The Long and Winding Road: the impact of road network on Peruvian farm technical efficiency

Mateus de Carvalho Reis Neves [a]; Felipe de Figueiredo Silva [b]; Carlos Otávio de Freitas [c]

Área ANPEC: Área 11 - Economia Agrícola e do Meio Ambiente.

Resumo: A infraestrutura rodoviária no Peru pode ser um fator limitante na expansão da produção agrícola. O Peru tem uma densidade de estradas consideravelmente menor em comparação aos países desenvolvidos, com um tempo médio de viagem para cidades com 50.000 habitantes ou mais, de cerca de 4 horas. Neste artigo, estimamos a eficiência técnica da propriedade rural usando uma função de produção estocástica para avaliar se uma infraestrutura viária maior ajuda a diminuir a ineficiência técnica da fazenda. Para isso, usamos a Pesquisa Agrícola Nacional de 2017 para o Peru e informações geográficas sobre a rede de estradas e tempo de viagem para a cidade mais próxima com 50.000 habitantes ou mais (acessibilidade). Nossas descobertas sugerem que uma maior rede de estradas diminui a ineficiência técnica da fazenda; a maior densidade da estrada (tempo de viagem) diminui (aumenta) a ineficiência técnica da fazenda. Regionalmente, províncias ocidentais são menos eficientes em comparação com as províncias orientais. Esses resultados podem estar associados ao acesso a mercados de insumos, serviços de extensão e mercados consumidores.
Palavras-chave: Fronteira Estocástica, Eficiência Técnica da Fazenda, Densidade da Estrada, Tempo de Viagem

Abstract: *The road infrastructure in Peru may be a limiting factor in farm production expansion. Peru has considerably lower road density compared to developed countries with an average travel time to towns with 50,000 inhabitants or more of about 4 hours. In this paper, we estimate farm technical efficiency using a stochastic production function to assess whether greater road infrastructure helps to decrease farm technical inefficiency. To do so, we use national agricultural survey of 2017 for Peru, and geographic information on road network and travel time to the nearest town with 50,000 inhabitants or more (accessibility). Our findings suggest that greater road network decreases farm technical inefficiency; higher road density (travel time) decreases (increases) farm technical inefficiency. Regionally, western provinces are less efficient compared to eastern provinces. These results might be associated to input markets, extension and output markets.*
Keywords*: Stochastic Frontier Approach, Farm technical efficiency, Road density, Travel time*

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[a] Professor do Departamento de Economia Rural, Universidade Federal de Viçosa-MG (UFV). mateus.neves@ufv.br
[b] Assistant Professor - Clemson University. fdsilva@clemson.edu
[c] Professor do Departamento de Ciências Administrativas, Universidade Federal Rural do Rio de Janeiro-RJ (UFRRJ). carlosfreitas87@ufrrj.br

1 Introduction

The Andean countries produced 16.3% of the agricultural value of production in South America in 2016 (Food and Agricultural Organization – FAO 2020). However, the road infrastructure in the Andean countries still a limiting factor on production expansion. Colombia, Peru, Ecuador, and Bolivia have lower road density compared to developed countries, generating considerably higher transport cost and limiting their competitiveness in the international agricultural market (Briceño-Garmendia et al. 2015). Colombia, Peru, Ecuador, and Bolivia had 205, 166, 89, and 43 thousand kilometers of roads in 2015, mostly unpaved (e.g., less than 8,500 km in Bolivia are paved – Meijer et al. 2018[1]). Road networks enable mobility and are a key factor in goods and services production and distribution, people mobility, and consumption of goods and services. The lack of a good road network leads to average farm travel time to the nearest large town (definition discussed below) ranging between 2.5 hours in Ecuador and 4 hours in Peru, but up to 90 hours in some places in Colombia (Weiss et al. 2018). A limiting road infrastructure may lead to inaccessibility to markets and limit the farm's ability to manage production inputs efficiently. In this paper we focus our analysis on Peru and investigate whether road density affects farmers' technical efficiency, estimating a stochastic frontier at farm level.

Road network distribution is not equally distributed across these countries, leaving aside a large population of mostly subsistence and small farms. More than 85% of the farms in Colombia and Bolivia and more than 55% in Peru and Ecuador have less than 10 ha. This pattern results in high travel time to the nearest town with 50,000 inhabitants or more. Low road density or great inaccessibility result in restricted access to information, extension (technical assistance), credit, and other essential services that contribute to raising agricultural production and farm income. There are three studies that have accounted for the distance to the nearest city for Andean countries: Peru (World Bank, 2017; Espinoza et al., 2018) and Bolivia (Larochelle and Alwang, 2013). Several studies estimated the effect of roads and road density on technical efficiency (change) and agricultural total factor productivity for Brazil and other countries (Mendes, Teixeira, and Salvato, 2009; Rada and Valdes, 2012; Rada and Buccola, 2012; Gasques et al., 2012). A few other papers investigate technical efficiency for Andean countries but focus in one region, activity, or product (Trujilo and Wilman, 2013; Melo-Becerra and Orozco-Gallo, 2015; Fletschner, Guirkinger and Boucher, 2010; Larochelle and Alwang, 2013; González-Flores et al., 2014). The studies find that these variables contribute positively to increased agricultural TFP. This paper contributes to this literature providing new information on the link between road infrastructure and farm technical efficiency for farms in Peru. Additionally, our results provide information on production elasticities and efficiency determinants, including extension and credit.

To estimate technical efficiency, we used information from the *Encuesta Nacional Agropecuaria of 2017* for Peru and geographic information on road network (explained later) to estimate a stochastic frontier. In our final sample, we have 26,966 farm observations with information on quantity produced and price sold, input use and price paid, district geographic location, and other factors such as access to extension and credit. We merge this farm information with geographic information on travel time (Weiss et al 2018) and road network (Meijer et al 2018) at the lowest political geographic unit (municipalities). We find that an average technical

[1] The information on road infrastructure (in km, density and travel time) provided in this paper was built using ArcGIS and R using the shapefiles provided by several sources such as Meijer et al (2018), *Ministerio de Transportes y Comunicaciones* (MTC), and Weiss et al. (2018).

efficiency of 0.64 for farms in Peru. An analysis of the inefficiency determinants confirms the hypothesis that road network affects the farm's ability to manage inputs in the production. Peruvian farm inefficiency decreases as road density increases and increases as travel time increases.

2 Literature Review

This section briefly describes the literature on technical efficiency and on the effect of road infrastructure on technical efficiency for Andean countries focusing in Peru. Using household data, Melo-Becerra and Orozco-Gallo (2017) estimate technical efficiency for small crop and livestock farmers in Colombia. They use a metafrontier analysis based on Huang, Huang, and Liu (2014) to compare household technical efficiency under different production systems, based on household location (different altitudes). They find that while technical efficiency is, on average, 56%, technical efficiency from the metafrontier is, on average, 46%, which translates to a technological gap ratio of 82%. Also related to our paper, they find that (Euclidian) distance to the market (between the centroid of the municipality in which the household is located, to the nearest market) is positive, implying that households farther away are more inefficient.

A few other papers investigate technical efficiency for these countries but focus on one region, activity, or product. Larochelle and Alwang (2013) estimate farm technical efficiency for the Bolivian Andes potato farms and find a low efficiency level (0.56), probably due to the region's high vulnerability to climate shocks. Trijulo and Iglesias (2013) estimate technical efficiency for small pineapple farms in Santader in Colombia and find that farmers' characteristics such as schooling and years of experience decrease technical inefficiency. They also account for credit in the inefficiency error term and find that credit decreases inefficiency. Perdomo and Hueth (2011) estimate technical efficiency for coffee farms in Colombia and find that farm efficiency varies considerably across functional forms, ranging from 0.52 to 0.98. (They do not account for inefficiency determinants.) González and Lopez (2007) estimate household efficiency in Colombia, focusing on the effect of political violence on inefficiency and using an input-oriented stochastic frontier. As in our paper, their model accounts for household distance to market, and they find that when distance is statistically significant, it decreases inefficiency. They argue that this variable might be capturing bias, in that they are using values rather than quantities for output and inputs.

Ortega (2018) also investigates the impact of road network improvements in Colombia on agricultural production and other key variables, using a difference-in-difference technique based on three years of survey data on (Euclidian) distance to the market. She finds that changes in the quality of rural roads affect the agricultural production nonlinearly; it depends on the distance to local and national markets. While households in central locations reduce their production, households in peripheral regions expand their production. Even though these results are not directly comparable to our simple analysis, they shed light on the dynamic of agricultural production-distance to markets.

Espinoza et al. (2018) estimate technical efficiency for Peruvian farms also using the metafrontier analysis proposed by Huang, Huang, and Liu (2014) and data from the *Encuesta Nacional of Agropecuaria* of 2015 to identify potential differences between regions (coastland - *Costa*, Andes Mountains - *Sierra* and Amazon rainforest - *Selva*). (We use the same source from 2017.) In their analysis, Huang, Huang, and Liu (2014) exclude large farms and livestock producers, working with a sample of 23,686.[2] Even though they focus on a subset of our sample, they built the output and inputs in similar fashion, considering labor, land, and capital as inputs and value of production as output. As in this paper, they account for accessibility by measuring road distance and travel time to cities with 50,000 inhabitants or more. They find mix results for the effect of distance on inefficiency (non-significant, positive, and negative for three different regions), and that extension and credit decrease inefficiency. The World Bank (2017) report finds similar results also for Peru.

Even though in this paper we estimate farm technical efficiency at one year at farm level, several studies have looked at technical efficiency and agricultural total factor productivity (Ag TFP) for the countries analyzed in this paper. Most of the studies estimated the Ag TFP for the Andean countries within a world or regional analysis. Trindade and Fulginiti (2015) find that, among the countries analyzed in this paper, Bolivia and Colombia had the lowest TFP growth during the period, 0.708 and 0.736 respectively for 1969-2009. On the other hand, Venezuela (1.731), Ecuador (1.639), and Peru (1.538) have among the highest rates for the region and period. Their analysis is a subset (but more detailed analysis) of Fuglie (2010) that looks at the entire world and finds an average TFP growth rate of 1.49 for Andean countries during the period 1967-2007. Ludena (2010) finds slightly different TFP rates for these countries when analyzing Latin America and Caribbean regions: 1961-2000 averages for Bolivia (0.6), Colombia (1.5), Ecuador (0.2), Peru (0.7), and Venezuela (1.2). Pfeiffer (2003) estimates the Ag TFP for all Andean countries, representing a subset of Trindade and Fulginiti (2015) and finds an average TFP of 0.61% per year for Bolivia, 0.64% for Colombia, 3.26% for Ecuador, 2.79% for Peru, and 1.37% for Venezuela. For Colombia, Jiménez, Abbott, and Foster (2018) estimate technical change in agricultural production using country data (as in Pfeiffer, 2003; Ludena, 2010; Fuglie, 2010; Trindade and Fulginiti, 2015). Using different approaches and functional forms for the production function, they find that technical change ranges from 0.8% to 1.3% and varies throughout the period of 1975 to 2013 due to six major events that affected agriculture in Colombia, such as armed conflict intensification (1998-2002) and commodities price boom (2003-2009).

In addition to analyzing the effect of roads on technical efficiency, we analyze whether access to extension and credit affect farm technical efficiency. On this topic, there is evidence, from analysis of different countries, that indicate that these two factors decrease inefficnecy. A few papers have indirectly investigated the effect of rural extension in Brazilian farm technical efficiency. Moura et al. (2000) find that rural extension increases farm efficiency but has no effect on the use of inputs. Helfand and Levine (2004), Gonçalves et al. (2008), and Freitas et al., (2019) find that rural extension services increase farm efficiency. Also investigating the effect of credit on agricultural Total Factor Productivity (Ag TFP), Jin and Huffman (2016) find that rural extension increases Ag TFP for most American states, and they estimate that the real social rate of return of investments on extension is more than 100%.

3.1 Road infrastructure in Peru

To test whether road network affects farm efficiency, we use several sources. In this section, we briefly describe the current road network. Road networks, based on Meijer et al. (2018), are

[2] As in the data used in our analysis of Peru (*Encuesta Nacional of Agropecuaria* of 2017), the survey was designed to have state representativity only for small and medium farms.

displayed in Figure 1. Along the same lines, Meijer et al. (2018) estimate road density for 222 countries, using 63 different sources. They overestimate road network for some of the countries, such as Colombia, compared to numbers from *Comisión Economica para America Latina y el Caribe* (CEPAL) and official information from the *Departamento Administrativo Nacional de Estatística* – DANE.

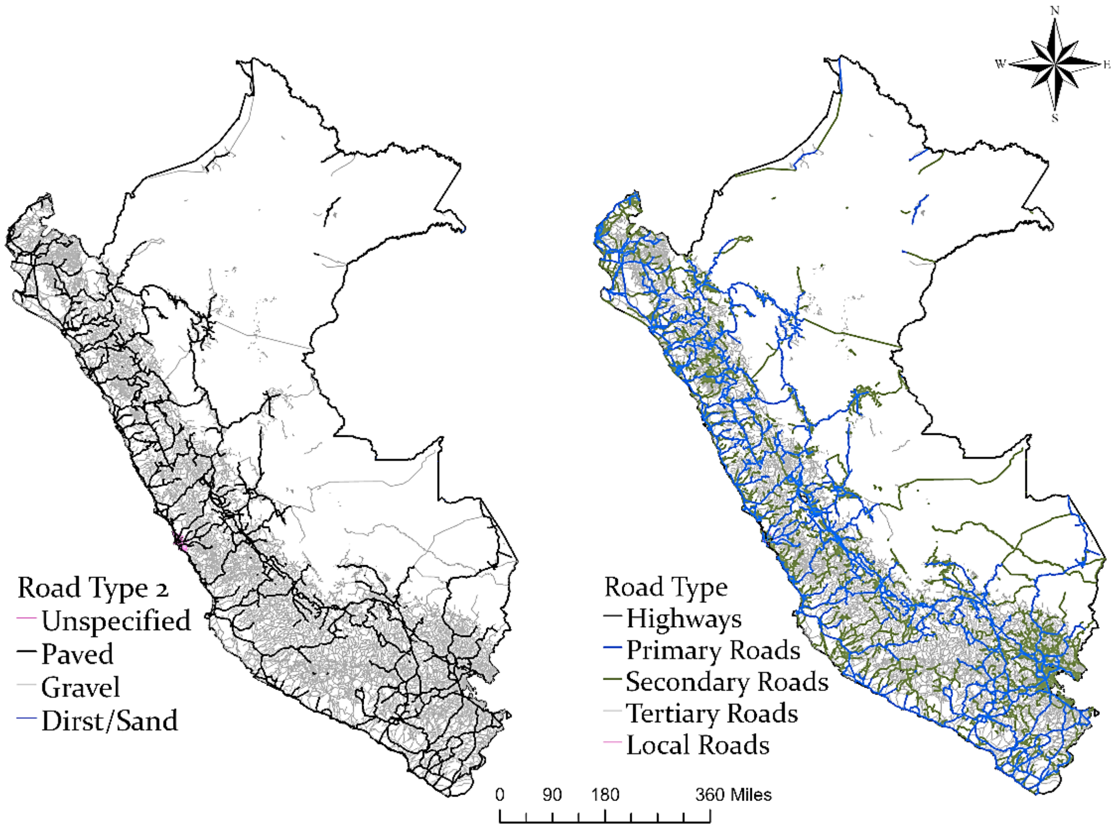

Figure 1. Road network by two types (highways, primary, secondary, tertiary and local on the right and paved, gravel and others on the left), Peru, 2017
Source: Authors' work using ArcGIS Pro and the information provided by Meijer et al. (2018)

For Peru, we use information from the *Ministerio de Transportes y Comunicaciones* (MTC)[3] for 2019 and from Meijer et al. (2018)[4] on all types of roads to calculate the road length in kilometers (km). While the MTC dataset provides information on 166 thousand km, Meijer et al. (2018) report 192 thousand km with 16% paved and another 12 thousand km unspecified. Both MTC and Meijer et al. (2018) report numbers close to numbers reported by CEPAL, almost 167 thousand km in 2017. We opted to use information provided by MTC for our analysis.

Based on the literature, we also constructed the variable roads density (z_1). To calculate this variable, we used geographic information (shapefiles) of roads available at governmental websites to calculate the roads' length (RL) by municipality in kilometers (km) and the geopolitical administrative information to calculate the municipality area (AM) in square kilometers (sqKm).

[3] The shapefile with information on roads is available online at https://portal.mtc.gob.pe/transportes/caminos/normas_carreteras/mapas_viales.html. There is one file for roads at the national level, one file for roads at the department level and several files for roads at the local level.
[4] Part of The Global Roads Inventory Project (GRIP), available at https://www.globio.info/download-grip-dataset

z_1 is the ratio of these two variables ($z_1 = RL/AM$) and is in km/sqKm. The road density variable depends on what it is considered roads; it increases as we include non-paved roads in the calculation of this variable. Because one of our objectives is to identify the effect of accessibility on agricultural production, we have included all types of roads on the calculation of the main road density variables. In Peru, the pattern observed in Figure 1 yields greater road density on the west coast of Peru. This pattern is driven by Peru's geography, with the presence of the Amazon forest in the eastern part of the country.

3.2 Travel time to the nearest large city

Rich geographic information on roads provided by governments and private institutions allowed an accurate analysis of the road network worldwide (Iimi et al., 2016; Weiss et al.; 2018, Meijer et al.; 2018). Using Open Street Map (OSM) and Google, Weiss et al., (2018) estimate travel time to the nearest urban center, establishing a link between travel time and countries' income. Both travel time and road density capture the link between road network and agriculture through the lenses of accessibility and availability, respectively. Greater travel time to urban centers would result in a lower likelihood of accessing extension services and financial tools, factors that yield higher agricultural productivity. Higher road density allows farmers to move more easily between farms and urban centers to purchase inputs and sell outputs, resulting in greater agricultural production. For instance, Meijer et al. (2018) find that wealthier countries have higher road density.

Briceño-Garmendia et al. (2015)[5] assess several aspects of the road network and accessibility in Colombia, Ecuador, and Peru using a few of the sources introduced in the supplementary material and others. Relevant to our discussion, they calculate accessibility scores and map them for these countries, finding results that resemble Weiss et al. (2018). This gives us support to use Weiss et al. (2018) measure, given that it is more comprehensive.

To estimate the impact of road network on the likelihood of accessing extension and credit, we used a country's average travel time to the nearest city of 50,000 people (or 1,500 or more inhabitants per square kilometer), based on Weiss et al. (2018)[6] as a proxy to road network. This measure captures not only distance but also quality of the roads and transportation services. We find that the average time per municipality (*distritos*) to the nearest large city for Peru is 213 minutes.

The country's geography plays a major role in transportation infrastructure such as road network, which is directly linked to the population's accessibility. Figure 2 displays travel time based on Weiss et al. (2018). The pattern observed in Figure 2 is partially produced by the Andean, which divides the country: urban areas in the west and forest area in the east. The lack of road network or other form of transportation and urban centers east of the Andean imposes a greater

[5] Briceño-Garmendia et al. use a robust decision-making approach to assess policy designs for road network under uncertainty, particularly associated to climate events, for Colombia, Peru and Ecuador. A wide range of datasets is used in their paper, including geographic information systems on road network used here and measures of agricultural production based on the International Food Policy Research Institute's (IFPRI's) Spatial Production Allocation Model (2000) and the FAO's Global Agro-Ecological Zones (GAEZ 3.0).

[6] Weiss et al. constructed a friction map that allows us to estimate the average travel time per county (or smallest unit of observation) for each country. They measure the travel time for 2015.

travel time to the inhabitants there. Weiss et al (2018) considers waterways in remote regions where this is the only or the fastest route. The region around *Iquitos* in Peru, for example, is connected by only a few roads and a few rivers such as the Amazon. The darker routes in the northeastern portion of Peru displayed in Figure 2 are partially driven by rivers such as the *Napo*, *Curaray*, *Tigre* and *Amazonas* (Amazon River). The travel time distribution displayed in Figure 2 resembles what Briceño-Garmendia et al. (2015) found for Peru.

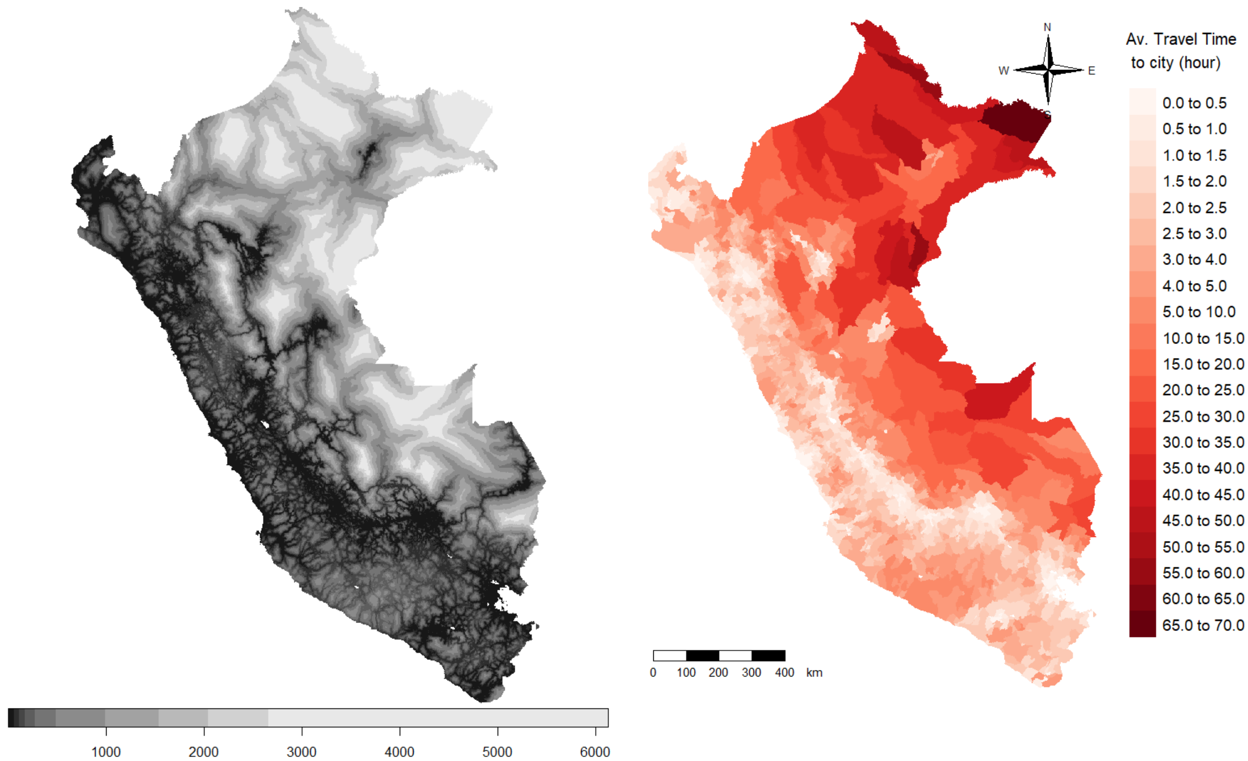

Figure 2. Travel time in minutes as constructed in Weiss et al. (2018) on the left and average travel time by municipalities (*distritos*) in hours on the right, Peru, 2017

Source: Authors' work using R Studio and the information provided by Weiss et al. (2018)

4 Analytical framework

The Stochastic Frontier approach is widely used to obtain efficiency measures. It consists of estimating a production function that represents the relation between agricultural input and output (González-Flores et al. 2013; Helfand and Levine, 2004; Rada and Valdes, 2012; Helfand et al. 2015). Aigner, Lovell, and Schmit (1977); and Coelli and Battese (1996) specify the model as follows:

$$Y_i = f(X_i, \beta)e^{(v_i - u_i)} \tag{1}$$

where Y_i is the value of production of *i-th* farm, X_i is the vector of expenses with inputs of the *i-th* farm, and β is a vector of the parameters to be estimated, which define the production technology. The error terms v_i and u_i are vectors that represent distinct components of the error. The random error component v_i, has a normal distribution, independent and identically distributed (*iid*), with variance $\sigma_v^2 [v \sim iid\ N(0, \sigma_v)]$, and captures the stochastic effects beyond the control of the productive unit, such as measurement errors and climate. The error term u_i is responsible for capturing the technical inefficiency of the i-th farm; that is, the distance from the production frontier, and these are non-negative random variables. This unilateral (non-negative) term can follow half-normal, truncated normal, exponential or gamma distributions with mean $\mu > 0$ and variance σ_u^2 (Aigner et al., 1977; Greene, 1980). We have assumed an exponential distribution to the inefficiency error term. Technical efficiency is obtained following the Battese and Coelli (1988) approach. We assume that the inefficiency term u_i is determined by a vector of variables $\boldsymbol{z}$, as follow:

$$\mu_i = z_i \delta \tag{2}$$

where $\boldsymbol{z_i}$ is a vector of explanatory variables that affect the technical inefficiency of Peruvian farms, such as road density (or travel time), extension, credit, and energy use (these variables are explained in later sections); and δ is a vector of the parameters to be estimated.

4.1 Data

To investigate the effect of road density on agricultural production, we used agricultural census and surveys for each country. Our goal in this paper was to estimate technical efficiency and its determinants at the lowest level possible, farms, using national datasets. We used the *Encuesta Nacional Agropecuaria of 2017*. We described data on roads in the previous section.

In the efficiency analysis, we also control for extension, and credit and describe these variables here. We used the *Encuesta Nacional Agropecuaria of 2017*, which has information on 29,218 and 1,537 small/medium and large farms (*unidade de produccion agropecuaria - UPA*) representing a total of 2.2 million Peruvian farms.

On credit and extension, 11.1% of the small and medium farms requested and obtained credit, and 32.5% of the large farms requested and obtained credit. In 2017, 7% of the small and medium farms had access to extension assistance, and 43% of the large farms had access. We measured labor as the sum of paid and unpaid employees in both agricultural and livestock production. We calculated capital as the sum of cost of machinery, equipment, fuel, maintenance expenses, crop inputs (such as fertilizer), and livestock inputs (such as animal medicines). To estimate the value of production, we considered all crops, cattle,[7] and milk. We used the value of production reported by the farmer and converted value of production to US$ of 2017 (PER$ 1 = 0.3 US$).In this paper, we only considered farmers who had a positive value of production and land greater than 0. To control for outliers, we dropped all observations at the bottom 1% and top 1% of the distribution of the value of production. Our sample size is 26,966. We display descriptive statistics in Table 1 and value of production per Peruvian province in Figure 3.

We also controlled for farm size, including categorical variables accounting only for the products used in the calculation of the value of production for each country. They are 0 to 5 hectares (ha), 5 to 10 ha; 10 to 50ha; 50 to 100 ha; 100 to 500ha; 500 to 1000 ha; and above 1000 hectares. Table 1 shows that most of the farms have less than 5 hectares.

[7] We used the monetary value reported by the farmer for sold cattle and cattle consumed inhouse.

Table 1. Descriptive statistics, Peru, 2017

Variables	Values	Std. Dev.
Value of Prod. (*US$*)	8777	53057.350
Labor (*sum of employees*)	14.496	81.806
Land (*ha*)	33.680	627.120
Capital (*US$)*	5254	212447.3
Extension (*yes or no*)	0.092	0.289
Credit (*yes or no*)	0.135	0.341
Roads density (*km / 100 sqKm*)	35.235	33.609
Travel Time (*hours*)	4.575	6.925
Pop. Density (*People / SqKm*)	85.820	355.51
Farm size (*dummy variables*)		
0 – 5 ha	0.421	0.493
5 – 10 ha	0.154	0.360
10 – 50 ha	0.270	0.443
50 – 100 ha	0.062	0.242
100 – 500 ha	0.070	0.255
500 – 1000 ha	0.012	0.109
1000+ ha	0.011	0.102

Source: Own elaboration with data from the *Encuesta Nacional Agropecuaria* of 2017.

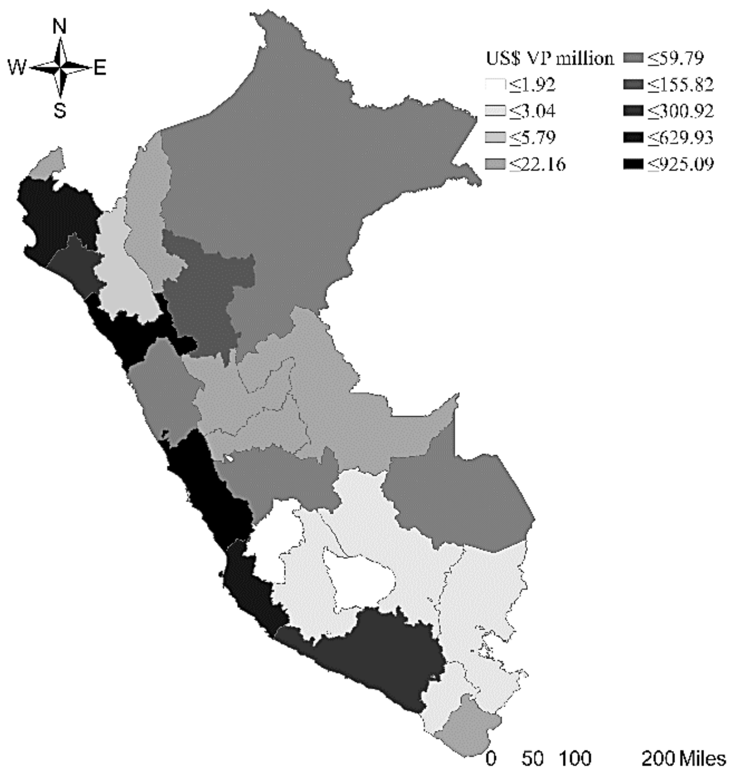

Figure 3. Value of production for selected products (see data section) by department/province, Peru, 2017

Source: Own elaboration.

Note: Value of production was build using information from the *Encuesta Nacional Agropecuaria* of 2017.

4.2 Empirical Strategy

We estimate the stochastic frontier assuming several functional forms, including Cobb-Douglas and *Translog* production function. The latter presents some desirable properties such as flexibility, linearity in parameters, regularity, and parsimony (Mariano et al., 2010). However, as in Battesi and Coelli (1992) and Helfand et al. (2015), Log-likelihood Ratio (LR) tests were performed to identify the best production frontier specification (Cobb-Douglas versus Translog), which pointed to the Translog functional form. As in Coelli et al. (2003), the technology can be represented as

$$y = \alpha + \beta^{'}\boldsymbol{x} + \boldsymbol{x}^{'}\boldsymbol{B}\boldsymbol{x} + \boldsymbol{\Gamma_1} + \boldsymbol{\Gamma_2} + \varepsilon \qquad (3)$$

where y represents the logarithm of the gross value of production; $\boldsymbol{x} = (x_1, x_2, x_3)$ is a matrix of three inputs: labor (x_1), land (x_2) and capital (x_3) $\boldsymbol{\Gamma_1}$ is a matrix of Peruvian states; $\boldsymbol{\Gamma_2}$ represents fixed effects for farm size; α, $\beta$and $\boldsymbol{B}$ are vectors of parameters to be estimated; and ε is the composed error term described before. Even though it is not the main objective of the paper, we calculate production elasticities for all inputs. To explain inefficiency, we include road density (or travel time), population density, access to extension, access to credit, and energy use (electricity, gasoline and diesel). We have added population density so we could estimate an unbiased effect of road density in the inefficiency error term, which could capture the effect of a large city (higher road density) on the inefficiency term. We expect road density (travel time), extension and credit to decrease (increase) inefficiency.

5 Results

In Table 2 we present the production elasticities[8] for equation (3)[9], using road density as an explanatory variable in the inefficiency term (results are quite similar when using travel time). The parameters estimated for this equation are displayed in the Appendix. On average, the elasticities indicate that our estimation is coherent with economic theory[10]. Our production elasticities for Peru lie on the range reported by the World Bank (2017), which estimates production elasticities for four types of production, such as that labor elasticity ranges from 0.16 to 0.38, and land elasticity ranges from 0.29 to 0.55.

Table 2. Average production elasticities for Peru, 2017

Variables	$\boldsymbol{\varepsilon_{x_1}}$ *(labor)*	$\boldsymbol{\varepsilon_{x_2}}$ *(land)*	$\boldsymbol{\varepsilon_{x_3}}$ *(capital)*
Peru	0.195**	0.345***	0.486***
Standard errors	0.012	0.012	0.007

Source: Own elaboration.
Note: We only calculate the capital elasticity for Peru, given that we only take the logarithm of capital measures for this country. Elasticity for land was calculated only for the observations with positive land. Standard errors were calculated using the delta method. Statistical significance: * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$. Violations: 2%, <1% and 2.5% for x_1, x_2 and x_3 do not satisfy monotonicity.

[8] We also obtained the production elasticities using a Cobb-Douglas functional form. They are very similar–see parameters estimated in the Appendix.
[9] The LR test indicates that *Translog* is more adequate to represent the technology than Cobb-Douglas.
[10] See Table 2 footnote for violations.

The main objective of this paper was to estimate technical efficiency and its determinants. In Table 3 we present the average technical efficiency and the determinants estimated for both models with road density and travel time. We find that road density (travel time) decreases (increases) inefficiency. Our results of the road density effect on technical efficiency for Peru reinforce the result found in the literature; namely, that road density decreases technical inefficiency (Mendes, Teixeira, and Salvato 2009; Rada and Valdes 2012; Rada and Buccola 2012; Gasques et al. 2012).

Closely related to our analysis, Espinoza et al. (2018) accounted for the distance to the nearest city with a population above 50,000 inhabitants in the inefficiency term for small and medium Peruvian farms. They found mixed results when analyzing the three regions separately: no effect on inefficiency for *Costa,* increased inefficiency as distance increases for *Sierra,* and decreased inefficiency as distance increases for *Selva*. The measure used by Espinoza et al. (2018) can be interpreted as a simpler version of the measure used in this paper, given that it does account for the quality of the road or the transportation mode taken. Their result for *Sierra* would then be the one that aligns with our findings. Also, for Peru, the World Bank (2017) finds that the same variable has a positive marginal effect on inefficiency for the majority of the categories in region and farms type except for the region *Sierra*. Our results corroborate their findings.

Table 3. Average technical efficiency and estimated parameters for the inefficiency error term using two set of estimation – with (1) road density, and (2) travel time, Peru, 2017

Variables	**Estimation**	
	(1)	**(2)**
Average TE	0.638	0.640
Road Density	-0.003*** (0.001)	–
Travel Time	–	0.011*** (0.003)
Pop. Density	0.0001** (5e+05)	0.0007 (5e+05)
Credit	-0.525*** (0.061)	-0.529*** (0.062)
Extension	-0.430*** (0.071)	-0.445*** (0.075)

Source: Own elaboration.
Note: Standard error in brackets. Statistical significance: * p < 0.10. ** p < 0.05. *** p < 0.01.For Ecuador we also included dummy variables for farm size given that the survey did not provide information on producer and farm characteristics. We also include farm size dummies in the inefficiency error term for Bolivia and Colombia.

Regionally, some departments stand out. *Loreto,* the largest Peruvian department, has one of the lowest technical efficiency rates (0.60), considering the estimation accounting for travel time. Farms in *Madre de Dios* have a similar average technical efficiency (0.61). Analysis of Figure 1 indicate that these departments have lower road infrastructure, mainly composed by secondary and tertiary roads of lower quality in these regions. On the other hand, farms in departments like *Ancash* and *Lambayeque* have average technical efficiency higher than 0.64. These farms are in the coastal region where they are better equipped with road infrastructure.

We also found that access to extension and credit are associated with lower technical inefficiency for Peru. We observe that credit has a stronger effect on inefficiency, compared to extension. Our results corroborate what others report on the effect of access to extension and credit on technical efficiency (Helfand and Levine, 2004; Bravo-Ortega and Lederman, 2004; Rada and Valdes, 2012; Rada and Buccolla, 2012; Gasques et al., 2012; Freitas et al., 2019). Espinoza et al. (2018) also found that credit and extension decreases inefficiency for Peruvian small and medium farms (for the three regions studied). In Figure 4, we display the histogram for the technical efficiency for the model that includes road density as explaining the inefficiency.

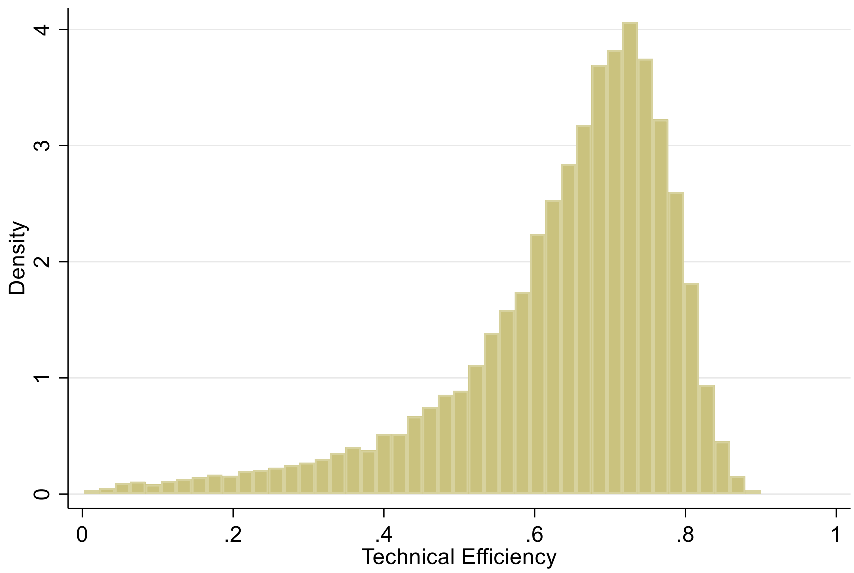

Figure 4. Histogram of technical efficiency, Peru, 2017
Source: Own elaboration.

We also estimated technical efficiency for the travel time model to compare technical efficiency averages under four different quantiles of travel time (description under Table 4). Technical efficiency (inefficiency) decreases (increases) as the farm is further away from towns with more than 50,000 people or 1,500 inhabitants per square km. We observe only a small change in technical efficiency of Peruvian farms as they are farther away from the larger towns.

Table 4. Average technical efficiency by travel time (quantiles), Peru, 2017

Intervals	**< 25%**	**25% > *x* < 50%**	**50% > *x* < 75%**	***x* > 75%**
Coefficients	0.647	0.643	0.637	0.633

Source: Own elaboration.
Note: The quantiles for travel time represent distance to the city – higher quantile implies further away from urban areas

Our findings displayed in Table 3 and Table 4 indicate that, overall, road network decreases technical inefficiency. In Table 3, we found evidence that supports this assertion, using two different measures: road density and travel time. Travel time is directly linked to road network; it measures both distance to the nearest large town and quality of the road. Improvements on road network (such as maintenance and constructions of new roads) would result in shorter travel time and lower inefficiency. In addition to the direct effect of road network on farm income (profit), through costs associated with output distribution and input demand, our results suggest that road network directly affects input use in farm production.

Table 5 displays the relationship between Peruvian farms technical efficiency on and farm size. Technical efficiency increases with the increase in the size of the property in both estimates. However, this trend is reversed in the average sizes and in the group of larger properties (1000+ ha), which is not new. Farms between 500 – 1000 ha stand out in terms of greater efficiencies, as well as farms with 10 - 50 ha. Freitas et al. (2018) found similar behavior for rural properties in Brazil - larger farms were more inefficient than the average size farm given that they used land more intensively.

Table 5. Average technical efficiency for farm size using two set of estimation – with (1) road density, and (2) travel time, Peru, 2017

Farm size	Estimation			
	(1)		(2)	
0 – 5 ha	0.634	(0.146)	0.636	(0.144)
5 – 10 ha	0.642	(0.141)	0.643	(0.140)
10 – 50 ha	0.643	(0.146)	0.645	(0.145)
50 – 100 ha	0.638	(0.160)	0.641	(0.158)
100 – 500 ha	0.628	(0.171)	0.632	(0.170)
500 – 1000 ha	0.643	(0.161)	0.648	(0.158)
1000+ ha	0.637	(0.167)	0.642	(0.165)
Average TE	0.638	(0.148)	0.640	(0.147)

Source: Own elaboration.
Note: Standard errors in brackets

5.1 Robustness check

In the analysis above, we have only three inputs, capital, labor and land. We estimated Equation (3) incorporating a dummy variable equal 1 if the farmer irrigated part of the land and 0 otherwise. This approach does not change technical efficiency averages for Peru (0.64), or the sign of the determinants. We still find road density (travel time) decreasing (increasing) inefficiency; and energy use, extension, and credit decreasing efficiency. The irrigation semi-elasticity is 18.9 for Peru. This number is the average of the first derivative of the production function with respect to the dummy variable (which interacts with capital, labor and land) evaluated at all observations.

Another alternative would be to use Battese's (1997) approach and insert a dummy equal 1 when land irrigated is equal zero and 0 otherwise in addition to the logarithm of land irrigated (inputting 0 when land irrigated is 0). This approach leads to average irrigation elasticity for Peru (0.18); but it does not alter the average technical efficiency estimated or the sign of the inefficiency determinants. Technical efficiency averages in Peru (0.654) do not change much, and distribution is quite similar. We still find road density (travel time) decreasing (increasing) inefficiency; and energy use, extension, and credit decreasing efficiency.

6 Conclusion

In this paper we estimate the production technology for farms in Peru to evaluate whether road network affects farm technical efficiency. To do so, we estimate a stochastic frontier production function using information on more than 20,000 farms. There are several ways to examine road network. We take a stab at two of them. We look at the effect of road density and travel time to the nearest large town on technical inefficiency. While road density is a measure of quantity, travel time measures both quantity and quality. This variable takes into account access to roads, transport availability, and road quality, given that it considers not only highways but also waterways. We measure road density using several sources. and most of the time, our findings match with official information on roads. We measure travel time as the average of the smallest political administrative boundary (unit) of each country, using Weiss et al. (2018). Here, we present a first look at the impact of these two measures on technical efficiency.

Our results suggest that road density and travel time affect farm efficiency. We find that road density decreases farm technical inefficiency, which corroborates the hypothesis that road network availability can help farmers better use inputs in their production. This hypothesis has been tested and confirmed for Brazil (Mendes, Teixeira and Salvato, 2009; Rada and Valdes, 2012; Rada and Buccola, 2012; Gasques et al., 2012); but by examining aggregate data. On the other hand, we find that farmers who take longer to reach large towns have higher technical inefficiency. Even though this result corroborates the effect of road density, it is even richer because it accounts for other transport modes and the quality of these modes. These results shed light on the relevance to farmers of road network and transportation.

References

Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1), 21-37.

Battese, G. E. (1997). A note on the estimation of Cobb-Douglas production functions when some explanatory variables have zero values. *Journal of Agricultural Economics*, 48(1-3), 250-252.

Battese, G. E., & Coelli, T. J. (1988). Prediction of firm level technical inefficiencies with a generalized frontier production function. *Journal of Econometrics*, 38, 387-399.

Battese, G. E., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. *Journal of Productivity Analysis*, 3(1-2), 153-169.

Bravo-Ortega, C. and D. Lederman, 2004. Agricultural Productivity and Its Determinants: Revisiting International Experiences. *Estudios de Economia*, 31(2), 133-163. Universidad de Chile, Santiago de Chile.

Briceño-Garmendia, Cecilia, Harry Moroz, and Julie Rozenberg. *Road Networks, Accessibility, and Resilience: The Cases of Colombia, Ecuador, and Peru*. World Bank, Washington, DC (2015).

Coelli, T. J., & Battese, G. (1996). Specification and estimation of stochastic frontier production functions.

Coelli, T., Estache, A., Perelman, S.; Trujillo, L. A. *A primer on efficiency measurement for utilities and transport regulators.* The World Bank, Washington, DC, 2003.

COSIPLAN (2015), *Iniciativa para a Integração da Infraestrutura Regional Sul-Americana*, Montevideo, 2015. Available at: http://www.iirsa.org/admin_iirsa_web/Uploads/Documents/CARTERA_InformeVersionFinal_Espa%C3%B1ol_2015.pdf (Accessed 02 2019).

Espinoza, M., Fort, R., Morris, M., Sebastian, A., & Villazon, L. (2018, July). Understanding heterogeneity in Peruvian agriculture: A meta-frontier approach for analyzing technical efficiency. In *2018 International Conference of Agricultural Economists*, July 28-August 2, 2018, Vancouver, British Columbia (No. 277134). International Association of Agricultural Economists.

FAO – Food and Agriculture Organization. *FAOSTAT - Statistics Division*. Accessed on Feb 2020. Available at http://www.fao.org/faostat/en/#home

Fletschner, Diana; Guirkinger, Catherine; Boucher, Steve. Risk, credit constraints and financial efficiency in Peruvian agriculture. The Journal of Development Studies, v. 46, n. 6, p. 981-1002, 2010.Fletschner, Diana; Guirkinger, Catherine; Boucher, Steve. Risk, credit constraints and financial efficiency in Peruvian agriculture. *The Journal of Development Studies*, v. 46, n. 6, p. 981-1002, 2010

Freitas, C. O., Figueiredo Silva, F., Neves, M. C., & Braga, M. J. (2018). Can rural extension reduce the income differential in rural Brazil?. In *2018 Proceedings of AAEA Annual Meeting*, August 5-7, Washington, DC (No. 274496). Agricultural and Applied Economics Association.

Freitas, C. O., Teixeira, E. C., Braga, M. J., & de Souza Schuntzemberger, A. M. (2019). Technical efficiency and farm size: an analysis based on the Brazilian agriculture and livestock census. *Italian Review of Agricultural Economics*, 74(1), 33-48.

Fuglie, K.O. (2010). Total factor productivity in the global agricultural economy: Evidence from FAO data. In *The Shifting Patterns of Agricultural Production and Productivity Worldwide*. Chapter 4. The Midwest Agribusiness Trade Research and Information Center Iowa State University, Ames, Iowa.

Gasques, J. G., Bastos, E. T., Valdes, C., & Bacchi, M. R. P. (2012). Produtividade da agricultura brasileira e os efeitos de algumas políticas. *Revista de Política Agrícola*, 21(3), 83-92.

Gonçalves, R. M. L., Vieira, W. C.; Lima, J. E.; Gomes, S. T. Analysis of technical efficiency of milk-production farms in Minas Gerais. *Economia Aplicada*, v.12, n.2, p.321- 335, 2008.

González, M. A., & Lopez, R. A. (2007). Political violence and farm household efficiency in Colombia. *Economic Development and Cultural Change*, 55(2), 367-392.

González-Flores, M., Bravo-Ureta, B. E., Solís, D., & Winters, P. (2014). The impact of high value markets on smallholder productivity in the Ecuadorean Sierra: A Stochastic Production Frontier approach correcting for selectivity bias. *Food Policy*, 44, 237-247.

Greene, W. H. (1980). On the estimation of a flexible frontier production model. Journal of *Econometrics*, 13(1), 101-115.

Helfand, S. M., Magalhães, M. M., Rada, N. E. *Brazil's agricultural total fator productivity growth by farm size*. Inter-American Development Bank, IDB Working paper series n. 609, 2015.

Helfand, S.M., Levine, E.S. Farm Size and the Determinants of Productive Efficiency in the Brazilian Center-West. *Agricultural Economics*, v. 31, p. 241-49, 2004.

Huang, C. J., Huang, T. H., & Liu, N. H. (2014). A new approach to estimating the metafrontier production function based on a stochastic frontier framework. *Journal of productivity Analysis*, 42(3), 241-254.

Humanitarian Data Exchange – HDX (2019). *Information on Ecuador administrative boundaries*. Available at https://data.humdata.org/dataset/ecuador-admin-level-2-boundaries.

Iimi, A., Ahmed, F., Anderson, E. C., Diehl, A. S., Maiyo, L., Peralta-Quirós, T., & Rao, K. S. (2016). *New rural access index: main determinants and correlation to poverty*. The World Bank.

Instituto Nacional de Estadistca e informatica – INEI, 2020. *Encuesta Nacional Agropecuaria 2017*: Principales resultados, pequenas, medianas y grandes unidades agropecuarias. Lima, Dec, 2018.

Jiménez, Manuel I., Abbott, Philip, & Foster, Kenneth. (2018). Measurement and analysis of agricultural productivity in Colombia. *Ecos de Economía*, 22(47), 4-37. https://dx.doi.org/10.17230/ecos.2018.47.

Jin, Y.; Huffman, E. Measuring public agricultural research and extension and estimating their impacts on agricultural productivity: new insights from U. S. evidence. *Agricultural Economics*, v. 47, n.1, p. 15-31, 2016.

Larochelle, C., & Alwang, J. (2013). The role of risk mitigation in production efficiency: a case study of potato cultivation in the Bolivian Andes. *Journal of Agricultural Economics*, 64(2), 363-381.

Ludena, C.E. (2010). *Agricultural productivity growth, efficiency change and technical progress* in Latin America and the Caribbean. Inter-American Development Bank, 2010.

Mariano, M. J., Villano, R., & Fleming, E. (2010). Are irrigated farming ecosystems more productive than rainfed farming systems in rice production in the Philippines?. *Agriculture, Ecosystems & Environment*, 139(4), 603-610.

Meijer, J. R., Huijbregts, M. A., Schotten, K. C., & Schipper, A. M. (2018). Global patterns of current and future road infrastructure. *Environmental Research Letters*, 13(6), 064006.

Melo-Becerra, L. A., & Orozco-Gallo, A. J. (2017). Technical efficiency for Colombian small crop and livestock farmers: A stochastic metafrontier approach for different production systems. *Journal of Productivity Analysis*, 47(1), 1-16.

Melo-Becerra, L. A., & Orozco-Gallo, A. J. (2017). Technical efficiency for Colombian small crop and livestock farmers: A stochastic metafrontier approach for different production systems. *Journal of Productivity Analysis*, 47(1), 1-16.

Mendes, S. M., Teixeira, E. C., & Salvato, M. A. (2009). Investimentos em infra-estrutura e produtividade total dos fatores na agricultura brasileira: 1985-2004. *Revista Brasileira de Economia*, 63(2), 91-102.

Ministerio de Transportes y Comunicaciones (2019). Information on roads for Peru. Available at https://portal.mtc.gob.pe/transportes/caminos/normas_carreteras/mapas_viales.html

Moura, A. C. F.; Khan, A. S.; Silva, L. M. R. Extensão rural, produção agrícola e benefícios sociais no Estado do Ceará. *Revista Econômica do Nordeste*, v. 31, n. 2, p. 212- 234, 2000.

Ortega, M. A. (2018). *Conectando Mercados: Vías Rurales Y Producción Agrícola En El Contexto De Una Economía Dual (Connecting Markets: Rural Roads and Agricultural Production in a Dual Economy)*. Documento CEDE, (2018-44).

Pebesma E (2018). Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal*, 10(1), 439–446. doi: 10.32614/RJ-2018-009

Perdomo, J. A., & Hueth, D. L. (2011). Estimation of the Production Functional Form, Returns to Scale and Technical Efficiency in Colombian Coffee Zone by Means Stochastic Frontier. *Revista Colombiana de Estadística*, 34(2), 377-402.

Pfeiffer, Lisa M. Agricultural productivity growth in the Andean Community. *American Journal of Agricultural Economics*. 85, no. 5 (2003): 1335-1341.

Rada, N. E., & Buccola, S. T. (2012). Agricultural policy and productivity: evidence from Brazilian censuses. *Agricultural Economics*, 43(4), 355-367.

Rada, N., & Valdes, C. (2012). *Policy, technology, and efficiency of Brazilian agriculture*. USDA-ERS Economic Research Report, (137).

Tennekes M (2018). tmap: Thematic Maps in R. *Journal of Statistical Software*, 84(6), 1–39. doi: 10.18637/jss.v084.i06.

Trindade, F. J., & Fulginiti, L. E. (2015). Is there a slowdown in agricultural productivity growth in South America?. *Agricultural Economics*, 46(S1), 69-81.

Trujillo, Juan C., & Iglesias, Wilman J.. (2013). Measurement of the technical efficiency of small pineapple farmers in Santander, Colombia: a stochastic frontier approach. *Revista de*

Economia e Sociologia Rural, 51(Suppl. 1), s049-s062. https://doi.org/10.1590/S0103-20032013000600003

Weiss, D. J., Nelson, A., Gibson, H. S., Temperley, W., Peedell, S., Lieber, A., ... & Mappin, B. (2018). A global map of travel time to cities to assess inequalities in accessibility in 2015. *Nature*, 553(7688), 333-336.

World Bank. 2017. *Tomando impulso en la agricultura peruana: oportunidades para aumentar la productividad y mejorar la competitividad del sector*. Banco Mundial, Washington, D. C.

Appendix

Table A1 - Stochastic frontier estimation of Equation (2) using two set of estimation – with (1) road density, and (2) travel time, Peru, 2017

Variables	Estimation	
	(1)	**(2)**
lx1	0.429***	0.419***
	(0.0215)	(0.0215)
lx2	0.559***	0.522***
	(0.0139)	(0.0142)
lx11	-0.0170*	-0.0165*
	(0.00872)	(0.00870)
lx22	0.00229	0.00149
	(0.00442)	(0.00440)
lx12	0.0642***	0.0660***
	(0.00435)	(0.00434)
lx3	-0.0187*	0.110***
	(0.0109)	(0.0168)
lx33	0.120***	0.100***
	(0.00224)	(0.00296)
lx13	-0.0515***	-0.0511***
	(0.00393)	(0.00393)
lx23	-0.0589***	-0.0541***
	(0.00226)	(0.00230)
Constant	4.812***	4.408***
	(0.0724)	(0.0815)
Farm Size FE	**Yes**	**Yes**
Municipality FE	**Yes**	**Yes**
Observations	**26,939**	

Source: Own elaboration.
Note: Standard error in parentheses. Statistical significance: * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$. FE – Fixed Effects. Determinants of inefficiency are omitted (results in Table 2). Variables: x_1 – labor, x_2 – land, x_3 – Capital.