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A Stochastic Frontier Approach Applied to Farms in Selected Andean Countries

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Abstract

In this paper, we estimate a stochastic production function for Bolivia, Ecuador, Colombia, and Peru to investigate whether road infrastructure affects farm technical inefficiency. We use agricultural censuses of Colombia and Bolivia in 2013 and 2014, respectively; national agricultural surveys in 2017 of both Ecuador and Peru; and data on the road network and travel time to the nearest town with 50,000 inhabitants or more. Our main findings are that irrigation increases the value of production and road network decreases farm technical inefficiency, that is, road density (travel time) increases (decreases) farm technical efficiency.

Keywords: energy use, irrigation, farm technical efficiency, road density, travel time

JEL Codes: C31, Q12, Q14

1. Introduction

The Andean countries produce 16.3% of the agricultural value of production in South America, equivalent to 1.2% of the world value of production in 2016 (Food and Agriculture Organization [FAO], 2020). However, farmers in these countries still face limited and poor-quality road network. Colombia, Peru, Ecuador, and Bolivia have lower road density compared to developed countries, generating considerably higher transport costs and limiting their competitiveness in the international agricultural market (Briceño-Garmendia et al., 2015). Road networks are a key factor in goods and services production and distribution, the mobility of people, and the consumption of goods and services. A poor-quality and limited road network and inaccessibility to markets might limit a farm's ability to manage production inputs efficiently. In this working paper, we estimate how road density affects technical efficiency at the farm level for Bolivia, Peru, Ecuador, and Colombia.

Road networks are not equally distributed across these countries, bypassing a large population of mostly subsistence and small farms.[1] This pattern results in high travel time to the nearest town with 50,000 inhabitants or more. Low road density and great inaccessibility might result in restricted access to information, extension (technical assistance), credit, and other essential services that contribute to raising agricultural production and farm income. Three studies have investigated distance to the nearest city for countries studied in this working paper, World Bank (2017) and Espinoza et al. (2018) for Peru and Larochelle and Alwang (2013) for Bolivia. Several studies have estimated the effect of roads and road density on technical efficiency (change) and agricultural total factor productivity for Brazil and other countries (Mendes et al., 2009; Rada & Valdes, 2012; Rada & Buccola, 2012; Gasques et al., 2012). A few other papers investigate

[1] More than 85% of the farms in Colombia and Bolivia and more than 55% in Peru and Ecuador have less than 10 ha.

technical efficiency for these countries, but focus on one region, activity, or product (Trujillo & Iglesias, 2013; Melo-Becerra & Orozco-Gallo, 2017; Fletschner et al., 2010; Larochelle & Alwang, 2013; González-Flores et al., 2014). They find that these variables contribute positively to increased agricultural production, efficiency, and total factor productivity (TFP). Our working paper adds to the literature by estimating farm technical efficiency and its determinants for these countries, including road networks.

Another objective of this working paper is to estimate the semi-elasticity for irrigation for these countries. The literature indicates that irrigation adoption can increase the value of agricultural production (Antle, 1983; Evenson, 2001; Burney & Naylor, 2012). Less than 50% of the farmers in the countries investigated in this working paper have adopted irrigation:[2] 30% of the farmers reported adopting irrigation in Bolivia (Primer Censo Agropecuario 2013), 33% in Colombia (Tercero Censo Nacional Agropecuario 2014), 27% in Ecuador (Encuesta de Superficie y Produccion Agropecuaria Continua 2017),[3] and 47% in Peru (Encuesta Nacional Agropecuaria 2017).

To estimate technical efficiency, we use information from the Encuesta Nacional Agropecuaria 2017 for Peru, the Censo Agropecuario 2013 for Bolivia, the Tercero Censo Nacional Agropecuario 2014 for Colombia, the Encuesta de Superficie y Produccion Agropecuaria Continua 2017 for Ecuador, and data on road network (explained below) to estimate a stochastic frontier for each country separately. We find that road density (travel time) is directly (inversely) associated

[2] The proportion of land irrigated is smaller. For instance, less than 10% of the summer and winter crop was irrigated in Bolivia in 2013 (Censo Agropecuario 2013). In Table 1 we display the share of the farms that reported using irrigation for the sample of farms considered in the estimation. The numbers also differ, because we did not consider all crops when composing the sample; see the section 3.2 for an explanation.
[3] For Ecuador, 32% of the farmers producing temporary crops and 26% of those producing permanent crops reported using irrigation in the survey examined.

with technical efficiency for most of the countries and that irrigation can increase, on average, the value of production by more than 20%.

2. Background[4]

2.1. Efficiency

This section briefly describes the literature on technical efficiency for one or more of the countries studied in this working paper. 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 et al. (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 working paper is their finding that (Euclidian) distance to the market (from 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.

Espinoza et al. (2018) estimate technical efficiency for Peruvian farms also using the metafrontier analysis of Huang et al. (2014) and data from the Encuesta Nacional Agropecuaria of 2015 to identify potential differences between regions (Costa, Sierra, and Selva). In their analysis, they exclude large farms and livestock producers, working with a sample of 23,686. Even though they focus on a subset of the survey sample, they build the output and inputs similarly to how we build them in this working paper: they consider labor, land, and capital as inputs and the value of production as output. Furthermore, they account for accessibility by measuring road distance and

[4] There is a large body of research that investigates the effect of road network and irrigation on agricultural production and efficiency. We review here a few studies that relate to the objective and method of the paper.

travel time to cities with 50,000 inhabitants or more. They find mixed results for the effect of distance on inefficiency (nonsignificant for one region, positive for another, and negative for a third), and that access to extension and credit services decreases inefficiency. World Bank (2017) reports similar results for Peru.

A few other papers investigate farm technical efficiency for these countries but focus on one region, activity, or product. Larochelle and Alwang (2013) estimate farm technical efficiency for Bolivian Andes potato farms and find a low level of efficiency (0.56), probably due to the region's high vulnerability to climate shocks. Trujillo and Iglesias (2013) estimate technical efficiency for small pineapple farms in the Department of Santander in Colombia and find that farmers' characteristics such as schooling and years of experience may be related to a decrease in technical inefficiency. They also account for credit in the inefficiency error term and find that credit decreases inefficiency.

González and Lopez (2007) estimate household efficiency in Colombia, focusing on the effect of political violence on inefficiency using an input-oriented stochastic distance frontier. Like our working paper, they include household distance to market and find that when distance is statistically significant, it decreases inefficiency.

As we do in this study, Ortega (2018) studies road networks, investigating the impact of improvements in them in Colombia on agricultural production and other key variables. This author uses a difference-in-difference technique based on 3 years of survey data following small farmers of four Colombian regions: Atlántica Media, Cundi-boyacense, Eje Cafetero, and Centro Oriente, and finds that changes in the quality of rural roads affect agricultural production nonlinearly. Production depends on the distance to local 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 findings, they do shed light on the dynamic relationship between agricultural production and distance to markets we investigate. Several studies have looked at technical efficiency and agricultural total factor productivity (Ag TFP) for the countries analyzed in this working paper (Pfeiffer, 2003; Fuglie, 2010; Ludena, 2010; Trindade & Fulginiti, 2015; Jiménez et al., 2018).[5] Jin and Huffman (2016), also investigating Ag TFP, specifically the effect of credit on it, find that rural extension services increase Ag TFP for most American states, and they estimate that the real social rate of return of investments on extension services is more than 100%.

In addition to analyzing the effect of road network on technical efficiency, we estimate whether access to extension and credit services affects farm technical efficiency. On this topic, a few papers have indirectly investigated the effect of rural extension services on 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. (2021) similarly find that rural extension services increase farm efficiency.

[5] Most of the studies estimated the Ag TFP for the Andean countries within a world or regional analysis. Trindade and Fulginiti (2015) find that Bolivia and Colombia had the lowest TFP growth during the period, 0.708% and 0.736% respectively, for the period 1969–2009. On the other hand, Venezuela (1.731%), Ecuador (1.639%), and Peru (1.538%) are among the countries with the highest rates for the region and period. Their analysis considers in more detail a subset of the countries investigated by Fuglie (2010), who 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: the 1961–2000 averages are 0.6% for Bolivia, 1.5% for Colombia, 0.2% for Ecuador, 0.7% for Peru, and 1.2% for Venezuela. Pfeiffer (2003) estimates the Ag TFP for all Andean countries (representing a subset of those considered by Trindade & 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 et al. (2018) estimate the technical change in agricultural production using country data (as in Pfeiffer, 2003; Ludena, 2010; Fuglie, 2010; Trindade & 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 during the period 1975–2013 due to six major events that affected agriculture in Colombia, such as the intensification of armed conflict (1998–2002) and the commodities price boom (2003–2009).

2.2. Road Network

2.2.1. Road density

To examine whether road network affects farm efficiency, we use several data sources on the road network for each country. For Peru, we use information from the Ministerio de Transportes y Comunicaciones (Gobierno del Perú, 2019) for 2019; for Bolivia, we use information from Consejo Suramericano de Infraestructura y Planeamiento (COSIPLAN) (2015); for Colombia, we use information from the Departamento Administrativo Nacional de Estadística (DANE, 2019c) on Marco Geoestadistico Nacional (MGN); and for Ecuador, we use information from the Ecuadorian Instituto Geografico Militar. The data, which were on all types of roads, was used to calculate[6] the road length in kilometers (km).

Based on the literature, we also constructed the variable road density (z_1). To calculate this variable, we used the data described in the previous paragraph to calculate the total roads' length (RL) in a municipality area, in kilometers (km), and the geopolitical administrative information to calculate this municipality area (AM) in square kilometers (sq. km). z_1 is the ratio of these two variables ($z_1 = RL/AM$) and is in km/sq. km. The road density variable depends on what is considered roads; it increases as we include nonpaved roads in the calculation. As one of our objectives is to identify the effect of accessibility on agricultural production, we have included all types of roads in the calculation of the main road density variables.

[6] To build this variable, we use the R version 3.6.1 programming language and software environment (https://www.r-project.org) and the sf package (Pebesma, 2018) to upload the shapefiles .

2.2.2. *Travel time to the nearest large city*

Rich geographic information on roads provided by governments and private institutions has enabled 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 Maps data, Weiss et al. (2018) estimate the travel time to the nearest urban center, establishing a link between travel time and countries' income.

Briceño-Garmendia et al. (2015) assess several aspects of the road network and accessibility in Colombia, Ecuador, and Peru using a few of the sources discussed.[7] Relevant to our discussion, they calculate accessibility scores and map them for these countries, finding results that resemble those of Weiss et al. (2018). In this working paper, we choose to use the measure provided by Weiss et al. (2018).

In our analysis, we used the county's average travel time to the nearest city of 50,000 inhabitants (or 1,500 or more inhabitants per square kilometer), based on Weiss et al. (2018). This measure captures not only distance, but also the quality of the roads and transportation services. A country's geography significantly influences the character of transportation infrastructure such as road networks, which are in turn directly linked to the population's accessibility.

The distribution of the roads and the travel time in these countries partially reflect the presence of the Andean Mountains. The region around Iquitos in Peru, for example, is connected by only a few roads and a few rivers such as the Amazon River. In an exploratory exercise, we compared

[7] Briceño-Garmendia et al. (2015) use a robust decision-making approach to assess policy designs for road networks under uncertainty, particularly associated to climate events, for Colombia, Peru, and Ecuador. They use a wide range of data sets 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).

the travel time geographic distribution calculated here for Peru based on Weiss et al. (2018) with that by Briceno-Garmendia et al (2015) for the same country and the results were similar.

In Ecuador, higher travel time is observed in forest areas, mainly the Amazon Forest. Urban areas are clustered in the coastal and central parts of the country; the capital Quito is in the central northern portion of the country. A similar pattern is observed in Colombia: in forest areas, mainly the Amazon Forest, travel time is considerably higher than in other regions of the country. The geographic distribution of this variable for both Ecuador and Colombia, provided by Weiss et al. (2018), resembles the results obtained in Briceño-Garmendia et al. (2015), which provides us assurance that this variable represents accessibility.

Bolivia's travel time geographical distribution differs slightly from those of the previous countries for three reasons. First, the forest areas (including the Amazon Forest) are in the west, not the south of the country, as in Colombia and Ecuador. Second, the lowest political-administrative boundary available to us is the municipal level. Some of the municipalities in Bolivia are considerably larger than in Ecuador and Peru. Third, there are urban centers in all regions of the country. Those in the central portion of the country (Santa Cruz de la Sierra, Cochabamba, and La Paz, east to west) are regional economic clusters. From north to south, Riberalta, Sucre, Potosi, and Tarija function as local economic centers for rural populations.

2.3. Irrigation

Colombia, Peru, Bolivia, and Ecuador have initiated several policies and projects aimed at increasing the amount of irrigated land and improving the quality of irrigation systems. The existence of these initiatives helps us to understand the importance these countries have placed on irrigation technology. In this section, we outline several projects completed and underway in the territories of these countries.

Over the past several years the Colombian government's interest in increasing irrigated land has been apparent (DANE, 2019b). Irrigation diffusion has the potential to have a significant impact on production in Colombia, because, as of 2014, only a small portion of land devoted to agriculture was irrigated (DANE, 2019a). In December 2019, the Colombian government announced an investment of COP 2.87 billion (equivalent to USD 850,000, based on the exchange rate in December 2019) to promote irrigation adoption over the next several years. These investments are part of the National Irrigation Plan (Plan Nacional de Riego) and support the objective of applying irrigation to 10% of the country's agricultural land—equivalent to 744 thousand hectares (ha)—by 2038 (Gobierno de Colombia, 2019).

In Peru, the main objective of the national policy formulated by the Peruvian Ministry of Agriculture and Irrigation is to further increase irrigation adoption (Gobierno del Perú, 2016), which has risen in recent years, reaching 21% of the land under cultivation in 2017 (Instituto Nacional de Estadística y Informática, 2019). The Peruvian Irrigation Subsector Project (PSI) was designed in the late 1990s and was implemented in two formal phases over the past nine years, the first between 1997 and 2004 and the second, initially planned for 2005, was launched in 2006. Project documents indicate that 313 km worth of canals were rehabilitated, rebuilt, or improved, including 165 main intakes, 1,257 structures, and 49 wells affecting 125,200 families and 443,000 ha of land associated with 40 water users' associations (or WUAs). Roughly one-third of Peruvians live in rural areas and the bulk of their income is linked to agriculture. The coastal region is abundant with small landholders who own on average fewer than 3 ha. The presence of inefficient irrigation schemes exacerbates the challenges many rural farmers face, particularly those below the poverty line (Del Carpio et al., 2011).

In Bolivia, through the construction of new irrigation systems and the improvement of existing ones the government has contributed to the increased in the total irrigated area in the country. This growth has occurred since the enactment of the 2004 Irrigation Law, which allowed for the regularization of water rights and established administrative processes for accessing water. In addition, the National Irrigation Development Plan, approved in 2007, aims to achieve 450,000 irrigated ha by 2025 (Gobierno del Estado Plurinacional de Bolivia, 2020).

Inefficient irrigation schemes exacerbate the challenges many rural farmers face, particularly those below the poverty line (Escobal, 2004). To address this problem, Bolivia has implemented two major irrigation programs over the past few years: the National Irrigation Program (PRONAR) and the National Irrigation Program with Focus on Cuenca (PRONAREC). PRONAR was initiated as a project in 1996 to minimize risk for small, regional producers operating in the inter-Andean valleys, the highlands, and the Chaco. In these regions, farmers have developed traditional irrigation systems through strong social organization and with autonomous management. However,there are some difficulties in the collection and conduction of water due to the topographic characteristics and how the sockets and channels were built. An estimated USD 37 million was invested and more than 160 projects completed through PRONAR between 1997 and 2005 (Interamerican Development Bank - Gesellschaft für Technische Zusammenarbeit, 2005). PRONAREC, an IDB-financed program, promotes the integrated and participatory management of water resources. The program finances public infrastructure for the implementation or rehabilitation of irrigation systems and offers agricultural extension services to farmers.[8] Lopez

[8] The third phase of this program (BO-L1106) is currently underway.

and Salazar (2017) find that the beneficiaries of the PRONAREC program, compared to the control group, observed an increase of 60–70% in the value of agricultural production, among other positive outcomes such as improvement in market access resulting in 20–30% higher sales and an increase of 35–45% in total household income.

Although Ecuador has estimated water resources of 38,372 m^3 per capita, such resources are inadequately distributed, being heavily concentrated in the country's Amazon and Coastal regions (Sotomayor & Garcés, 1996). The Ecuadorian Ministry of Agriculture and Livestock has implemented the National Irrigation Plan, which seeks to (1) expand coverage and improve the social, economic, and environmental efficiency of all irrigation systems; (2) strengthen irrigation groups so they can assume the management of irrigation systems and drainage sustainably and efficiently; and (3) promote a sustained process of reorganization and flow redistribution that ensures equitable access to irrigation water. It is estimated that as of 2012, 942,000 ha have access to water. The goal of the ongoing program is to irrigate 1.5 million ha, which is expected to benefit 420,000 families. By 2027, the objective is to irrigate 1.6 million ha, benefitting 453,000 farming families. (Gobierno de la República del Ecuador, 2020). As of 2017, 27% of the land under cultivation in the country was able to be irrigated, which is a considerably high share compared to other Andean countries (FAO, 2020).[9] However, it is estimated that 95% of the country's irrigation structures use outdated technologies (Instituto Nacional de Estadística y Censos, 2021).

[9] According to data from FAOSTAT (FAO, 2020), when considering all irrigation techniques, 2.5% of Colombia's land under cultivation could be irrigated in 2017. This is compared to 8% in Bolivia, 11% in Peru, and 5% in Venezuela.

3. Analytical framework

To obtain the farm technical efficiency, we estimate a stochastic frontier production function, which consists of estimating a production function that represents the relation between agricultural input and output (González-Flores et al., 2014; Helfand & Levine, 2004; Rada & Valdes, 2012; Helfand et al., 2015). We 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 the *i-th* farm, X_i is the vector of inputs of the *i-th* farm, and β is a vector of the parameters to be estimated, which define the production technology. The error term v_i represents the random error term and the error term u_i captures the technical inefficiency of the *i-th* farm, that is, the distance from the production frontier. We assume that u_i follows an exponential distribution. Technical efficiency is obtained following the approach of Battese and Coelli (1988). We assume that the inefficiency term u_i is determined by a vector of variables $\boldsymbol{z}$ such as road density (or travel time), population density, access to extension, access to credit, and energy use (these variables are explained in later sections).

3.1 Data

We used agricultural census and surveys for each country that were designed and implemented in different ways. We sought to build the variables for each country as close as possible across countries. Even where one data set is especially rich, such that for Peru, we limited our analysis to the same variables. For Peru, we used the Encuesta Nacional Agropecuaria of 2017, for Bolivia the Agricultural Census of 2013 (Censo Agropecuario 2013 [Instituto Nacional de Estadística, 2020]), for Colombia the Agricultural Census of 2014 (Tercero Censo Nacional Agropecuario

2014), and for Ecuador the Encuesta de Superficie y Produccion Agropecuaria Continua of 2017 (ESPAC). We described the data on roads we used in the previous section.

In the efficiency analysis, we also look at energy, extension, and credit, aiming to control for such characteristics in our model. Lack of access to energy sources might also have restricted farmers' ability to access information or use better inputs. In Bolivia, fewer than 8.5% of the farmers used electricity in farm production; 54.5% used firewood. And, as mentioned above, there is evidence in the literature that these variables decrease farm inefficiency.

3.1.1. Peru

For Peru, we used the Encuesta Nacional Agropecuaria of 2017, which has information on 29,218 and 1,537 small-/medium- and large-size farms (*unidade de produccion agropecuaria*) representing a total of 2.2 million Peruvian farms. In terms of credit, 11.1% of the small- and medium-size farms and 32.5% of the large-size farms requested and obtained credit (question: *¿Obtuvo el crédito solicitado?*). In 2017, 7% of the small- and medium-size farms and 43% of the large-size farms had access to extension assistance (question: *¿En los últimos 3 años, ud. ha recibido asistencia técnica?*).

We measured labor as the sum of paid and unpaid employees in both agricultural and livestock production. We classified unpaid employees as the number of persons who answered the question "*¿Participa en las labores agropecuarias de sus parcelas o chacras o en la crianza de sus animales?*" and added 1 to account for the main producer. We calculated capital as the sum of the cost of machinery, equipment, fuel, maintenance expenses, crop inputs (such as fertilizer), and livestock inputs (such as animal medicine). To estimate the value of production, we considered all crops, cattle,[10] and milk. We used the value of production reported by the farmer and converted the value of production to USD of 2017 (SOL 1 = USD 0.3). In addition to these inputs, we also considered whether the producer used irrigation of any type.

3.1.2. Bolivia

For Bolivia, we used the Agricultural Census of 2013, which has information on 871,927 farms (*unidade de produccion agropecuaria*) with 2,760,238.6 ha under cultivation. In 2013, 73,413 farmers had access to credit (question: *¿Obtuvo el crédito solicitado?*), 147,725 (17%) had access to at least one type of extension service (53,952 had access to extension services associated with equipment, 18,853 to services associated with machinery, 86,585 to services associated with inputs, 45,534 to technical assistance, and 48,953 to courses) (question*: ¿Tipo de asistencia o apoyo recibido?*). In 2013, 475,589 farms used firewood as an energy source, 166,493 farms used gasoline, and 122,767 used crop residues (question: *¿Para sus actividades agropecuarias utiliza Energía eléctrica de red?*). Only 73,984 farms reported electricity as a principal source for energy for agricultural production.

Labor was measured as the sum of paid and unpaid employees in both agricultural and livestock production. Capital was calculated as the sum of four groups: machinery, equipment, vehicles, and constructions (buildings).To estimate the value of production, we considered both winter and

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

summer crops,[11] cattle,[12] and milk. The census does not provide information on prices; we used average prices for domestic markets by the department for each of these products from the Encuesta Agropecuaria 2015. We converted the value of production to USD of 2015 (BOB 1 = USD 0.14). We also considered, in addition to these inputs, whether the producer used irrigation of any type.

3.1.3. Colombia

For Colombia, we used the Agricultural Census of 2014 (Tercero Censo Nacional Agropecuario 2014), which has information on 2,913,163 observations, of which 81.4% are farms (*unidade de produccion agropecuaria*) with a total area of 108,993,335 ha. Of the 10.7% of farmers who requested credit, 88.4% obtained it, which implies that 9.5% of the farms obtained credit (requested and were approved).

The census reports information on 10 different aspects of extension services (question: *¿Durante el 2013, Usted recibió asistencia o asesoría para el desarrollo de las actividades agropecuarias?*) such as technical assistance associated with agricultural practices for crop and livestock production, environmental practices, soil management, postharvest management, commercialization, business management, etc. A total of 16.5% of the farms had access to

[11] Wheat, corn, rice with husk, sorghum, barley, oats, quinoa, amaranth, cassava, cabbage, cauliflower, broccoli, lettuce, spinach, celery, parsley, chard, coriander, wild marigold, heart of palm, watermelon, melon, locoto, green chili pepper, pod chili pepper, bell pepper, cucumber, eggplant, tomato, pumpkin, squash, *achojcha*, green pea, green bean, vanilla, carrot, beet, turnip, radish, garlic, onion, avocado, banana (banana), banana (dessert), fig, mango, papaya, pineapple, *achachairú*, star fruit, passionfruit, custard apple, *noni*, *copoazu*, *ocoró*, grapefruit, lemon, orange, tangerine, lime, grape, strawberry, blackberry, apple, pear, quince, peach, plum, almond in shell, nut, *pacay*, *tuna*, *camu camu*, soy, peanut, linseed, sesame, chia, coconuts in shell, palm nuts, potato, sweet potato, , *hualuza*, *izaño*, *oca*, *papaliza*, *racacha*, *maca*, *ajipa*, *aricoma*, coffee, cocoa, pepper, chili, anise, chamomile, annatto, peppermint, stevia, rue, oregano, jamaica, bean, chickpea, *tarwi*, rowing sugar cane, sugar cane, alfalfa, fodder barley, fodder oats, forage sorghum, broom sorghum, fodder cana, fiber cotton, coca, carnation, gladiolus, illusion, poplin, broom, cardigan, *bombomose* flower, *beiby* flower, sparkle flower, *quico*, *bara de San Jose*, and tobacco.

[12] We assume that only 80% of the cattle 2 to 3 years old are sold and therefore included in the value of production.

extension services. Of the 32.8% of farms reporting the use of any source of energy in agricultural production, 83.4% used electricity, 10.8% used fuels, and 7.1% used their own electrical plant (question: *¿Para el desarrollo de las actividades agropecuarias la energia que utiliza es?*).

Labor was measured as the sum of permanent and additional employees in agricultural production (question regarding permanent employees: *¿En total; cuántas personas trabajaron de manera permanente para realizar las actividades agropecuarias; en los últimos 30 días?*; question regarding additional employees: *¿Cuántos jornales adicionales contrató directamente para realizar las actividades agropecuarias; durante los últimos 30 días?*).

We calculated capital as the sum of the values of new and old machinery (e.g., tractors and combines) and equipment (e.g., chainsaws). To estimate the value of production, we considered crops,[13] cattle,[14] and milk. The census does not provide information on prices; we used prices from the FAO for 2014. We converted the value of production to USD of 2015 (COP 1 = USD 0.0003). In addition to these inputs, we also considered whether the producer used irrigation of any type.

3.1.4. Ecuador

For Ecuador, we used the Encuesta de Superficie y Producción Agropecuaria of 2017, a national survey of farms that represents 12.4 million ha in agriculture, 2.4 million ha in cultivated pasture, and 2.3 million ha in crops. Even though this survey asks questions regarding producer and farm characteristics such as access to credit and extension services, we did not have access to this information. Labor was measured based on the question: *¿Total de trabajadores en el terreno?*.

[13] Coffee, grape, banana, avocado, guava, sugarcane, potato chips, yellow corn, white corn, pineapple, apple, barley, green bean, carrot, cocoa beans, lemon, mango, bighead bait, bait long, cebolla leek, papaya, orange, peach, soybean, strawberry, tomato, wheat grain, sorghum, pear, cotton, beans, sorgof, rice, palm, potatoes, coconut, blackberry, soursop, and celeriac.

[14] We assume that only 80% of the cattle 2 to 3 years old are sold and therefore included in the value of production.

To measure capital, we built several variables on the quantity used of organic fertilizers, NPK, N, herbicides, insecticides, and fungicides. To estimate the value of production, we considered crops,[15] cattle,[16] and milk. This survey does not provide information on prices; we used prices from the FAO for 2017. Similar to the countries discussed above, we also considered whether the producer used irrigation of any type.

In this working paper, we only considered farmers who had a positive value of production and land in terms of at least one of the products considered (positive land). To control for outliers, we dropped all observations at the bottom 1% and top 1% of the distribution of the value of production. For Ecuador, our sample size for the estimation of Equation 1 is 23,239; for Colombia, 1,091,916; for Bolivia, 720,316; and for Peru, 26,966. We display descriptive statistics in Table 3.1.

[Table 3.1]

In Table 3.1, we also present the average value for the dummy variable capturing irrigation, equal to 1 if the farmer reported using irrigation or having positive land irrigated and produced at least one of the outputs (agricultural products) used in our analysis (discussed above). These numbers are based on the sample used in the regression and indicate that approximately 30%, 12%, 27%, and 52% of the farmers in Bolivia, Colombia, Ecuador, and Peru, respectively, used irrigation to produce at least one of the selected outputs. We also controlled for farm size by 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 ha, 5 to 10 ha, 10 to 50 ha, 50 to 100 ha, 100 to 500 ha, 500 to 1000 ha, and more than 1000 ha. Table 3.1 shows that most of the farms have less than 5 ha.

[15] Maize, soy, rice, yuca, beans, papa, melon, tomatoes, tobacco, onion, lechuga, pimento, pepino, carrote, cebada, ervilha, cacao, coffee, apples, banana, sugarcane, aguacate, palma, orange, pera, papaya, pina, mandarin orange, pina, and tea.

[16] We account only for the cattle sold.

3.2 Empirical Strategy

We estimate a translog stochastic frontier. It presents some desirable properties such as flexibility, linearity in parameters, regularity, and parsimony (Mariano et al., 2010). However, as in Battese and Coelli (1992) and Helfand et al. (2015), log likelihood ratio (LLR) tests were performed to identify the best production frontier specification (Cobb-Douglas versus translog), which pointed to the translog functional form. The stochastic production function is represented as (farm subscripts were dropped for simplicity):

$$y = \beta_0 + \sum_{i=1}^{N} \beta_i x_i + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \beta_{ij} x_i x_j + \delta' \boldsymbol{z} + \boldsymbol{\Gamma_1} + \boldsymbol{\Gamma_2} + \varepsilon \tag{2}$$

where y represents the natural logarithm of the gross value of production; x_i for $i = 1,..,N$ represents the logarithm of the following inputs: labor (x_1) and land (x_2), irrigation (dummy variable represented as x_3, not in logarithm) for all countries, and capital (x_4) for Peru; $\boldsymbol{z}$ is a matrix of variables representing capital, such as the number of tractors, for Colombia, Ecuador, and Bolivia; $\boldsymbol{\Gamma_1}$ is a matrix of municipalities dummy variables (for Bolivia and Colombia) or state dummy variables (for Peru and Ecuador); $\boldsymbol{\Gamma_2}$ represents fixed effects for farm size; β_0, $\beta_i s$, $\beta_{ij} s$, and δ are vectors of parameters to be estimated; and ε is the composed error term described before ($v_i - u_i$). We calculate production elasticities for all inputs as in Helfand et al. (2015) and the semi-elasticity for irrigation. To explain inefficiency, we include road density (or travel time), population density (to control for the effect of a large city), access to extension, access to credit, and energy use (electricity, gasoline, diesel, and wind power for Bolivia; electricity, gasoline, diesel, wind power, and solar power for Colombia).

4. Results

In Table 4.1 we present the production elasticities for equation (2) for Colombia, Bolivia, Peru, and Ecuador, 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 consistent with economic theory. Our production elasticities for Peru lie within the range reported by the World Bank (2017), which estimates production elasticities for four types of production: for example, labor elasticity ranges from 0.16 to 0.38 and land elasticity ranges from 0.29 to 0.55.

[Table 4.1]

For irrigation, we report the semi-elasticity in Table 4.1. The average semi-elasticity for Bolivia is 0.25, for Colombia it is 0.50, for Ecuador it is 0.29, and for Peru it is 0.20. Caution is needed when interpreting these elasticities and semi-elasticity and comparing across countries: they are estimates for a selected number of farms based on selected outputs and the value of production for each country is not the same. However, these average estimates indicate that adopting irrigation generates a boost in the value of production that ranges between 20% and 50% for farmers in these countries.

In Table 4.2 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, except in Colombia. Our results of the road density effect on technical efficiency for Bolivia, Peru, and Ecuador confirm the result found in the literature, namely that road density decreases technical inefficiency (Mendes et al., 2009; Rada & Valdes, 2012; Rada & 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-size Peruvian farms. They found mixed results when analyzing the three regions separately: no effect on inefficiency for the Costa region, increased inefficiency as distance increases for the Sierra region, and decreased inefficiency as distance increases for the Selva region. Their result for the Sierra region aligns with our findings. In addition, for Peru the World Bank (2017) finds that the same variable has a positive marginal effect on inefficiency except for the Sierra region. Our results corroborate their findings.

[Table 4.2]

The average technical efficiency for Bolivia was 0.55, which implies that farmers could potentially increase production by as much as 45% while keeping input constant. While farmers in La Paz (0.57), Potosi (0.56), and Oruro (0.57) were more efficient on average, farmers in Beni and Santa Cruz were the least efficient, with an average of 0.49. We found very similar results for Peru, where road density, extension, and credit decrease efficiency. While Loreto and Madre de Deus have average efficiencies of 0.62 and 0.61, respectively, Lambayeque and Ancash show average efficiencies of 0.65 and 0.64, respectively. The average efficiency across Ecuador was 0.34; Guayas and Los Rios have an average efficiency of 0.41 and Chimborazo and Azuay have average efficiencies of 0.28 and 0.25, respectively. The average technical efficiency for Colombia is 0.46, with Antioquia (0.47), Santander (0.47), and Vichada (0.45) around the average.

We also found that access to extension and credit services and energy use is associated with lower technical inefficiency for Bolivia, Colombia, and Peru. Our results corroborate what others report on the effect of access to extension and credit services on technical efficiency (Helfand & Levine, 2004; Bravo-Ortega & Lederman, 2004; Rada & Valdes, 2012; Rada & Buccola, 2012;

Gasques et al., 2012; Freitas et al., 2021). Espinoza et al. (2018) also found that credit and extension decrease inefficiency for Peruvian small- and medium-size farms (for the three regions studied).

Our findings indicate that overall, road network decreases technical inefficiency. 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. In Table 4.2, we present evidence that supports this assertion, using two different measures for Bolivia, Peru, and Ecuador: road density and travel time. Travel time is directly linked to road network; it measures both distance to the nearest large town and the quality of the road. Improvements in road networks (such as maintenance and upgrading of existing roads and construction of new ones) would result in shorter travel times and lower inefficiency.

5. Summary

In this working paper, we estimate the production technology for farms in Colombia, Peru, Bolivia, and Ecuador to examine whether road network affects farm technical efficiency. To do so, we estimate a stochastic frontier production function for each country using information on more than 1 million farms in Colombia, 700,000 farms in Bolivia, and 20,000 farms in Ecuador and Peru each. There are several ways to examine road networks. We look at the effect of road density and average 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 considers access to roads, transport availability, and road quality, in that it considers not only highways but also waterways. We measure travel time as the average of the smallest political-administrative boundary (unit) of each country, using Weiss et al. (2018).

Our results suggest that road density and travel time affect farm efficiency for the four countries. We find that increases in road density decrease farm technical inefficiency for Bolivia, Peru, and Ecuador. Similar results have been found for Brazil (Mendes et al., 2009; Rada & Valdes, 2012; Rada & Buccola, 2012; Gasques et al., 2012). On the other hand, we find that farmers who take longer to reach large towns have higher technical inefficiency in Bolivia, Peru, and Ecuador. 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 networks. However, we found an opposite effect of these variables on technical efficiency for Colombia. Several factors might have led to this unexpected result, such as the level of aggregation of our analysis, the sample of outputs selected, and the prices used in the analysis. Other studies have found mixed results for these variables, as discussed in the literature review (World Bank, 2017; Espinoza et al., 2018). For Colombia, Ortega (2018) using a richer data set found that road network affects agricultural production nonlinearly. Future research should consider a nonlinear effect in the estimation in addition to breaking down the effect by region. Our results also indicate that the adoption of irrigation increases, on average, the value of production by at least 20%.

In terms of limitation to our analsys, the agricultural censuses and surveys for these countries do not provide information on the geographic location of the farms, limiting our ability to measure travel time from the farm to the nearest large town and access to roads (a better measure than road density). These data sets only provide information for one year, so that we are not able to estimate the impact of new roads or network policies on technical efficiency. The data sets for Colombia, Bolivia, and Ecuador do not provide information on prices or the value of production. We use prices from FAO and other sources to build the variable of production for selected products. There are two drawbacks to this approach: it can potentially not capture the entire production of a farm (the farmer could be producing two crops, one considered in our sample and one not) and it assumes the same price for producers across the country. The goal of this working paper was to estimate technical efficiency and its determinants; we did not attempt to construct a unique measure of capital. Instead, we added several measures of capital to control for this variable. Future researchers should attempt to build a unique measure of capital for each country. We also did not consider climate variables in the model, which are known to explain the value of agricultural production (Mendelsohn & Massetti, 2017) and the effect of irrigation. Future research should explore how irrigation's effect on the value of production can mitigate climate change consequences.

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Tables and Figures

Table 3.1 Average values of the variables used to estimate Equation (2) for Colombia, Bolivia, Peru, and Ecuador

	Bolivia	Colombia	Ecuador	Peru
Value of prod. (*USD*)	3747	5449	27353	8777
Labor (*sum of employees*)	6.766	6.476	4.953	14.50
Land (*ha*)	6.15	11.46	21.84	33.68
Capital (*USD)*	-	-	-	5254
Irrigation (*dummy variable*)	0.298	0.116	0.266	0.521
Extension (*yes or no*)	0.0539	0.102	-	0.0922
Credit (*yes or no*)	0.0872	0.144	-	0.135
Energy (*yes or no*)	0.358	0.377	-	
Road density (*km /100 sq. km*)	0.115	31.41	0.783	35.24
Travel time (*hours*)	3.62	2.971	1.218	4.575
Pop. density (*People /sq. km*)	44.87	109.1	-	85.82
Farm size (*dummy variables*)				
0–5 ha	0.873	0.752	0.642	0.421
5–10 ha	0.0570	0.101	0.118	0.154
10–50 ha	0.0519	0.117	0.156	0.270
50–100 ha	0.0103	0.0165	0.0329	0.0625
100–500 ha	0.00672	0.0123	0.0455	0.0700
500–1000 ha	0.000869	0.00155	0.00450	0.0122
1000+ ha	0.000556	0.000998	0.00129	0.0107

Source: Own elaboration.

Table 4.1 Average production elasticities on road density for Colombia, Bolivia, Peru, and Ecuador

	$\boldsymbol{\varepsilon_{x_1}}$ *(labor)*	$\boldsymbol{\varepsilon_{x_2}}$ *(land)*	$\boldsymbol{\varepsilon_{x_3}}$ (*Irrigation*)	$\boldsymbol{\varepsilon_{x_4}}$ *(Capital)*
Bolivia	0.131*** (0.002)	0.582*** (0.002)	0.289*** (0.006)	-
Colombia	0.099*** (0.002)	0.769*** (0.002)	0.540*** (0.009)	-
Ecuador	0.473** (0.03)	0.722*** (0.017)	0.336* (0.065)	-
Peru	0.188** (0.010)	0.371*** (0.013)	0.242** (0.035)	0.475*** (0.008)

Source: Own elaboration.

Note: We calculate the capital elasticity for Peru only, given that we take the logarithm of capital measures for this country only. Elasticity for land was calculated only for the observations with positive land. ε_{x_3} represents the semi-elasticity for irrigation. Standard errors are in brackets and were calculated using the delta method. Statistical significance: * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$. Violations: for Bolivia, 4%, 0%, and <1% of the observations for labor (x_1), land (x_2), and irrigation, respectively, do not satisfy monotonicity; for Peru, 2%, <1%, 9.7%, and 2.5% for x_1, x_2, irrigation, and x_4, respectively, do not; for Ecuador, <1%, 0%, and 0% for x_1, x_2, and irrigation, respectively, do not; and for Colombia, 6%, 6%, and 19% for x_1, x_2, and irrigation, respectively, do not.

Table 4.2 Average technical efficiency and estimated parameters for the inefficiency error term

	Bolivia		Colombia		Ecuador		Peru	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Average TE	0.551	0.552	0.460	0.461	0.337	0.335	0.638	0.638
Road density	-1.568*** (0.058)	-	0.0007*** (7e+05)		-0.1443*** (0.0194)		-0.003*** (0.001)	-
Travel time	-	0.037*** (0.001)	-	-0.026*** (0.0004)	-	0.0658*** (0.0113)	-	0.011*** (0.003)
Pop. density	0.0005*** (2e+05)	0.0005*** (2e+05)	0.0003*** (6e+06)	-8.21e-0.6 (6e-06)	-		0.0001** (5e+05)	0.0007 (5e+05)
Energy	-0.024*** (0.007)	-0.034*** (0.007)	-0.076*** (0.005)	-0.096*** (0.005)	-		-	-
Credit	-0.241*** (0.011)	-0.239*** (0.011)	-0.254*** (0.006)	-0.267*** (0.006)	-		-0.519*** (0.061)	-0.516*** (0.061)
Extension	-0.186*** (0.013)	-0.179*** (0.013)	-0.457*** (0.008)	-0.463*** (0.008)	-		-0.439*** (0.071)	-0.429*** (0.071)

Source: Own elaboration.
Note: We used two sets of estimation, one with road density and a second with travel time, for Colombia, Bolivia, Peru, and Ecuador. 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. Standard error in brackets. Statistical significance: * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Appendix

Table A1. Stochastic frontier estimation of Equation (2)

	Bolivia		Colombia		Ecuador		Peru	
Variables	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
lx1	0.0356***	0.0356***	0.129***	0.123***	0.485***	0.481***	0.429***	0.419***
	(0.00293)	(0.00293)	(0.00259)	(0.00260)	(0.0306)	(0.0308)	(0.0215)	(0.0215)
lx2	0.615***	0.616***	-0.0278***	-0.0259***	0.759***	0.754***	0.559***	0.522***
	(0.00189)	(0.00189)	(0.00150)	(0.00150)	(0.0130)	(0.0130)	(0.0139)	(0.0142)
lx11	0.0758***	0.0757***	0.754***	0.756***	0.0924***	0.0980***	-0.0170*	-0.0165*
	(0.00176)	(0.00175)	(0.00133)	(0.00133)	(0.0229)	(0.0233)	(0.00872)	(0.00870)
lx22	0.0161***	0.0161***	0.205***	0.205***	0.0389***	0.0410***	0.00229	0.00149
	(0.000904)	(0.000904)	(0.000610)	(0.000610)	(0.00596)	(0.00598)	(0.00442)	(0.00440)
lx12	-0.0245***	-0.0243***	-0.00761***	-0.00776***	-0.0823***	-0.0837***	0.0642***	0.0660***
	(0.000831)	(0.000831)	(0.000523)	(0.000523)	(0.0103)	(0.0104)	(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	6.260***	6.268***	8.165***	8.170***	7.216***	7.243***	4.812***	4.408***
	(0.0132)	(0.0132)	(0.00398)	(0.00398)	(0.0870)	(0.0876)	(0.0724)	(0.0815)
Capital Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Departmental or Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	732,649	732,649	1,083,026	1,083,026	23,227	23,227	26,939	26,939

Source: Own elaboration.
Note: We use two sets of estimation, one with road density and a second with travel time, for Colombia, Bolivia, Peru, and Ecuador. FE are Fixed Effects. Determinants of inefficiency are omitted (results are shown in Table 4.1). The statistically significant capital variables in the models were, for Bolivia, machinery and equipment; Colombia, tractors and harvesters; and Ecuador, quantity used of NPK. For Peru, the capital elasticity was 0.486. The variables were x_1 – labor, x_2 – land, and x_3 – capital. Standard error in brackets. Statistical significance: * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.