

From (13), it is possible to get the expression for the participation of Δz_1 observed on the productivity change of observation i ($P_{z_{1_i}}$), which is

$$P_{z_{1_i}} = \frac{1}{M_{O,i}^{2006}(x,y)} \int_{z_{2006}}^{z_{2017}} \frac{dM_{O,i}^{2006}(x,y)}{d\Delta z_{1_i}} d\Delta z_{1i} = -\left[(\gamma_1 + \eta_1)\Delta z_{1_i} + \int_{z_{2006}}^{z_{2017}} \frac{dE[u_{i,2017}]}{d\Delta z_{1_i}} d\Delta z_{1i}\right]$$

$$P_{z_{1_i}} = -\{(\gamma_1 + \eta_1)\Delta z_{1_i} + (E[u_{i,2017}|z_{1_{2017}}, \Delta z_{1_i}] - E[u_{i,2017}|z_{1_{2006}}])\} \quad (16)$$

Equation (16) allows to make inferences effect of Δz_1 on the productivity change and the production level. By integrating (9) from $z_{1_{2006}}$ to $z_{1_{2017}}$, and due to the property of homogeneity of degree 1, it is obtained that $\frac{dlny_{m,i,2017}}{d\Delta z_{1_i}} = \frac{dlny_{n,i,2017}}{d\Delta z_{1_i}}$, for $m \neq n$ and $\sum_{m=1}^{4} \alpha_m = 1$, then

$$\int_{z_{2006}}^{z_{2017}} \frac{dlnY_{i,2017}}{d\Delta z_{1_i}} d\Delta z_{1i} = -\int_{z_{2006}}^{z_{2017}} \left(\gamma_1 + \eta_1 + \frac{dE[u_{i,2017}]}{d\Delta z_{1_i}}\right) d\Delta z_{1i} = P_{z_{1_i}} \quad (17)$$

Equation (17) shows the participation of Δz_{1i} change between 2006 and 2017 at the gross production value observed in 2017, which is equal to the participation of Δz_1 observed in the productivity change of observation i ($P_{z_{1_i}}$). It is worth to mention that there is no annual data to allow the estimation of an impact from Δz according to the speed it happened between 2006 and 2017. Then, the parametrization of expression including both $z_{n_{i,t}}$ and $\Delta z_{n_{i,t}}$ is a way to model the effect of that change given the average speed in which it happened between 2006 and 2007, and the simulations done according to the average speed in which $\Delta z_{n_{i,t}}$ happened between 2006 and 2017.

3.2.3. Estimating the impact of a policy based on changes in internet access along the time

Based on equations (13), (14) and (15), it is possible to analyze both the impact of changes Δz_1 on the agricultural productivity and the mechanism through which the effects happen, if hanging technical efficiency or through the technical change.

Although the internet impact can be analyzed through the equation (9), changes in Δz_1 would be implemented along the time in steps, so a more realistic impact should take into account the dynamic of the productivity and the steps of a public policy implementation process. Because of that, we estimated the impact of a proposed public policy implemented along the time in n annual steps, considering the beginning on t, and the end on $t + n$.

To consider the dynamic aspect of productivity evolution, it was considered that both, the inputs set and the productivity, change in a constant rate verified between 2006 and 2017[11], and we derived the marginal effect of Δz_1 considering that assumption

$$M_{0_{ANNUAL,i}} = \left(M_{O,i}^{2006}(.)\right)^{\frac{1}{11}} \rightarrow \frac{d\, M_{0_{ANNUAL,i}}}{d\Delta z_{1_i}} = \frac{1}{11\left(M_{O,i}^{2006}\right)^{\frac{10}{11}}} \frac{dM_{O,i}^{2006}(x,y)}{d\Delta z_{1_i}} \quad (18)$$

$$\Delta inputs_{ANNUAL,t} = \left(\frac{1}{M_{O,i}^{2006}(.)} \frac{Y_{i,t}}{Y_{i,t-1}}\right)^{1/11} \quad (19)$$

$$M'_{0_{ANNUAL,i}} = \left(M_{O,i}^{2006}(.) - \left(\Delta internet_{2006\rightarrow 2017}.\frac{dM_{O,i}^{2006}(x,y)}{d\Delta int_i}\right)\right)^{\frac{1}{11}} \quad (20)$$

[11] Besides it is a strong assumption, this is the best approximation for the dynamic behavior of the inputs set and productivity increasing for the two periods database.

$$M_{0_{ANNUAL,i,t}} = M_{0_{ANNUAL,i,t-1}} + \int_{z_{t-2}}^{z_{t-1}} \frac{d\, M_{0_{ANNUAL,i}}}{d\Delta z_{1_i}} d\Delta z_{1i} \quad (21)$$

Where $M_{0_{ANNUAL,i}}$ is the estimated annual Malmquist for observation i; $\frac{d\, M_{0_{ANNUAL,i}}}{d\Delta z_{1_i}}$ is the estimated impact of a change in Δz_{1_i} at the annual Malmquist based on the 2006 to 2017 dynamic; equation (19) shows the inputs set annual change ($\Delta inputs_{ANNUAL,t}$), measured as the estimated annual rate of residual growth (excluding productivity change effect) in production observed from 2006 to 2017; $M'_{0_{ANNUAL,i}}$ is yearly observed Malmquist between 2006 and 2017, estimated using (20) as the annual productivity change observed between 2006 to 2017 excluding Δz_{1_i} effect, which is used as the Malmquist basis to the years, departing from 2017, in which Δz_{1_i} is yet not implemented.

Using (21), considering $M_{0_{ANNUAL,i,0}} = M'_{0_{ANNUAL,i}}$, it is possible to estimate the annual Malmquist, by iteration, for each year, considering the policy implementation in n annual steps, starting in t' and finishing in $t' + n$.

Based on the estimated Malmquist series, and considering the behavior of the Brazilian agriculture between 2006 and 2017, it is possible to estimate the GPV growth using the equation (22).

$$Y_{i,t} = Y_{t-1} \Delta inputs_{ANNUAL,t} . Malmquist_{ANNUAL,i,t} \quad (22)$$

$$Impact_{i,\, t \to t+m} = \sum_{t'}^{t'+m} Y'_{i,t} - Y_{i,t} \quad (23)$$

Using (23), it can be estimated the cumulated impact between t' and $t' + m$ due to the public policy to increase Δz_1, which is measured as the difference between the expected behavior of GPV considering Δz_1 change ($Y'_{i,t}$) and in absence of that ($Y_{i,t}$).

3.3. Results

The parameters of the Stochastic Output Distance Function, are presented at Table 6.

Table 6. Estimated parameters for the stochastic frontier

	β_{0j} or α_{0m}	β_{1j} or α_{1m}	Average β_j	Standard deviation	Average p-value
Livestock	0.52	0.11	0.55	0.02	0.00
Temporary crops	0.14	0.24	0.21	0.03	0.01
Permanent crops	0.10	-0.16	0.05	0.02	0.00
Other productions	0.24	-0.19	0.19	0.03	0.00
Land	-0.23	-0.51	-0.38	0.07	0.00
Labor	-0.49	0.51	-0.34	0.07	0.00
Capital	-0.31	0.08	-0.29	0.01	0.00
year	-0.33	-0.39	-0.45	0.05	0.00

Source: estimated model.

As seen in Table 6, the expected properties for an Output Distance Function are verified. The estimated ODF is increasing in outputs and decreasing in inputs. The aggregated technology presents constants returns to scale, a desirable property to stablish duality between ODF, the revenue function, and the indirect output distance function, as discussed by Färe and Primont (2012).

The two highest average elasticities of the output distance function in respect to livestock and to temporary crops show the shadow revenues for both are higher than the observed for permanent crops and for other productions (an aggregation of diversified productions as vegetables, flowers, timber, extractivism and production of animals other than livestock). It is also observed that higher aptitude levels increase the shadow revenue for temporary crops and livestock, while decreased the ones for permanent crops and other productions.

When analyzed the average marginal revenue product, the difference among land, labor and capital are small, despite land presents the highest observed value (0.38) and capital presents the smallest one (0.29). The aptitude is found to increase land marginal revenue product, which is consistent to the idea that land presenting higher aptitudes are more productive, while decreasing the ones observed for labor and capital.

The signals of the impact from each variable at the frontier, the efficiency, and the productivity, directly derived from the parameters of the Output Distance Function, are shown at Table 7.

Table 7. Signal of the impact from each variable at technology, efficiency, and productivity.

	Semi-elasticity of the technology $\left(\frac{dln\Delta T(.)}{d\Delta z_{1_i}}\right)$	**Semi-elasticity of the efficiency change** $\left(\frac{dln\Delta TE(.)}{d\Delta z_{1_i}}\right)$	**Semi-elasticity of the productivity** $\left(\frac{dlnM_O^{2006}(x,y)}{d\Delta z_1}\right)$
Internet coverage	0.37	0.28	0.65
Storage capability	0.07	-0.02	0.06
Technical assistance	0.11	0.37	0.48
Energy access	0.33	-0.01	0.32
Higher education	-2.90	6.89	3.99
Other time fixed effects	0.45	-0.49	-1.12

Source: Own elaboration based on the estimated model.

When analyzed the effects of each efficiency/technical changing variable, it is observed the only three variables affecting negatively some dimension of productivity, more specifically the efficiency change, are storage capability, energy access, higher education and the dummy for time fixed effects. However, storage capability and energy access affected positively the technical change, and higher education affected positively the efficiency level, leading to a positive final effect on productivity.

The evolution of internet access coverage had a statistically significant effect on productivity, which is due to the positive impact on both, efficiency and technological progress. This effect is in consonance with the results found by researches in labor and firm productivity (Grimes, Ren & Stevens, 2012; Najarzadeh, Rahimzadeh & Reed, 2014; Bertschek & Niebel, 2016), which show positive impact of internet access to labor and firm productivity. The effect from increases in internet access on the efficiency level and technological progress is sufficiently large to manifest itself as a positive effect on the evolution of productivity, which allows the simulation of hypothetical scenarios of expansion in internet access at the 2017 agricultural GPV.

In respect to the negative impact of higher education in technology, Rada et al (2019) found positive effects from education at the TFP in Brazilian agriculture for smallest and biggest farmers, and non-significant effect for a medium size class. Sumner (1982) points out the individual allocation of time are assumed to adjust so that the marginal remuneration of time in all uses are equivalent, which leads to ambiguous effect of education on farm and off-farm work (Tao Yang, 1997). In this sense, the observed effect on the technology can be related to trade-offs in time allocation among rural and non-rural activities.

By the other side, in line with the international literature, the share of farmers with higher education was identified as the main determinant of productivity and efficiency changes, presenting positive effects at those variables.

The role of human capital is well known in the literature (see Schultz, 1963), and in productivity it is usually explained by the fact that schooling can enhance labor quality and economic efficiency in agriculture (Wozniak, 1987; Huffman, 2001), highlighting the relevance of investment in educational programs as an instrument of rural development.

The share of farmers with access to technical assistance also had a statistically significant effect on technology, efficiency and productivity, suggesting that, in average, those services has been able to stimulate the efficient use of existing technologies, which is in the same line of many studies about the impacts of extension programs in agricultural production (Evenson, 2001; Egziabher et al., 2013; Freitas et al., 2018; Baiyegunhi, 2019, Rocha Junior et al., 2020). Access to electricity had a statistically significant effect on technical progress, which is possibly a result of access to more productive forms of capital, as well to the more traditional sources of information such as radio and television, since access to energy showed a Pearson correlation of 0.70 with the presence of TV in establishments[12]. The average storage capacity also had a statistically significant effect on technology and productivity, showing the importance of infrastructure to increase agricultural productivity.

Although it is possible to obtain insights about the effects from those efficiency and technical changing variables from Table 7, I am particularly interested in the dynamic relation between internet coverage and productivity. The impact from the installation between 2006 and 2017 of one transmission tower with radial coverage of 40 km² in a municipality, according to the formula (17), is directly related to the representativeness of this increase in coverage in respect to the agricultural land of the municipality (which gives us $d\Delta z_{1i}$), the marginal effect on the technology ($\gamma_1 + \eta_1$ for all municipalities), the marginal effect from this increase at the inefficiency term (observation specific) level and the gross value of production. That is, the economic impact of the expansion in coverage of internet access is greater in municipalities with larger production and smaller areas, also where the efficiency is more sensitive to the increase in internet.

From equation (17), the relative and absolute impacts from the installation of an additional new transmission tower between 2006 and 2017, were estimated. Those results are summarized in Table 8.

Table 8. Impact from a new transmission antenna installation between 2006 and 2017, in municipality level, at the observed GPV in 2017.

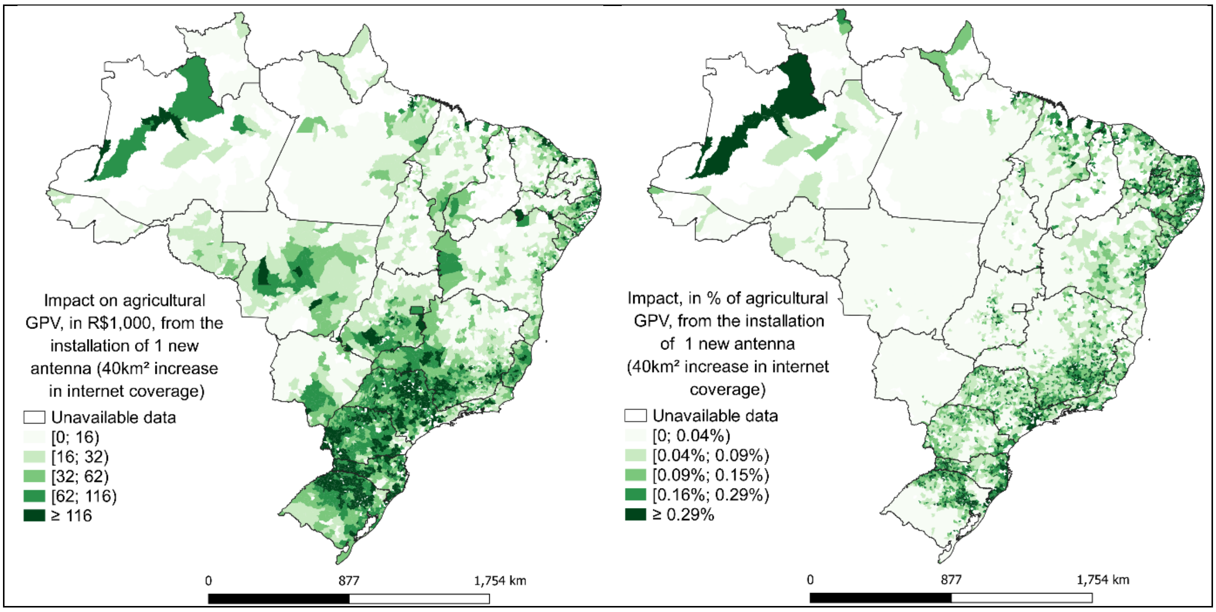
	Observations	Mean	Std. Dev.	Min	Max
Impact in % of the agricultural GPV	4,684	0.25%	1.15 p.p.	0.00%	51.47%
Impact in 1,000 BRL$	4,684	78	133	0	3,580

Source: Own elaboration based on the estimated model.

As a result of this estimate, it was found that the installation of one transmission tower with radial coverage of 40 km² between 2006 and 2017, which constitutes the average coverage of a common tower, results in impacts ranging from R$314 to R$3,580,056, according to the municipality, with average effect of R$78,563 (Table 8). In relative terms, it represents a range changing between 0.0005% and 51.47% of the respective GPV, according to the municipality (Table 8). This first conclusion based on this result is that the impact of internet expansion can be very different depend on the agricultural conditions in each municipality, which can be take into account for policy decisions.

[12] The access to television and radio were not included because there is no information available at the 2017 Brazilian Agricultural Census. Thereby, considering the high correlation between these variables and the energy access, the latter can be considered the best proxy available to the most traditional sources of information.

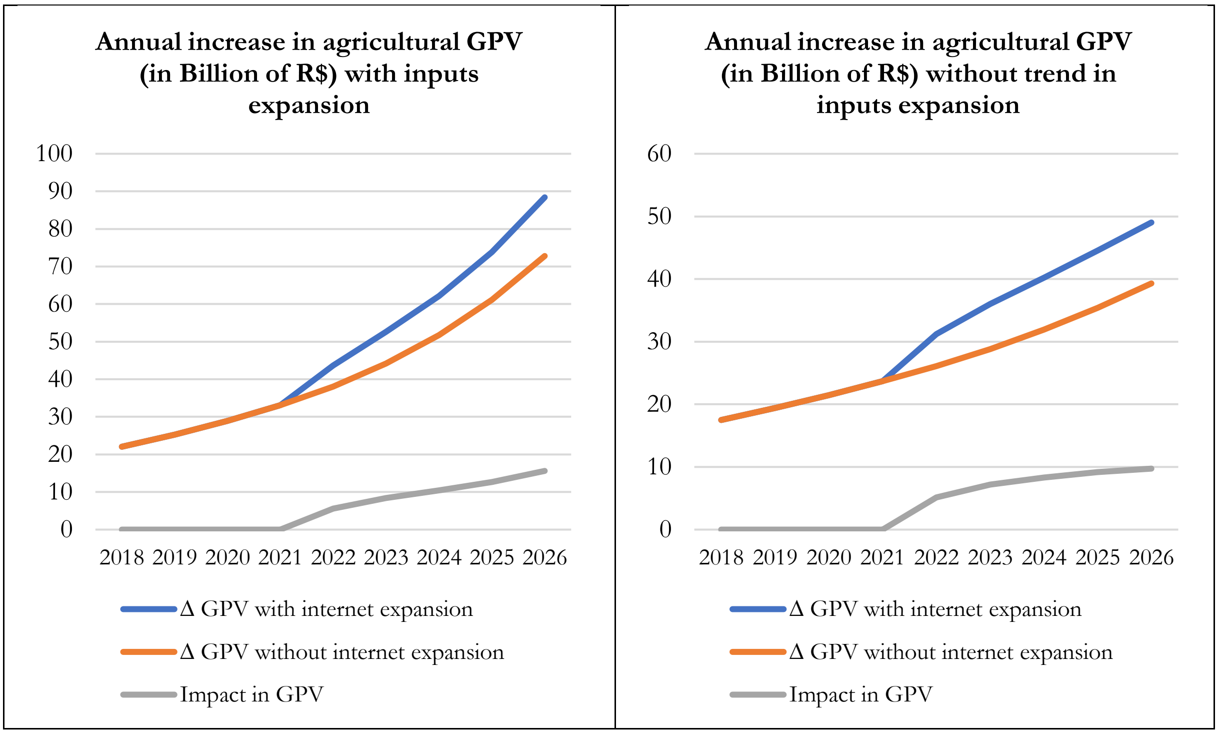
Figure 5. Absolute and relative impact at the municipality agricultural GPV due to a new transmission antenna (40km²) installed between 2006 and 2017.



Source: the author, based on the estimated model.

In spite of the fact that the impact of a typical antenna provides some useful insight about the internet expansion, the main objective of this paper is analyzing the impact from the public policy implementation in 4 steps, as proposed by FEALQ/IICA/MAPA (2020), which is shown at Figure 6.

Figure 6. Annual increase in agricultural GPV (in R$1,000,000,000).



Source: the author, based on the estimated model.

It is observed in Figure 6 that the expected impact of internet expansion in the Brazilian agricultural GPV is as bigger as the input expansion. The cumulated impact between 2018 and 2026 without considering inputs expansion is equal to R$39.53 billion, which represents 8.55% of the Brazilian agricultural GPV observed in 2017.

Considering the historic trend in inputs expansion, this value can achieve R$52.70 billion, representing 11.40% of the Brazilian agricultural GPV observed in 2017.

The considerable difference observed in the comparison of the two estimates is due to the fact that the expansion in the set of available inputs (Table 9) represented an important element of the evolution of production between 2006 and 2017, mainly in the North and Mid-West regions. The effect of increased productivity due to the expansion in internet coverage, when associated with the expansion of the use of inputs, enhances the growth of agricultural production.

Table 9. Evolution in the use of agricultural inputs in Brazilian municipalities between 2006 and 2017.

	Arable area (millions of ha)	Tractors (thousand units)	Labor (millions of people)
North	6.56	31.36	0.22
Northeast	-2.48	21.35	-2.01
Southeast	2.56	117.03	-0.60
South	0.77	169.48	-0.78
Mid-West	5.15	68.22	-0.10
Brazil	12.55	407.43	-3.26

Source: Own elaboration based on data from the Agricultural Censuses of 2006 and 2017.

*Inflated values for R$ June 2017 using the IGP-DI index.

In Table 9 it is shown there was considerable decrease in the number of people employed in the field between 2006 and 2017, while there was a considerable increase in the number of tractors and in the arable area. This observed growth of 407,000 tractor units is equivalent to an average increase of 37,000 tractors/year, which explains the difference in the potential for increasing the GPV presented in Figure 6 when considering this trend of expansion for the inputs set.

It is verified that the impact of the expansion of internet depends on the evolution in inputs use. It provides insights about the importance of public policy coordination: stimulating investment in tractors and machines and increasing the arable land and labor use intensify the impact of internet expansion.

It is noteworthy that all the inferences made here are based on the behavior of agriculture between 2006 and 2017, but it is likely that there are macroeconomic and structural differences between this period and the period for which the implementation of the Scenario in Figure 6 was estimated. The Coronavirus pandemics is an example of such unexpected events, but the results obtained here supports the idea that the implementation of the public policy increasing signal coverage, coordinated with policies that stimulate the trend of intensification in agricultural production, is a promising path for economic development in Brazilian countryside, being able to improve the economic recovery process after Coronavirus pandemics.

3.4. Conclusion and remarks

The internet access is an important factor in fostering the economic development of Brazilian agriculture. The effect of the increase in internet access in the efficiency level and technological progress estimated for the period between 2006 and 2017 was sufficiently large to manifest itself like a positive effect on the evolution of productivity. The derivation of marginal effect from changes in internet access between 2006 and 2017 shows that the impact from internet access expansion is greater in municipalities with a larger scale of production in smaller areas, and where the efficiency is more sensitive to the increase in internet. Considering that the expansion of internet access presents permanent impact on the agricultural productivity, and given the specificities of Brazilian rural environment, which often make private investments in the expansion of transmission lines unviable, the results of this study support the discussion around the importance of public policies to stimulate private investments in expansion of internet coverage in the countryside, which can be a promising path to promote economic development in Brazilian agriculture.

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4. FINAL REMARKS

The objective of this dissertation was to analyze two policy issues, technical assistance and rural extension (TA) access and internet access expansion on the Brazilian agricultural production. The scarcity of data disaggregated among different activities as well the absence of farm level data readily available required the adoption of modelling strategies in primal space allowing for the estimation of multiple inputs and outputs technologies. The main results from those analysis go beyond the impact evaluation conducted at the two papers, because they also provide derivations of effects from efficiency and frontier changing variables on PPF, efficiency, productivity and production, in a parametric approach, what is useful for future studies in situations when there is no data available for dual analysis.

The estimated impacts presented in both papers also represent relevant collaborations for policy makers, by providing measures of the positive impact from technical assistance for family farmers, and evidences about differences among impacts of TA from different sources; and the simulation of the impact from a real public policy which has the potential of generating permanent increases at the Brazilian productivity.

Beyond the advances and useful results from both papers, they also provide insights for other applied researches with methodological advances, as the inclusion of spatial spillovers in both models to understand how such aspect can have theoretical and econometric implications.