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Agricultural Total Factor Productivity and Road Infrastructure in South American Countries

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Abstract

In this working paper, we estimate agricultural total factor productivity (Ag TFP) for South American countries over the period 1969–2016 and identify how road density affect technical efficiency. In 2015, Colombia, Peru, Venezuela, Ecuador, and Bolivia, the Andean countries, had 205,000; 166,000; 96,000; 89,000; and 43,000 kilometers of roads, respectively. A poor-quality and limited road network, along with inaccessibility to markets, might limit the ability of farms to efficiently manage production inputs, raising technical inefficiency. We find that the Ag TFP growth rate per year for South American countries, on average, is 1.5%. For the Andean countries, we find an even smaller growth rate per year of 1.4% on average. Our findings suggest that higher road density is associated with lower technical inefficiency.

Keywords: Agricultural total factor productivity, Andean countries, South American countries, Road density

JEL Codes: D24, Q13, Q18

1. Introduction

In 2016, the Andean countries—Venezuela, Colombia, Ecuador, Peru, and Bolivia—produced 16.3% of the agricultural value of production in South America, equivalent to 1.2% of the world agricultural value of production that year (FAO, 2020). Estimates of agricultural total factor productivity (Ag TFP) indicate that these countries saw average growth rates greater than 1% per year in the 1990s and 2000s (Pfeiffer, 2003; Ortega & Lederman, 2004; Fuglie, 2010; Ludena, 2010; Trindade & Fulginiti, 2015). Except for Pfeiffer (2003), these studies estimate Ag TFP at the world or regional level, examining the Andean countries indirectly and excluding data after 2009. None of these studies investigate the role of road density in technical efficiency for these countries, a key component for agricultural production and distribution. Colombia, Peru, Ecuador, Bolivia, and Venezuela have low road density compared to developed countries, resulting in a considerably high cost of transport that in turn limits their competitiveness in the international agricultural market (Briceño-Garmendia, Moroz, & Rozenberg, 2015). As of 2015, Colombia, Peru, Ecuador, and Bolivia had 205,000; 166,000; 89,000; and 43,000 kilometers of road, respectively. In this working paper we use stochastic frontier analysis to estimate the Ag TFP for countries in South America, focusing on the Andean countries, from 1969 to 2016, and identify how road density affects technical efficiency.

Road investments have the potential to increase agricultural competitiveness and production. South American countries lack an integrated and uniform road infrastructure (De Souza & Liu, 2019). These countries face similar challenges with respect to incentivizing investments in their road networks, given the relevance of this infrastructure and the lack of other modes of transportation (Clavijo, Vera, & Cuellar, 2019). Latin American and Caribbean countries have a considerably lower road density compared to developed countries. While these countries have a road density of 15 km/100 sq. km, Europe has a road density of 26 km/100 sq. km, North America 42 km/100 sq. km, and South Asia 96 km/100 sq. km (Briceño-Garmendia et al., 2015). To overcome this deficiency, Brazil, Chile, Bolivia, Peru, and other South American countries have shifted the burden of road investments to the private sector, sometimes arranging for road concessions via public-private partnerships (Bitran, Nieto-Parra, & Robledo, 2013).

Several studies have estimated the Ag TFP for some or all South American countries (Pfeiffer, 2003; Fuglie, 2010; Ludena, 2010; Trindade & Fulginiti, 2015), but these papers have not estimated the effect of road density on technical efficiency for the Andean countries. Here we estimate a stochastic frontier for 10 countries over the period 1969–2016, which complements the Trindade & Fulginiti (2015) data for 1969–2009. We account for seven more years (2010–2016), a period that includes changes in the agricultural sector in South America and analyze how road density affects technical efficiency for these countries. Our study complements studies by Rada, Buccola, & Fuglie (2011), who examined the effect of roads on the technical efficiency of Indonesian agriculture, and studies by Rada & Valdes (2012), Rada and Buccola (2012), and Rada (2013), who analyzed this topic for Brazilian agriculture.[1] These papers find that road density decreases inefficiency variance and increases the efficiency mean. Our results show that the Ag TFP growth per year for South American countries as a weighted average is 1.55%, while for the Andean countries, we find a smaller average growth per year of 1.1%. Our findings suggest that lower technical inefficiency is associated with higher road density.

[1] Mendes, Teixeira, and Salvato (2009) found that roads (in kilometers) increase Brazilian TFP. While in this study we investigate the effect of road networks on the technical efficiency of South American countries, this might shift the frontier. Future research could explore this line of investigation.

2. Literature Review[2]

Most existing studies estimate the Ag TFP for the Andean countries within a world or regional analysis. Trindade & Fulginiti (2015) estimate the Ag TFP for all Latin America countries using data at the country level over the period 1969–2009 and find that, among the countries analyzed in this paper, Bolivia and Colombia have the lowest average Ag TFP growth during the period, 0.708% and 0.736%, respectively. On the other hand, the rates in Venezuela (1.731%), Ecuador (1.639%), and Peru (1.538%) are among the highest average for the region and period. Trindade & Fulginiti (2015) consider a subset (with a more detailed analysis) of the data set in Fuglie (2010), which 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 growth rates for these countries when analyzing the Latin American and Caribbean regions, with the following averages for 1961–2000: Bolivia, 0.6%; Colombia, 1.5%; Ecuador, 0.2%; Peru, 0.7%; and Venezuela, 1.2%.

A few papers estimate the Ag TFP growth specifically for the Andean countries or for one of the countries investigated in this working paper. Pfeiffer (2003) estimates the growth for all Andean countries, which represent a subset of those discussed in Trindade & Fulginiti (2015), and finds average TFP growth 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, & Foster (2018) estimate technical change in agricultural production from 1975 to 2013 using country data (as in Pfeiffer, 2003; Fuglie 2010; Ludena, 2010; Trindade & Fulginiti, 2015). Using different approaches and functional forms for the production function, they find that annual technical change ranges from 0.8% to 1.3% and varies throughout the period due to six major events,

[2] In this section, we present a brief discussion of a few articles relevant to our working paper. There is a vast literature investigating Ag TFP and the role of road density, which have not been discussed here.

including armed conflict intensification (1998–2002) and the commodities price boom (2003–2009), which affected agriculture in Colombia.

Several studies estimate the Ag TFP growth just for Brazil, a country that is also included in our sample (Gasques, Bastos, & Bacchi, 2008; Mendes, Teixeira, & Salvato, 2009; Gasques, Bastos, Valdes, & Bacchi, 2012; Rada & Buccola, 2012; Rada & Valdes, 2012; Rada, Helfand, & Magalhães, 2019). A few of these papers are directly relevant to our study, given that they investigate the impact of roads on Ag TFP and efficiency. Mendes, Teixeira, and Salvato (2009) find that total road length increases Ag TFP for Brazilian agriculture. In this paper, authors first estimate Ag TFP and then estimate the impact of road length on Ag TFP. Rada & Valdes (2012) and Rada & Buccola (2012) focus on the impact of roads density on the technical efficiency of Brazilian agriculture and find that greater road density increases technical efficiency. In a specific study on agriculture in the Brazilian Cerrado, Rada (2013) highlights the role of paved road infrastructure in expanding production opportunities. Finally, Rada et al. (2011) investigating the impact of roads on technical efficiency in the context of Indonesian agriculture, find that roads (also measured as road density) do increase technical efficiency.

3. Background[3]

Andean countries have developed several policies targeting road networks, and in this section we briefly discuss some of them. Looking at all countries studied in this working paper, Andrian, Beverinotti, Castilleja-Vargas, Díaz-Cassou, & Hir (2019) argue that continuous investment in road networks is necessary to improve road quality and to increase countrywide coverage.

[3] This section briefly discusses some of the programs targeting road networks in these countries. It is not a complete analysis of the infrastructure policies in these countries.

In Bolivia, road infrastructure is part of the Social and Economic Development Plan (PSDE 2016–2020), which has 48 projects that involve either building new roads or repairing and improving existing ones, such as expanding export corridors, double roads, integration with productive regions, department-capital connections, west-to-north and north-to-south corridors, and the construction of bridges (Estado Pluracional de Bolivia, 2016). Currently, 32 projects in the PSDE are underway in nine different locations (ABC, 2018a). Administradora Boliviana de Carreteras (ABC) official reports indicate that these projects will help expand tourism in the Beni department (ABC, 2018b) and the development of the Andean Amazon (ABC, 2018c). Paved roads are seen as the axis for regional integration, and are expected to improve the quality of life of those living in department of Oruro (ABC, 2019) and in Cochabamba and Santa Cruz (ABC, 2018d) through access to markets and to different goods and services.

Andrian et al. (2019) point out that Colombia has one of the lowest road densities per habitant values for Latin American countries, as well as high transport costs, because of road vulnerability to exogenous events and the low level of investment in connecting cities. One possible benefit of increasing road density in the country is an increase in firm productivity. Using annual manufacturing surveys for Colombia, Cárdenas, & Sandoval (2008) find that road infrastructure increases the total factor productivity (TFP) of companies. Investing in the transportation sector was one of the country's investment goals implemented via concession programs, an important instrument to reduce costs and increase productivity (Cárdenas, Gaviria, & Meléndez, 2005). These private investments have helped the development of the road network in Colombia (Cárdenas et al., 2005; Muriel & Felipe, 2015). Studies also conclude that these investments should prioritize the construction of a binational infrastructure, as well as construction and improvement of priority highways (Zamora Fandiño & Barrera Reyes, 2012), but also consider the effects on the environment (Etter, McAlpine, Wilson, Phinn, & Possingham, 2006).

Andrian et al. (2019) indicate that the investments in roads in Ecuador seek to improve the road network, but the execution of funded projects faces efficacy challenges. The authors indicate that poor resource management and implementation practices, given a fiscal crisis in the country, reinforce road network degradation. Benedictis Villacreses, Calfat, & Flôres Jr (2006) point out the unequal resource distribution in Ecuador when examining investments by surface area of the provinces. Bilsborrow, Barbieri, & Pan (2004) also spotlight the underinvestment in the Amazon region. While the Andean areas have the highest road density, the Amazon provinces have the lowest. Vaca, Soqueb, & Castro (2016) analyze the relationship between road infrastructure and economic growth in Ecuador (in the parishes of Sevilla Don Bosco and San Isidro, which are both in Morona Santiago Province) and did not find any effect of private investment in roads on the economic growth in the region.

According to Acuña & Riojas (2011), improvements in road networks can increase agricultural productivity. In the case of Peru, for example, the road network is of poor quality and leads to high logistical costs (Andrian et al., 2019). Escobal (2001) finds that road network improvement in that country can reduce transaction costs, especially among small farms, which would be able to bring their products to outlet markets at lower cost. Corahua Benites & Mendoza Silva (2018) purposed a logistical process model for a Peruvian agricultural cooperative to increase its revenues. Their suggestion set a precedent for other initiatives—private ones included—to draw up their own functional road models.

4. Method

For this working paper, we estimated the agricultural total factor productivity (Ag TFP) for 10 countries in South America (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) from 1969 to 2016, based on Trindade & Fulginiti (2015). These authors estimate the Ag TFP for the same countries for a shorter period (1969–2009) and do not account for road density in their model. As in Trindade & Fulginiti (2015), we represent the agricultural technology of these countries as a translog production function and estimate the agricultural productivity growth rate using a stochastic frontier approach (SFA). The production function can be defined as

$$Y_{it} = f(X_{it}, t;\ \beta)e^{(v_i - u_i)} \quad i = 1, \dots, I \ \ t = 1, \dots, T \tag{1}$$

where Y_{it} is the output of *i-th* country over the time period *t* (1969 to 2016)*;* X_{it} is the vector of inputs used for the *i-th* country in year *t*; 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; v_i, the random error component, has a normal distribution, independent and identically distributed (*iid*), with variance $\sigma_v^2[v \sim iid\ N(0, \sigma_v)]$; and u_i is responsible for capturing the technical inefficiency of the *i-th* country, that is, the distance from the production frontier (Battese & Coelli, 1995).

As in Trindade & Fulginiti (2015), the change in Ag TFP can be decomposed in technical change (TC), which represents the shift of the production frontier over time, and technical efficiency (TE) change, which represents the rate at which a country moves toward or away from the frontier (Bharati & Fulginiti, 2007; Pfeifer, 2015). The country-year technical efficiency is defined as the ratio between the observed product (Y_{it}) and the potential (Y_{it}^*) product of the sample with a value range of [0, 1], where 0 represents complete inefficiency and 1 complete efficiency. Given the technical inefficiency term, u_{it}, we can define μ_{it} as the mean of TE:

$$\mu_{it} = z_{it}\delta \tag{2}$$

where z_{it} is a vector of explanatory variables that affect the efficiency of countries in the time period: road density, education and GDP per capita; and δ is a vector of the parameters to be estimated. Then, u_{it} is the error term associated with the technical inefficiency of production technology and is estimated by truncation of the normal distribution with mean μ and variance σ^2.

4.1 Data

To estimate the Ag TFP for South American countries we used several sources. Based on Trindade & Fulginiti (2015), we collected information primarily from the Food and Agriculture Organization of the United Nations (FAO, 2020) for the period 1969–2016, specifically

- *output*, measured in agricultural gross production value in international dollars, an index with the base 2004–2006, from FAO;
- *fertilizer*, measured in metric tons of N, P_2O_5, and K_2O equivalents, using data from the International Fertilizer Association, except for Bolivia, for which we obtained data from the Comisión Economica para America Latina y el Caribe (CEPALStat);
- *machinery*, in number of tractors used, based on data from FAO;
- *livestock*, in thousands of cattle equivalents, constructed using weights provided in Hayami & Ruttan (1985)[4] with data from FAO;

[4] Based on Trindade & Fulginiti (2015), we aggregate in the livestock variable the stocks of buffalo, camelids, cattle, horses, and other equine species (asses and mules), pigs, poultry species (chickens, ducks, and turkeys) and small ruminants (sheep and goats). The weights for aggregation, based on Hayami & Ruttan (1985), are 1.25 for buffalo and horses, 1.38 for camelids, 1.00 for cattle and other equine species, 0.25 for pigs, 12.50 per 1,000 head of poultry, and 0.13 for small ruminants.

- *labor*, measured in thousands of economically active persons in agriculture, collected from FAO;
- *land*, based on permanent crops, annual crops, and pasture area in thousands of hectares, collected from FAO.

Missing information for these variables was added using several different sources plus interpolation based on the exponential growth rate from previous years, as in Trindade & Fulginiti (2015). We also followed this process when necessary for infrastructure and socioeconomic data. These variables were used to help explain the productivity differentials of the countries investigated, in addition to the traditional inputs already mentioned. These data sources are:

- *roads*, measured in kilometers (km), uses data collected from several sources, including CEPALStat, the Montevideo-Oxford Latin American Economic History Data Base (MOxLAD), World Bank Data website, and the CIA World Factbook, as well as official sources in each country;
- *Gross Domestic Product (GDP) per capita* (US$, 2010 = 100), which represents a proxy for overall economic development, comprising aspects such as financial instruments and infrastructure for transportation; data were obtained from the World Bank Data website;
- *education* is based on total public expenditure on education expressed as a percentage of the Gross Domestic Product (GDP) each year. Education expenditure was obtained from World Bank Data website.

Following Fuglie (2010) and Trindade & Fulginiti (2015), we applied the Hodrick-Prescott (HP) filter to the output series of each country, where the smoothing parameter λ was defined as 6.25, as suggested by Ravn & Uhlig (2002). This was done to minimize the effect of short-term shocks that are not accounted for by the variables considered. In Table 4.1.1 we present descriptive statistics for these variables by country.

[Table 4.1.1]

In Table 4.1.1 we display the z variables used to explain inefficiency. In addition to road density (kilometers per square kilometer), we account for GDP per capita (US$, 2010 = 100) and education.

Briceño-Garmendia et al. (2015) indicates that while road density in South Asia, North America, and Europe and Central Asia are 96, 42, and 29 km/100 sq. km, respectively, in Latin America and the Caribbean this value is 15 km/100 sq. km. Road density in Table 4.1.1 is in *km* of roads per *square kilometers*. To convert to the same scale, we must multiply by 100. For example, the average road density for Colombia would then be 10.1 km/100 sq. km. In Figure 4.1.1 we display the evolution of the road networks in the Andean Countries. In 2015, Colombia had slightly more than 200,000 km of roads, equivalent to 18 km/100 sq. km. In South America, Uruguay and Brazil have the highest road density, 26.7 and 20.2 km/sq. km, respectively, and Argentina and Bolivia have the lowest, 9.9 and 8.1 km/sq. km. These numbers clearly indicate one of the weaknesses of these countries compared to developed countries. Low road density results in high costs of transport in the agricultural sector, limiting these countries' ability to compete in the international market.

[Figure 4.1.1]

5. Empirical Strategy and Results

We estimate the stochastic frontier assuming a translog production function, given its desirable properties such as flexibility, linearity in parameters, regularity, and parsimony (Mariano, Villano,

& Fleming, 2010). However, as Battesi & Coelli (1992) and Helfand, Magalhães, & Rada (2019) describe, 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. The technology (with subscripts for time and country dropped for clarity) is represented as

$$y = \beta_0 + \sum_{j=1}^{5} \beta_j x_j + \frac{1}{2}\sum_{j=1}^{5}\sum_{i=5}^{5} \beta_{ji} x_j x_i + \beta_t t + \beta_{tt} t^2 + \sum_{j=1}^{5} \beta_{x_j t} x_j t + v - u \tag{3}$$

where y represents the logarithm of the gross value of production; x_j for $j = 1,..,5$ represent the five inputs as logarithms: fertilizer (x_1), machinery (x_2), livestock (x_3), labor (x_4), and land (x_5); t is a trend capturing exogenous technological change; v is the usual random error term; and u represents technical inefficiency. To explain inefficiency (u), we use a vector of z variables that include road density, education, and GDP per capita. The LR test result of 4603.74, which is statistically significant, indicates that the functional form used (translog) is more adequate in terms of fitting the production function compared to Cobb-Douglas. From equation (3)[5] we estimate technical changes as

$$TC = \frac{\partial y}{\partial t} = \beta_t + \beta_{tt} t + \sum_{j=1}^{5} \beta_{x_j t} x_j\,, \;\; j = 1,..,5 \tag{4}$$

Equation (4) results are presented in Tables 5.2 and 5.3. All countries have positive technical change during the entire period (Table 5.1), and the weighted average suggests that the technical change rate was 1.42% per year. Trindade & Fulginiti (2015) find a weighted TC average of 1.73% per year for these countries over the period 1969–2009.[6] For comparison, we calculate the weighted TC average for the same period to be 1.42%, close to what they find. Among the

[5] The average production elasticity for fertilizer is 0.05, machinery 0.12, livestock 0.34, labor 0.21, and for land 0.16. Elasticities for machinery livestock and labor are statistically significant at the average at 10% (calculated using the delta method). Violations to monotonicity for these inputs are 24%, 30%, 13%, 20%, and 51%. These results are similar to Pfeiffer (2003) and Trindade & Fulginiti (2015).

[6] The unweighted TC average (1.45% per year) is statistically significant at 1% (the standard error of 0.001 was calculated using the delta method).

countries studied, we find that Chile has the highest average rate of TC change, corresponding to what was reported in Trindade & Fulginiti (2015). Pfeiffer (2003) estimates the unweighted average TC to be 1.64% per year for the Andean countries over the period 1972–2000. For the same period and countries, we estimate the unweighted average TC to be 1.37% per year (and 1.41% for the weighted average).

[Table 5.1]

As in Trindade & Fulginiti (2015) and in Fuglie (2010), we calculate averages for technical change, and TFP per decade—see Tables 5.2, and 5.3. In Trindade & Fulginiti (2015), average technical change growth rates increase over time for all countries, especially in the 1990s and 2000s. Table 5.2 displays the same pattern and adds the post-2009 period to their analysis. In our results, we observe that these growth rates increase considerably from the 2000s to the period 2010–2016. We find a weighted average TC of 1.42% per year during the entire period and 1.45% per year for the last partial decade (2010–2016).

[Table 5.2]

Average efficiency change is positive for all countries except for Bolivia, Ecuador, Uruguay, and Venezuela (Table 5.1). In our results, we find that the last partial decade (2010-2016) is driving the negative overall average efficiency for these countries. The pattern observed for efficiency change for these countries offset, in part, the effect of technical change for these countries and for the region as a whole.

The weighted overall average Ag TFP change for South American countries is 1.50% per year, with it being 1.43% for the Andean countries and 1.51% for non-Andean countries. The Andean countries grew, on (weighted) average, more slowly than the non-Andean countries as a group. An analysis of the results of individual countries indicates that Chile is the country growing the fastest in South America. We find that Chile's Ag TFP growth rate is 2.47% over the entire period and 2.52% per year during the period 1969–2009, compared to 2.5% reported by Trindade & Fulginiti (2015), which also reports Chile as the fastest-growing country. On the other hand, Bolivia displayed growth of less than 1% per year. Considering only the period 1969–2009, we find that only Bolivia (0.45%) has a growth rate smaller than one, compared to 0.7% in Trindade & Fulginiti (2015).

[Table 5.3]

The results in Table 5.1 are overall averages. In Table 5.3 we present results for the Ag TFP per decade for each country. Even though Ecuador has positive overall Ag TFP averages (Table 5.1), we find that Ecuador faced, on average, negative growth in the last years of our sample. Trindade & Fulginiti (2015) find that Ecuador grew 2.55% during the period 2000–2009, while we find that the country grew 1.9% in the same period. The next years were crucial in agricultural production for this country. While we present the output growth of the value of production using an HP filter,[7] it is important to notice that the value of production in Ecuador decreased 16% from 2009 to 2016. We observe the same pattern for Venezuela. USDA/ERA (2020) finds negative annual rates for Ag TFP for Ecuador for the period 2010–2016 (except for 2014 and 2015).[8] The same report finds negative annual rates for Venezuela for 2012, 2014, and 2016 (we find negative rates for the last three years of our sample).

During this period, both Ecuador and Venezuela faced economic challenges (Doocy, Ververs, Spiegel, & Beyrer, 2019) that affected agricultural performance, especially Venezuela. Doocy et al. (2019) indicate that food production has been declining since 2008 in Venezuela, mainly due

[7] Output growth for the Andean countries shows a drastic decrease for Venezuela after 2011, and negative rates after 2014 (of -0.5%), reaching -2.3% in 2016. Ecuador also faces a worsening scenario, with negative rates from 2008 to 2016.

[8] Our estimated rates for these two years are -0.6% and -0.4%.

to government regulations, currency and fiscal policies, and property seizures. To their point, Mansilla (2016) reports that agriculture's GDP share published by the Central Bank of Venezuela now appears as "others" along with "restaurants and private hotels" and "public diverse activities." It is also a result of the low level of investment in this sector in the last few years.

The Ag TFP growth rate can also be represented as in Trindade & Fulginiti (2015) and in Ludena (2010) (see Figure 5.1), which represents the TFP indexes for all countries. In Figure 5.1 we can see that Ecuador is affected after 2009 and 2013, as argued in the previous paragraph. As in Trindade & Fulginiti (2015), Bolivia is very volatile in the first four decades (up to the late 1990s).

[Figure 5.1]

In our model we included road density to explain inefficiency (see Table A.1), in addition to education and GDP per capita as control variables. We find that it decreases technical inefficiency. This is in line with the literature, which finds that road density (Rada & Valdes 2012; Rada & Buccola, 2012; Rada, 2013) and road length (Mendes et al., 2009) decrease inefficiency and increase Ag TFP for Brazil and Indonesia (Rada et al., 2011). South American countries have considerably lower road density compared to developed countries, generating considerably high costs of transport and limiting their competitiveness in the agricultural international market (Briceño-Garmendia et al., 2015). Our results indicate that higher road density is associated with lower technical inefficiency.

6. Summary

In this working paper we estimate agricultural total factor productivity (Ag TFP) for South American countries over the period 1969–2016 and identify how road density affect technical efficiency. Our focus is on the Andean countries (Venezuela, Colombia, Ecuador, Peru, and Bolivia), which in 2016 produced 16.3% of the overall agricultural value of production in South America, equivalent to 1.2% of the world value of production that year. Compared to developed countries, these countries have poor-quality and limited road networks that are mostly unpaved, which might limit the ability of farms to efficiently manage production inputs, thereby increasing technical inefficiency.

For South American countries, complementing the analysis of Trindade & Fulginiti (2015), we find weighted averages for technical change and for Ag TFP of 1.42% and 1.5% per year, respectively. We find smaller numbers for the Andean countries, with a weighted average of 1.4% for both TC and Ag TFP. We find that road density reduces technical inefficiency. Future research should also explore the effects of road networks on both frontier shift and technical efficiency.

References

Acuña, A., & Riojas, J. (2011). Public policies assessment to improve the small agricultural producer profitability. In *International Conference of the System Dynamics Society and Productivity: Evidence from Colombia*. Caracas: Corporación Andina de Fomento.

Andrian, L., Beverinotti, J., Castilleja-Vargas, L., Díaz-Cassou, J., & Hir, J. (2019). *Notas de infraestructura de país: Región andina*. Washington, DC: Inter-American Development Bank.

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.

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, *20*(*2*), 325–332.

Belotti, F., Daidone, S., Atella, V., & Ilardi, G. (2013). SFCROSS: Stata module for cross-sectional stochastic frontier models estimation. *Statistical Software Components S457635*. Department of Economics, Boston College, Boston, MA.

Benedictis Villacreses, G., Calfat, G., & Flôres Jr, R. G. (2006). *Infrastructure and trade: Challenging the pro-development role of trade agreements when regions differ. The Ecuadorian experience* [mimeo]. IOB. Antwerp, Universiteit Antwerpen.

Bilsborrow, R. E., Barbieri, A. F., & Pan, W. (2004). Changes in population and land use over time in the Ecuadorian Amazon. *Acta Amazonica*, *34*(*4*), 635–647.

Bitran, E., Nieto-Parra, S., & Robledo, J. S. (2013). Opening the black box of contract renegotiations: An analysis of road concessions in Chile, Colombia and Peru. OECD Development Centre Working Papers, No. 317. Paris: OECD Publishing. https://doi.org/10.1787/5k46n3wwxxq3-en.

Briceño-Garmendia, C., Moroz, H., & Rozenberg, J. (2015). *Road networks, accessibility, and resilience: The cases of Colombia, Ecuador, and Peru*. Washington, DC: World Bank.

Cárdenas, M., Gaviria, A., & Meléndez, M. (2005, August). *La infraestructura de transporte en Colombia*. Unpublished manuscript.

Cárdenas, M., & Sandoval, C. E. (2008). *Transportation infrastructure and productivity: Evidence from Colombia* (Research Department Working Papers 205). CAF Development Bank of Latinamerica.

Clavijo, S., Vera, N., & Cuellar, E. (2019). *Financing public investment through concessions and future budgetary obligations (FBO): The case of Colombia 2002–2018*. Accessed in February 2020. Retrieved from http://www.anif.co/sites/default/files/investigaciones/anif-infra-wpaper0119.pdf.

Corahua Benites, A. A., & Mendoza Silva, P. H. (2018). *Propuesta del diseño del proceso logístico para mejorar la productividad del sector agrícola, palta Hass, en la irrigación cabeza de toro del departamento Ica, Perú*. Lima: Universidad Peruana de Ciencias Aplicadas.

De Souza, H. P., & Liu, T. (2019). Belt and Road Initiative and the South American integration initiatives: A comparative analysis between Asian and Latin American initiatives with a complementary proposition. *Contemporary Chinese Political Economy and Strategic Relations*, *5*(*1*), 253-XI.

Doocy, S., Ververs, M. T., Spiegel, P., & Beyrer, C. (2019). The food security and nutrition crisis in Venezuela. *Social Science & Medicine*, *226*, 63–68.

Escobal, J. (2001). The determinants of nonfarm income diversification in rural Peru. *World Development*, *29*(*3*), 497–508.

Etter, A., McAlpine, C., Wilson, K., Phinn, S., & Possingham, H. (2006). Regional patterns of agricultural land use and deforestation in Colombia. *Agriculture, Ecosystems & Environment*, *114*(*2–4*), 369–386.

FAO (Food and Agriculture Organization of the United Nations). (2020). FAOSTAT - Statistics Division. Accessed in February 2020. Retrieved from http://www.fao.org/faostat/en/#home.

Fuglie, K. O. (2010). Total factor productivity in the global agricultural economy: Evidence from FAO data. In Alston, J. M., Babcock, B., & Pardey, P. G. (Eds.), *The Shifting Patterns of Agricultural Production and Productivity Worldwide*, pp. 63‑98. Ames: Iowa State University, Midwest Agribusiness Trade Research and Information Center.

Gasques, J. G., Bastos, E. T., & Bacchi, M. R. P. (2008). Produtividade e fontes de crescimento da agricultura Brasileira. *Revista de Política Agrícola*, *13*, 73–90.

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.

Helfand, S. M., Magalhães, M. M., & Rada, N. E. (2015). *Brazil's agricultural total factor productivity growth by farm size* (IDB Working Paper Series No. 609). Washington, DC: Inter-American Development Bank.

Jiménez, M. I., Abbott, P., & Foster, K. (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.

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

Mansilla, D. (2016). Venezuela and the international crisis. In Santarcángelo, J. E., Justo, O., & Cooney, P. (Eds.), *Latin America after the Financial Crisis. Palgrave Studies in Latin American Heterodox Economics*, pp. 193–227. New York: Palgrave Macmillan.

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

Melo-Becerra, L. A., & Orozco-Gallo, A. J. (2015). Technical efficiency for Colombian small crop and livestock farmers: A stochastic metafrontier approach for different production systems. *Borradores de Economia*, *914*. Banco de la Republica de Colombia.

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.

Muriel, R., & Felipe, A. (2015). *Inversión en infraestructura vial y su impacto en el desarrollo económico: Un análisis al caso Colombia (1993–2014).* Escuela de Ingeniería de la Organización, Universidad Nacional de Colombia.

Ortega, C. B., & Lederman, D. (2004). Agricultural productivity and its determinants: Revisiting international experiences. *Estudios de Economía*, *31*(*2*), 133–163.

Pfeiffer, L. M. (2003). Agricultural productivity growth in the Andean Community. *American Journal of Agricultural Economics*, *85*(*5*), 1335–1341.

Rada, N. (2013). Assessing Brazil's Cerrado agricultural miracle. *Food Policy*, *38*, 146–155.

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

Rada, N. E., Buccola, S. T., & Fuglie, K. O. (2011). Government policy and agricultural productivity in Indonesia. *American Journal of Agricultural Economics*, *93*(*3*), 867–884.

Rada, N., & Valdes, C. (2012, July). *Policy, technology, and efficiency of Brazilian agriculture*. USDA-ERS Economic Research Report No. 137.

Rada, N., Helfand, S., & Magalhães, M. (2019). Agricultural productivity growth in Brazil: Large and small farms excel. *Food Policy*, *84*, 176–185.

Ravn, M. O., & Uhlig, H. (2002). On adjusting the Hodrick-Prescott filter for the frequency of observations. *Review of Economics and Statistics, 84*(*2*), 371–376.

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

USDA/ERS (United States Department of Agriculture, Economic Research Service). (2020). Agricultural total factor productivity growth indices for individual countries, 1961–2016. Data on Agricultural Total Factor Productivity. Accessed in February 2020. Retrieved from https://www.ers.usda.gov/data-products/international-agricultural-productivity/.

Vaca, M. Z., Soqueb, R. A., & Castro, E. B. (2016). Infraestructura vial y crecimiento económico: Caso parroquias Sevilla Don Bosco y San Isidro, Provincia de Morona Santiago, Ecuador. *Revista Investigaciones Altoandinas*, *18*(*1*), 83–92.

Zamora Fandiño, N., & Barrera Reyes, O. L. (2013). *Diagnóstico de la infraestructura vial actual en Colombia* (Bachelor's thesis, Universidad Ean, Bogota, Colombia).

Tables and Figures

Table 4.1.1 Descriptive statistics of the output and inputs used to estimate Equation (1) and the inefficiency error term (1969–2016)

	Value of Production (Intl. US$)	Fertilizer (metric ton)	Machinery (# of tractors)	Livestock (cattle equiv.)	Labor (thous. person)	Land (thous. ha.)	Road density (km/sq. km)	GDP per capita (US$/pop)	**Education** *(share)*
Argentina	29046914	596717	233434	62980355	1417	132586	0.08	5667.02	3.189
	(9226690)	(547378)	(39851)	(3455610)	(40)	(7500)	(0.009)	(3708.9)	(1.634)
Bolivia	2100890	12307	4981	11685209	1378	35254	0.048	1096.93	5.703
	(1007052)	(11224)	(1371)	(3223390)	(436)	(2216)	(0.018)	(762.52)	(0.89)
Brazil	80205151	5868735	664872	184700000	13776	237878	0.186	4214.41	4.845
	(41300000)	(3942474)	(233331)	(50600000)	(2059)	(20966)	(0.023)	(3567.75)	(0.6)
Chile	5188444	321644	43847	5931504	849	15897	0.102	1602.52	3.65
	(2187239)	(148149)	(9228)	(645128)	(109)	(591)	(0.006)	(2353.12)	(0.742)
Colombia	9970024	522060	24979	29515610	3393	44314	0.101	2610.81	3.37
	(3109253)	(228091)	(4700)	(2735757)	(227)	(1308)	(0.046)	(2265.12)	(0.945)
Ecuador	4197051	147382	10358	6561351	1200	6950	0.132	2455.59	4.354
	(1729181)	(102533)	(4368)	(1605793)	(278)	(1088)	(0.027)	(1618.37)	(2.002)
Paraguay	2829411	104837	16286	9617060	633	17048	0.089	1992.93	3.21
	(1485494)	(138281)	(8418)	(2924785)	(158)	(3614)	(0.043)	(1617.04)	(0.286)
Peru	5092534	209542	12567	14128130	2874	20524	0.06	2259.71	2.531
	(2471530)	(116447)	(828)	(1968046)	(649)	(1998)	(0.025)	(1875.76)	(0.907)
Uruguay	2675977	122097	34046	13510612	193	14846	0.277	5471.18	2.718
	(821154)	(99274)	(2237)	(745799)	(6)	(213)	(0.012)	(4681.75)	(0.767)
Venezuela	4593318	303652	42273	16882314	821	21315	0.089	5237.42	4.053
	(1509937)	(160281)	(9767)	(4172103)	(74)	(637)	(0.019)	(4325.69)	(0.548)

Note: Mean (Standard deviation). Value of production is in US$ of 2006–2011-based index. In equation (5) we use the variable "road density" in km per 100 square km, as it is usually treated in the literature.

Figure 4.1.1 Total road length (in km) in Bolivia, Colombia, Ecuador, Peru, and Venezuela, 1975–2015 (by decade)

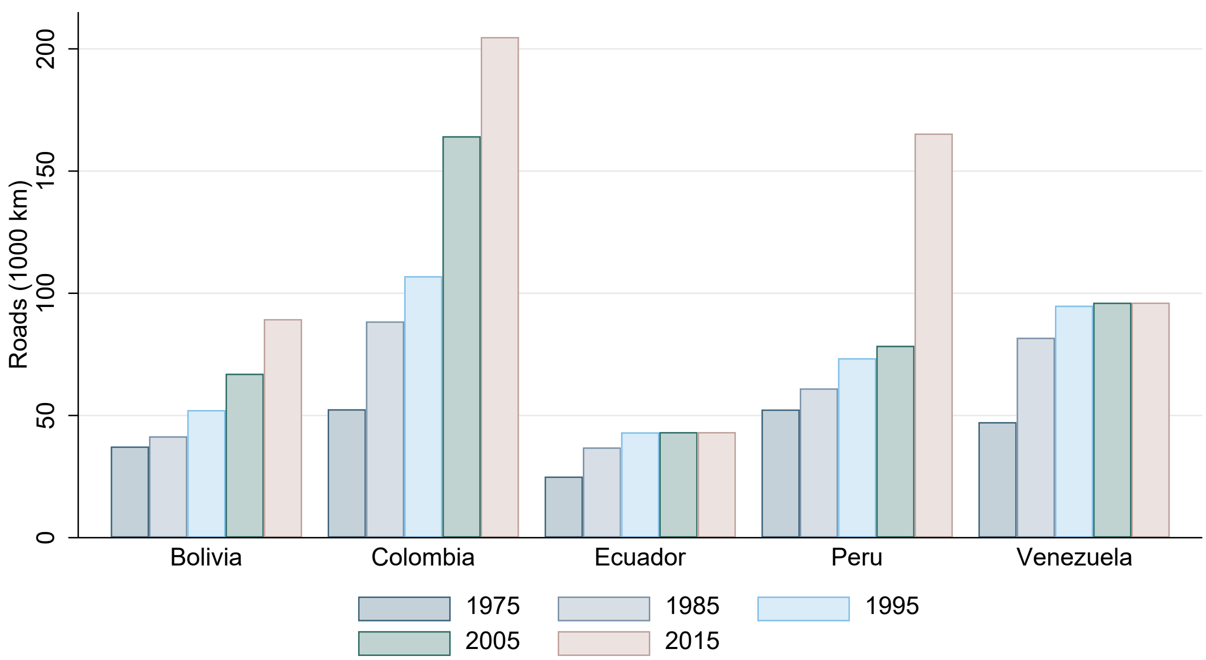


Table 5.1 Overall average technical change, efficiency change, agricultural total factor productivity, and output growth for South American countries, 1969–2016

	TC	EC	Ag TFP	Output Growth
Argentina	1.172	0.039	1.210	2.250
Bolivia	0.517	-0.066	0.453	3.555
Brazil	1.480	0.102	1.580	3.673
Chile	2.369	0.102	2.469	2.680
Colombia	1.268	0.111	1.377	2.499
Ecuador	1.857	-0.429	1.437	2.220
Paraguay	1.272	0.248	1.514	3.983
Peru	1.448	0.291	1.734	2.863
Uruguay	1.450	-0.004	1.446	1.744
Venezuela	1.662	-0.057	1.606	2.370
Weighted	1.424	0.072	1.495	3.100

Note: Weighted average was calculated using the yearly country output and the total output.

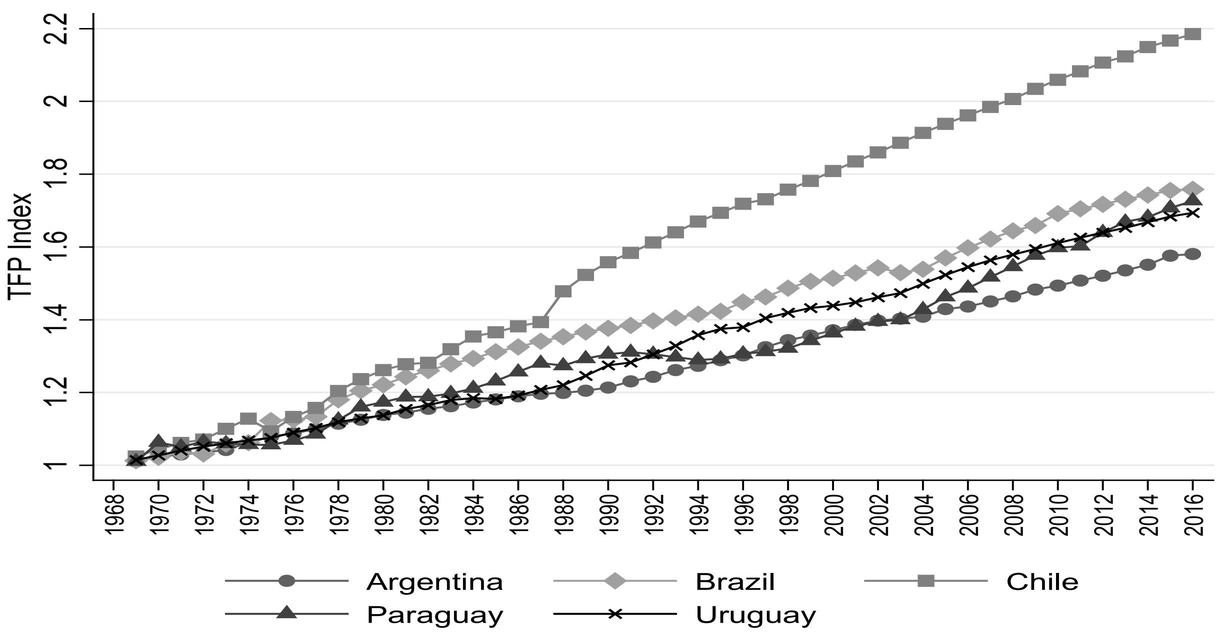
Table 5.2 Average technical change for South American countries, 1969–2016 (by decade)

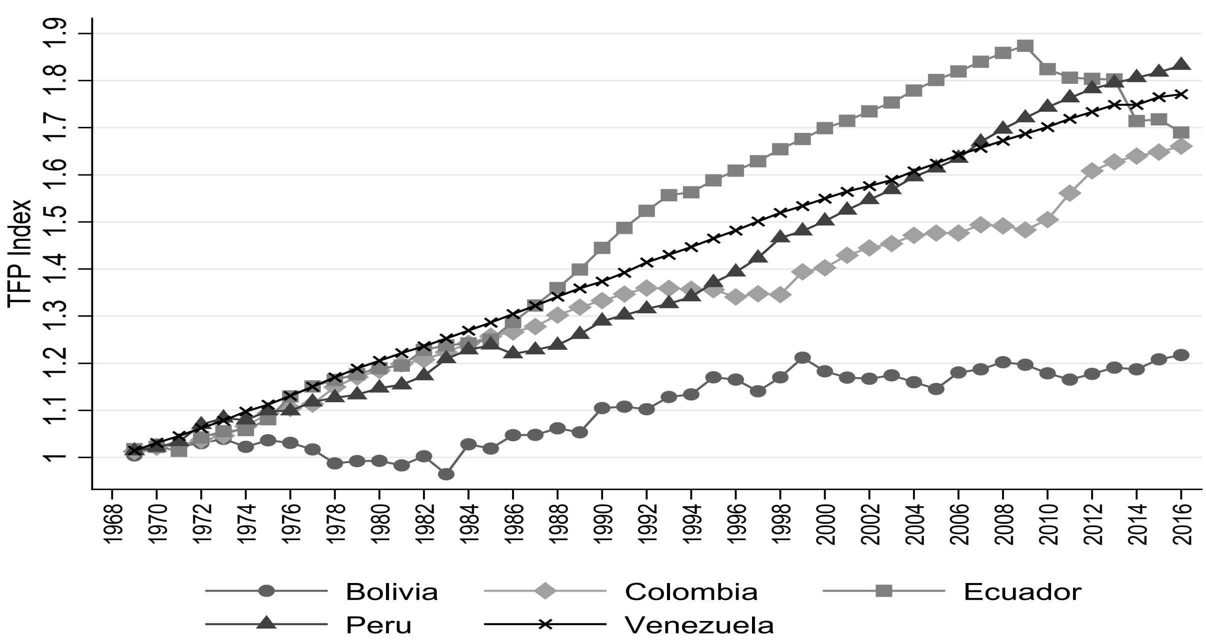
	1969–1979	1980–1989	1990–1999	2000–2009	2010–2016
Argentina	0.911	1.036	1.273	1.338	1.394
Bolivia	0.456	0.532	0.551	0.526	0.532
Brazil	1.447	1.573	1.495	1.448	1.426
Chile	2.330	2.308	2.423	2.415	2.373
Colombia	1.303	1.372	1.247	1.180	1.220
Ecuador	1.845	1.787	1.775	1.923	1.999
Paraguay	0.937	1.130	1.275	1.571	1.567
Peru	1.471	1.495	1.454	1.429	1.366
Uruguay	1.476	1.397	1.420	1.429	1.558
Venezuela	1.698	1.821	1.662	1.496	1.613

Table 5.3 Average total factor productivity for South American countries, 1969–2016 (by decade)

	1969–1979	1980–1989	1990–1999	2000–2009	2010–2016
Argentina	1.139	0.796	1.514	1.263	1.403
Bolivia	-0.071	0.612	1.584	-0.151	0.297
Brazil	1.863	1.614	1.387	1.537	1.425
Chile	2.153	2.865	2.586	2.524	2.153
Colombia	1.555	1.481	0.748	0.893	2.536
Ecuador	1.608	2.222	2.772	1.978	-2.632
Paraguay	1.457	1.329	0.494	2.343	2.141
Peru	1.210	1.282	2.196	2.399	1.592
Uruguay	1.170	1.175	1.862	1.621	1.424
Venezuela	1.716	1.704	1.747	1.528	1.203

Figure 5.1 Stochastic frontier TFP index (1969 = 1) for Andean countries, 1969–2016





Appendix

Table A.1 Stochastic frontier estimation of equation (4)

Variable	Parameter	Variable	Parameter
lx1	-1.663***	*lx34*	-0.114
	(0.386)		(0.077)
lx2	5.641***	*lx35*	0.235*
	(0.512)		(0.128)
lx3	-5.811***	*lx45*	-0.052
	(0.840)		(0.078)
lx4	3.360***	*t*	0.072***
	(0.711)		(0.017)
lx5	-6.933***	*t2*	-5.83e-05
	(1.011)		(7.82e-05)
lx11	0.038**	*lx1t*	0.002**
	(0.017)		(0.001)
lx22	0.313***	*lx2t*	0.003**
	(0.046)		(0.001)
lx33	0.479***	*lx3t*	-0.006***
	(0.122)		(0.001)
lx44	0.001	*lx4t*	0.001
	(0.049)		(0.001)
lx55	0.241*	*lx5t*	-0.002
	(0.125)		(0.002)
lx12	-0.113***	*Constant*	61.81***
	(0.026)		(3.663)
lx13	0.157***	*Road density*	-0.018**
	(0.048)		(0.009)
lx14	-0.045*	*GDP per capita*	-4.67e-05***
	(0.024)		(1.66e-05)
lx15	0.008	*Education*	0.034***
	(0.041)		(0.008)
lx23	-0.500***	*Constant*	0.286***
	(0.067)		(0.094)
lx24	-0.018	σ_u	-5.066***
	(0.045)		(0.540)
lx25	0.09	σ_v	-6.009***
	(0.074)		(0.475)
Observations	480		

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Variables: x_1 – fertilizer, x_2 – machinery, x_3 – livestock, x_4 – labor, and x_5 – land.