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The Effect of Extension Services and Credit on Agricultural Production in Bolivia, Peru, and Colombia

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Abstract

In this working paper we estimate the average treatment effect on the treated (ATET) from access to extension services and credit on agricultural production in selected Andean countries (Bolivia, Peru, and Colombia). To estimate the treatment effect and measure the effect of accessibility on these variables, we use data from the Colombian and Bolivian Agricultural Censuses of 2013 and 2014, respectively; a nationwide agricultural survey from 2017 for Peru; and geographic information on travel time. We find that the ATET for credit is higher compared to that of extension services for farms in Bolivia and Peru and lower for Colombia. The ATET of the interaction of credit and extension services is higher than each separately in all three countries. We also find that accessibility and the likelihood of accessing these services are nonlinearly related. Our results indicate that lower travel time is associated with a higher likelihood of access credit.

Keywords: Average treatment effect, Credit, Extension services, Travel time

JEL Codes: C31, Q12, Q14

1. Introduction

In Bolivia, Peru, and Colombia, access to extension services and to credit is limited to a small percentage of farms. Based on data from the Agricultural Censuses in Colombia (2013) and Bolivia (2014) and a nationwide agricultural survey in Peru (2017), in Colombia 12.3% of the farms had access to extension services (a definition will be provided below), followed by Peru with 7.1% and Bolivia with 5.2%. Regarding credit, 12.3% of the farmers had access to credit in Colombia, 11% in Peru and only 8.4% in Bolivia. Access to extension services and credit can raise agricultural production, technical efficiency, and total factor productivity (Bravo-Ortega & Lederman, 2004; Helfand & Levine, 2004; Gasques, Bastos, Valdes, & Bacchi, 2012; Rada & Buccola, 2012; Rada & Valdes, 2012). The limited access to these services in these countries might be associated with farmer accessibility factors such as distance to market, access to road networks, or travel time to the nearest large town. Rural residents of these countries rely heavily on roads to obtain services, which most of the time are available only in urban centers. Only a small percentage of the road network is paved in these countries, which leads to a high average travel time to the nearest town. In this working paper, our objective is thus two-fold. We estimate (1) the average treatment effect on the treated of extension services and credit and their interaction on the value of production for selected products for farms in Colombia, Peru, and Bolivia; and (2) the effect of accessibility on the likelihood of utilizing these services.

In 2016, these three countries produced 11.1% of the value of agricultural production in South America, equivalent to 1.1% of the world value of agricultural production during that year (FAO, 2020). The poor-quality and limited transport networks in these countries lead to considerably high costs of transport compared to those of developed countries (Briceño-Garmendia, Moroz, & Rozenberg, 2015), undercutting the competitiveness of these countries in the international agricultural market. Road networks, which serve as a key component of transport infrastructure, enable the mobility of people and the consumption of goods and services, in addition to playing a crucial role in goods production and distribution. These networks can potentially improve access to extension services (Gebresilasse, 2019) and credit, to new technologies (Jacoby, 2000; Aggarwal, 2018; Shamdasani, 2016), and to markets (Jacoby, 2000; Shamdasani, 2016), resulting in increases in productivity and farm income.

Regional economic development is associated with mobility and with access to essential services, and as such requires an adequate transport infrastructure. Analyzing the correlation between travel time and income across countries, Weiss et al. (2018) find that in low-income countries almost 51% of individuals live within an hour of an urban center, but that in high-income countries this figure is almost 91%. This income-accessibility correlation is also found in Colombia and Peru (Briceño-Garmendia et al., 2015). The distribution of access to extension services and credit in these countries is highly unequal and might be associated with the national road networks, the locations of urban centers and country's geography. In Colombia, the proportion of farmers who have access to extension services and credit is higher in regions where the road network is more extensive, compared to regions where roads are scarce. While access to extension services is driven by a variety of factors, notably the design of public policies, farm and farmer characteristics, and farmers' distances to service providers such as public institutions and universities, access to credit is largely tied to farmers' access to urban centers, where banking institutions are usually located.

In this working paper, we use matching techniques to estimate the average treatment effect on the treated of access to extension services and to credit on the value of agricultural production. Accessibility, defined as travel time to the nearest town with 50,000 inhabitants or more, may be one of the key factors that determine access to extension services and credit, which establishes the link between roads and the value of agricultural production. We use geographic information on travel time (Weiss et al., 2018) and agricultural census and surveys to quantify this link. The simple analysis performed in this working paper is a first step toward understanding the connection between roads and agricultural production through the effect on access to extension services and credit. Overall, we find that both extension services and credit increase the value of agricultural production, and that higher travel time decreases the probability of accessing extension services and credit.

In the following sections we review the current literature on road networks and discuss public policies associated with road infrastructure. Then, we discuss this study's empirical strategy and the datasets used. Finally, we present and discuss our results in light of the literature considered to this point and the context of the Andean countries.

2. Literature review

This working paper's focus aligns with that of other papers investigating the impact of extension services and credit on agricultural productivity (Helfand & Levine, 2004; Guanziroli, 2007; Guirkinger & Boucher, 2008; Garcias & Kassouf, 2016; Jin & Huffman, 2016; Luan & Bauer, 2016). Helfand and Levine (2004) estimate technical efficiency and its determinants for a region in Brazil using data from representative farms, finding that access to both extension services and credit decreases technical inefficiency. Guanziroli (2007) reviewed 13 evaluative publications of the Brazilian credit program Program for Strengthening Family Agriculture (Programa Nacional de Fortalecimento da Agricultura Familiar, PRONAF). He finds that even though PRONAF has increased farm income and improved agricultural efficiency, it still faces challenges associated with providing extension services to farmers who receive this line of credit. Guirkinger & Boucher (2008) estimate the effects of credit restriction on Peruvian rural households and find that relaxing credit constraints would raise the value of output per hectare by 26%.

Along these lines, Garcias & Kassouf (2016) estimate the impact of rural credit on land productivity and labor productivity for family farmers in Brazil. They use the same matching technique that we use, propensity score matching, at the municipal level and find that an increase in access to credit leads to an increase in labor and land productivity. Focusing on credit's effect on agricultural Total Factor Productivity (Ag TFP), Jin & Huffman (2016) find that rural extension services increase Ag TFP for most American states and estimate that the real social rate of return of investments on extension services is more than 100%. Using data on households, Luan & Bauer (2016) also apply propensity score matching and find that rural credit increases household income among households with higher income for Vietnam.

In addition to studying productivity change due to extension services or access to credit, Gebresilasse (2019) stands out by analyzing the effect of public policies relating to extension services and to roads on agricultural productivity. He finds that access to both roads and extension services leads to an increase of 6% in productivity in Ethiopian farms. Also looking at Ethiopia, Dercon, Gilligan, Hoddinott, & Woldehanna (2009) find that access to extension services and roads reduces poverty and increases consumption.

Several studies using aggregate datasets at the country or state level—examined through the lenses of profit, production, and cost functions—find a positive effect on economic production (Deno, 1988; Baltagi & Pinnoi, 1995; Boopen, 2006; Jiwattanakulpaisarn, Noland, & Graham, 2011; Wang, Plastina, Fulginiti, & Ball, 2017). Melo, Graham, & Brage-Ardao (2013) and Deng (2013) summarize studies along these lines. While these studies are mostly applied to aggregated datasets, there is a growing literature investigating the impact of new roads on household outcomes using microdata from surveys (de Janvry, Fafchamps, & Saudolet, 1991; Key, Saudolet, & de Janvry, 2000; Jacoby, 2000; Renkow, Hallstrom, & Karanja, 2004; Khandker, Bakht, & Koolwal, 2009; Khandker, Shahidur, & Koolwal, 2011; Ortega, 2018; Asher & Novosad, 2020).[1] This literature mostly investigates natural experiments such as the construction of new roads around small villages. These studies find mixed results, depending on the variable of interest they investigate.

Asher & Novosad (2020) find that the main effect of investments in rural roads in India was the shift in labor from agriculture to other activities. They find that farm production does not considerably increase, because of the presence of roads and that roads alone are not enough to promote economic development in remote villages in India. Also looking at rural India, Shamdasani (2016) finds that improvement in rural road connectivity results in higher farm diversification, demand for modern inputs (fertilizer), adoption of new technologies (high-yielding varieties), and an increase in output commercialization. Aggarwal (2018) likewise finds that the presence of rural roads in India increases the use of newer agricultural technologies.

Ortega (2018) investigates the impact of improvements in road networks on agricultural production and other key variables in Colombia by using a difference-in-difference technique based on (Euclidean) distance to the market plus three years of survey data. Ortega (2018) finds that changes in the quality of rural roads affect agricultural production nonlinearly, depending on the distances to local and national markets. While households in central locations reduce their production, households in peripheral regions expand their production. Even though these results

[1] Jacoby (2000) develops a model aligned with the von Thünen land use model that incorporates distance (time) to market center to analyze how access to the market affects farm value, which is correlated to farm production/productivity as examined in this paper. They find that as distance (time) to the market center increases, the demand for fertilizer and farm rent decreases.

are not directly comparable to our simple analysis, they shed light on the relation between agricultural production and distance to markets.

One of the key variables in this working paper is travel time to the nearest large town, a measure of accessibility and road network strength. The availability of rich geographic information on roads that was provided by governments and private institutions has enabled accurate analysis of the road network worldwide (Iimi et al., 2016; Meijer et al., 2018; Weiss et al., 2018). Using Open Street Map (OSM) and Google, Weiss et al. (2018) estimate travel time to the nearest urban center in addition to establishing a link between travel time and national income. Along the same lines, Meijer et al. (2018) estimate road density for 222 countries using 63 different sources. Both variables, travel time and road density, evaluated through the lenses of accessibility and availability, respectively, can help to capture the link between road networks and agriculture. Greater travel time to urban centers could result in a lower likelihood of accessing extension services and financial tools, factors that yield higher agricultural productivity. And higher road density might allow farmers to move more easily between farm and urban centers to purchase inputs and sell outputs, resulting in greater agricultural production. For instance, Meijer et al. (2008) find that wealthier countries have higher road density.

Briceño-Garmendia et al. (2015) assess several aspects of the road networks and accessibility in Colombia, Ecuador, and Peru using multiple sources,[2] including a few introduced here. Relevant to our discussion, they calculate accessibility scores and map them for these countries, finding results that resemble those of Weiss et al. (2018) and giving us support to use the Weiss et al.

[2] They use a robust decision-making approach to assess policy designs for road networks under uncertainty, particularly associated with climate events, for Colombia, Peru, and Ecuador. A wide range of datasets is used in their paper, including the geographic information systems for road networks 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).

(2018) measure. Our study adds to this literature by shedding light on the link of accessibility, measured as travel time, to services that can shape regional and national agricultural production.

3. Empirical strategy

To identify the effect of extension services and credit on agricultural production, we need to compare farms that have had access to both with similar farms that have not had access. We identify these effects using the propensity score matching (PSM) technique, developed by Rosenbaum and Rubin (1983), and widely used in the literature to study quasi-experiments (e.g., Pufahl & Weiss, 2019; Heckman & Vytlacil, 2005; Silva, Freitas, & Costa, 2018). In this working paper, access to extension services and credit are considered the treatments and agricultural production the outcome variable. This technique allows us to estimate the average treatment effect on the treated (ATET) on the outcome variable while controlling for observable characteristics (such as farm size and farmer characteristics, including education, age, and gender) that determine the treatment. It creates a counterfactual scenario based on the identification of farm observations to compose a similar sample of farms that have not accessed extension services and credit (control group) using a matching technique for observable characteristics such as land under cultivation, travel time to urban centers, and demographic characteristics. The sample observed, a cross-sectional picture of each country, does not enable the selection of a farm pre- and posttreatment. The technique described below allows us to compose a control group based on characteristics that are also observed pretreatment and might not change in the short run.[3]

To isolate the effect of each treatment, first we perform the analysis using observations of farms that have access to only one of the treatments at a time. To estimate the average treatment effect

[3] An analysis of pre- and posttreatment to evaluate policies that affect access to extension services and credit would be ideal, but cannot be applied to the sample observed.

of access to extension services, we select farms that have only access to extension services (and not to credit) and repeat the process for the analysis of access to credit. Then, to capture the synergy of these two treatments, we select farms that have access to both extension services and credit. The control group for the three estimations described is composed of farms that did not access to either of the two treatments. A comparison of the outcome of the ATET of accessing both extension services and credit to the ATET of either alone provide a measure of synergy between the two treatments.

To construct the control group, the propensity score is estimated using logit, which represents the conditional probability of treatment (access to extension services or credit or both extension services and credit) and is used along with the nearest neighbor matching technique to identify the control group. There are several matching techniques used in the literature. One common technique is the "1-to-1 nearest neighbor without replacement" technique used in Bravo-Ureta, Greene, & Solís (2012). Our results do not change considerably whether we use this technique or others such as kernel matching. Additionally, a test of means by group (treatment and control) for each of the treatment variables and countries was performed to verify whether the matching technique was successful; it indicates that the matching technique was applied successfully in the identification of the control group.

4. Data

To investigate the effect of the infrastructure component, roads, on the treatments we use two sets of data—geographic and economic. We first introduce the variable associated with roads: travel time. Second, we analyze a few key variables in agricultural production that rely on road networks and access to urban centers, such as extension services and credit, using agricultural census and survey data for each country.

As a proxy for roads, we use the research outcome of Weiss et al. (2018) to estimate the average travel time at the lowest available level of geographic information. For Colombia it is *veredas* and for Bolivia *municipios*. Weiss et al. (2018) use both Open Street Map and Google to capture the transportation network to estimate the travel time to the nearest urban center with 1,500 or more inhabitants per square kilometer or, coincidently, to cities with at least 50,000 inhabitants. They argue that travel time is a more accurate measure of accessibility than Euclidean and network distance, because it considers the transportation network (roads and railroads) and local geography (elevation and slope angle, rivers and other bodies of water, and topographical conditions). Their measure also captures the effect of road quality on accessibility. To estimate travel time, they consider unpaved roads and exurban residential streets and use the Global Human Settlement Grid of high-density land cover.

Each country's geography plays a major role in shaping transportation infrastructure, such as road networks, which is linked to accessibility on the part of the population.[4] The geographic distribution is partially produced by the Andes, which divide Peru, for example—urban areas are to the west, and forest is to the east. The lack of road networks (or other types of transport routes) and urban centers to the east of the Andes imposes greater travel time on those living in that region. Waterways are considered in remote regions where this is the only or the optimal transport route. Though the region around Iquitos, for example, is connected by only a few roads, a few rivers such as the Amazon River are present, and Weiss et al. (2018) takes that into account. The travel time

[4] Weiss et al. (2018) indicate in the supplementary material that 87.8, 62.8, and 58.3% of the cumulative land area is within 900 minutes for their travel time variable for Bolivia, Colombia, and Peru respectively. These numbers are higher than 96% for the cumulative population of all three countries.

geographic distribution resembles what Briceño-Garmendia et al. (2015) found for Peru, displayed in their Figure 32 (p. 55).

A similar pattern is observed in Colombia, where in forested areas, mainly the Amazon Forest, travel time is much higher compared to other regions of the country. The geographic distribution of this variable for Colombia, provided by Weiss et al. (2018), resembles the results obtained in Briceño-Garmendia et al. (2015), which provides us assurance that these variable captures accessibility.

Within Bolivia, the geographical distribution of road networks is slightly different from that found in the other two countries for three reasons. The forest areas (including the Amazon Forest) are in the east rather than in the south of the country, as in Colombia. Second, the lowest level of political administrative boundary available to us is that of the municipality. However, it should be noted that some of the municipalities in Bolivia are considerably larger than in Peru (and the *veredas* in Colombia). Finally, there are urban centers in all regions of the country, and large urban centers are clustered in the central portion of the country. From west to east, La Paz, Cochabamba, and Santa Cruz de la Sierra function as regional economic clusters. From north to south, Riberalta, Sucre, Potosi, and Tarija function as local economic centers for rural populations. The travel time variable for Bolivia is less precise than for Peru and Colombia, because of the intersection of the municipality variable and the dataset provided by Weiss et al. (2018). The lowest level of political administrative boundary available in the Bolivian agricultural census is likewise that of the municipality.

4.1 Agricultural census and surveys

To investigate the effect of access to extension services and credit on agricultural production, we use the agricultural census and surveys for each country. For Bolivia, we use the Agricultural Census of 2013 (Censo Agropecuario 2013); for Peru, we use the National Agricultural Survey of 2017 (Encuesta Nacional Agropecuaria 2017); and for Colombia, we use the Agricultural Census of 2014 (Tercero Censo Nacional Agropecuario 2014).

4.1.1 Bolivia

The Bolivian Agricultural Census of 2013 contains information on 871,927 farms (*unidade de produccion agropecuaria, UPA*), with 2,760,238.6 hectares of area planted. In 2013, 73,413 farmers had access to credit (survey question: *¿Obtuvo el crédito solicitado?*), and 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 with machinery, 86,585 with inputs, 45,534 with technical assistance, and 48,953 with courses) (question*: Tipo de asistencia o apoyo recibido*). In 2013, 475,589 farms used firewood as an energy source, followed by gasoline (166,493 farms), and crop residues (122,767) (question: *¿Para sus actividades agropecuarias utiliza Energía eléctrica de red?*). Only 73,984 farms reported electricity as a principal source for agricultural production. To estimate the value of production we considered winter and summer crops,[5] cattle,[6] and milk. The

[5] 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, chili pepper pod, 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.

[6] We assume that only 80% of cattle two or three years old are sold and are therefore included in the value of production.

census does not provide information on prices, so we use average prices for domestic markets by department (administrative unit) from the Encuesta Agropecuaira 2015. We converted the value of production to USD in 2015 (BOB 1 = USD 0.14).

The Agricultural Census of 2013 also reports the age of everyone in the household, including the head of the house/farm. In a few cases, one single farm would assign two or more people as the head of the farm. Age was then formulated as the average age reported for these people. Overall, the average age for the head of a farm is 49 years old. The census also reports the years of schooling for the producer, and the average years of education found is 5.75. We built three categorical variables based on years of education: (1) 0 years to 8 years, (2) between 8 and 11 years, and (3) more than 11 years.

In this working paper, we considered only farms that had a positive value of production and land with at least one of the products considered. To control for outliers, we dropped all observations in the bottom 1% and top 1% of the distribution of the value of production. We also limited the model to farms that are individual producers. After these modifications, our sample size was greater than 700,000 observations (descriptive statistics are displayed in Table 5.1).

The travel time might be capturing the effects of being close to a populated area. We also calculated the population density of municipalities to control for potential bias in the estimated parameter for travel time. This geographic distribution of the road network is associated with the distribution of the value of agricultural production. While in the largest state, Santa Cruz, located in the southeastern portion of the country, 17.7% of farms had access to credit, in Pando and Beni, states located in the north of the country, only 6.6% and 9.4% of farms, respectively, had access to credit. We also found that 9.6%, 7.1%, and 7.7% of the farms in Santa Cruz, Pando, and Beni, respectively, had access to extension services.

4.1.2 Peru

For Peru, we use the Encuesta Nacional Agropecuaria of 2017, which includes information on 29,218 and 1,537 small/medium and large farms (*unidade de produccion agropecuaria - UPA*) representing a total of 2.2 million Peruvian farms. While 11.1% of small and medium farms requested and obtained credit, 32.5% of large farms did so (question: *¿Obtuvo el crédito solicitado?*). In 2017, 7% of small and medium farms had access to technical assistance, compared to 43% of large farms (question*: En los últimos 3 años, ud. ha recibido asistencia técnica?*). To estimate the value of production we considered all crops, cattle,[7] and milk. In this working paper, we used the value of production reported by the farmer to build the value of production. Also, we converted the value of production to USD from 2017 (PER 1 = USD 0.3).

After cleaning the data, as we did for Bolivia, our final sample was greater than 25,000 observations (descriptive statistics are displayed in Table 5.1). We merged the information on roads with the information on the agricultural survey. Traveling from farms in the northeastern portion of the country takes considerably longer to reach an urban center for two reasons. In this region, there are only a few urban centers, and the road network is lacking, requiring farmers to use waterways. Peru is divided into three regions: the Highland (Sierra) is the Andean region, the Coastal (Costa) is the coastal region, and the Amazon (Selva) is east of the Andean region. Travel time and road network are directly associated and partially explain the pattern in the agricultural production values. While 13.9% of the farmers in the Amazon region received extension services compared to 5.6% in the Highland, the number of farmers who have received extension services in the Highland region is almost 10% higher than in the Amazon. We observe the same pattern regarding access to credit. While 13.8% had access to credit in the Amazon region and 9.3% had

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

access in the Highlands, the number of farmers who obtained credit is twice as large in the Highlands region compared to the Amazon.

4.1.3 Colombia

For Colombia, we use the Agricultural Census of 2014 (Tercero Censo Nacional Agropecuario 2014), which contains information on 2,913,163 observations, of which 81.4% are farms (*unidade de produccion agropecuaria*). In 2014, 10.7% of farmers requested credit, and 88.4% of those accessed it, which implies that 9.5% of the total number of farmers accessed 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. According to the data, 16.5% of the farmers had access to extension services. To estimate the value of production we considered crops,[8] cattle,[9] and milk. The census does not provide information on prices, so here we use prices from the Food and Agriculture Organization of the United Nations (FAO) for 2014. We converted the value of production to USD from 2015 (COL 1 = USD 0.0003).

After cleaning the data, as we did for Bolivia and Peru, our final sample is larger than one million observations (descriptive statistics are displayed in Table 5.1). We merged the information from the census with the travel time information at the level of *veredas*, because we did not have the geographical information for each farm. Travel time and road network are directly associated

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

[9] We assume that only 80% of two or three years old are sold and are therefore included in the value of production.

and partially explain the pattern in the value of agricultural production. Farmers in the northern region have better road networks and accessibility (lower travel time). In the state of Amazonas, located in the south of Colombia, only 7.3% of the farmers had access to extension services (using the narrowest definition), while in central and northern states like Antioquia and Santander, 12.2% of the farmers had access to such services. An even more unequal distribution is associated with access to credit: in the state of Amazonas less than 1% of farmers had access, while 12.2% and 17.6% of the farmers in Antioquia and Santander, respectively, had access.

5. Sample analysis and results

The matching procedure applied to the extension services treatment in Peru resulted in a sample of 21,345 farm observations. In Table 5.1, the average value of production for those that did not receive extension services is much lower, when controlling for observable characteristics (USD 4,329.72 versus USD 6,701.78). The average value of production is USD 2372.06 higher for those farms did report receiving extension services (see the ATET displayed in Table 5.2).

[Table 5.1]

[Table 5.2]

A similar pattern is observed when analyzing access to credit. Value of production is higher even among farmers who only obtain credit, and the ATET is USD 3,214.29. Farmers who had access to both extension services and credit have an ATET of USD 7,629.56, which is higher than the ATET for each treatment separated. It indicates that the interaction of the two treatments increases even more farmers' value of production.

In Bolivia, access to extension services results in an increase in the value of production of USD 620.62 (see Table 5.2).[10][11] Access to credit also has a positive effect on the value of production, and the average treatment effect on the treated is USD 926.25. Value of production is consistently higher among farms that had access to credit independent of travel time values. As in Peru, the interaction of the two treatments increases the ATET on the value of production. For Bolivia, the ATET for farmers who had access to both credit and extension services is USD 1,910.85.

For Colombia, the average treatment effect on the treated for extension services is USD 1,493.58 (see Table 5.2). We also observe a large ATET of USD 1,308.99 associated with access to credit. We find that farms that had access to credit had a higher value of production than those that did not across the travel time spectrum. The interaction of the two treatments resulted in a higher ATET, USD 1,528.38, for Colombia.

In addition to the analyses shown in Table 5.2, we analyze how travel time affects the likelihood of accessing extension services and credit. Average travel time per municipality (or the lowest political administrative boundary) was found to have a nonlinear effect on the access to extension services and credit. We included both linear and quadratic terms in the logit model used in the treatment effect estimation. Overall, results indicate that as travel time increases, the likelihood of having access to extension services and credit decreases.

For Peru, we find that travel time has a statistically significant effect on the likelihood of accessing extension services (see Table A.1 in the appendix) with an inverted U-shaped

[10] It is proportionally smaller than the average treatment found for Peru. This might be associated with the fact that for Peru we included considerably more crops, because the survey provided the value of production for each crop, whereas the Bolivian census did not (the same pattern is observed for Colombia).

[11] The results for the link between travel time and extension services and credit have to be interpreted with caution, given that average travel time was calculated at the municipal level (the lowest political administrative unit available). A few municipalities in Bolivia are very large compared to those in Peru and Colombia (for which we used *veredas* as the unit level). This average might be misrepresenting the time to the nearest larger city, especially for farmers in these municipalities.

relationship (see Figure 5.1, top panel). Even though the effect on the probability of accessing extension services is increasing first, after a few hours the confidence interval of the estimate increases, which indicates that the estimate is not precise. This might be related to the policy on the provision of extension services, which focuses on farms in rural areas. For credit, we find a U-shaped relationship with travel time, where the probability of accessing credit decreases as travel time increases. Banking institutions are usually located in larger cities, which might be associated with lower transaction costs incurred by farmers for accessing credit and therefore a higher probability of requesting and obtaining credit.

[Figure 5.1]

We find similar results for Bolivia (see Table A.2), with an inverted-U relationship between access to extension services and travel time and a U-shaped relationship for access to credit and travel time. The poor-quality and limited road network might be responsible for these findings. The costs for providing these services might increase as the distance to large cities increases, given that we observe paved roads only near large cities. As for Peru, we find that the probability of accessing credit decreases as travel time increases.

[Figure 5.2]

For Colombia, we find that access to both extension services and credit decreases as travel time increases (see Table A.3). For credit, we find a U-shaped relationship with travel time that reaches the minimum point at a high travel time not displayed in the figure (see Figure 5.3).

[Figure 5.3]

Improvements in road networks (such as maintenance of existing roads and construction of new ones) would result in shorter travel times. In addition to the direct effect of road networks on farm income (profit) through the reduction of costs associated with output distribution and input demand discussed in the literature, our results suggest that road networks indirectly affect farm income through an impact on access to extension services and credit.

6. Summary

In this working paper, we estimate the average treatment effect on the treated (ATET) of extension services, credit and combined on the value of agricultural production in Bolivia, Peru, and Colombia. To estimate the ATET, we apply propensity score matching using information about agricultural production from agricultural censuses (for Bolivia and Colombia) and a survey (for Peru) and about travel time to the nearest city with 50,000 people or 1,500 inhabitants per square kilometer (Weiss et al. 2018). The travel time variable provides a better understanding of the road network than Euclidean distance to a center, given that it measures both distance to the nearest large town and the quality of the road (or transport route). The effect of accessibility on the probability of accessing extension services and credit, services that indirectly affect farm production, was estimated for each country.

Our results indicate that the provision of extension services and of credit separately and together results in greater value of agricultural production. Throughout this working paper, we avoided direct comparisons between countries, because of how the variable value of production was constructed. Caution regarding the interpretation and comparison of the results among countries is needed. We also find that accessibility and the likelihood of accessing these services are nonlinearly related. The results indicate that a higher likelihood is associated with lower travel time, especially in the analysis of credit.

We observe that in the northeastern region of Peru, deep in the Amazon Forest, travel time to an urban center is greater because of the poor quality of the road network. One may argue that this region is still mostly forested for the same reason. Perz et al. (2008) discuss the environmental effects of road building in the Amazon Forest region, among them loss of biodiversity, water-quality issues, and deforestation. Even though in this working paper we also measure the association between accessibility and access to extension services and credit and do not discuss the environmental impacts of road investment, several studies find that factors associated with decreasing cost of transportation and increasing market access—such as greater road density and reduced distances to urban centers—also increase deforestation (Reis & Margulis, 1991; Pfaff, 1997; Margulis, 2003; Chomitz & Thomas, 2001; Pfaff et al., 2007; Barber et al., 2014).

The agricultural censuses and surveys for these countries do not provide information on the geographic locations of the farms, limiting our ability to measure travel time from each farm to the nearest large town and access to roads (a better measure than road density). This data structure also limits the ability to measure potential farm spillovers. These datasets provide information for only one year, which does not allow estimation of the impact of new roads or road network policies on the access to extension services and credit and, indirectly, on the value of agricultural production. The method used in the paper to estimate the ATET does not account for potential endogeneity issues from unobserved characteristics. Future research could explore the spatial correlation at a higher level, such as that of the municipality, and account for the potential endogeneity problem.

The datasets for Colombia and Bolivia do not provide information on prices or on the value of production. We use prices from FAO to construct the variable value of production for selected products for Colombia and information on prices available from a national survey for Bolivia. There are two issues with this approach, as it can potentially fail to represent the entire farm production (a farmer could be producing two crops, one considered in this procedure and the other not), and it assumes a unique price for producers across the country (for Bolivia we calculated the average at the department level).

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Figures and Tables

Table 5.1 Descriptive statistics of key variables explaining the probability of access to extension and credit

		Credit effect				Extension effect				Credit & extension effect			
	Overall mean	*Unmatched sample*		*Matched sample*		*Unmatched sample*		*Matched sample*		*Unmatched sample*		*Matched sample*	
		Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated
Bolivia													
Value of production	1996.97	1682.66	4288.66	3362.40	4288.66	1680.63	3280.45	2659.83	3280.45	1727.40	6999.62	5088.77	6999.62
Extension	0.053	-	-	-	-	-	-	-	-	-	-	-	-
Credit	0.085	-	-	-	-	-	-	-	-	-	-	-	-
Energy	0.353	0.32	0.59	0.58	0.59	0.32	0.52	0.51	0.52	0.33	0.77	0.78	0.77
Travel time	3.617	3.59	3.99	3.98	3.99	3.58	3.52	3.51	3.52	3.61	4.03	4.06	4.03
Peru													
Value of production	8675.54	2739.98	8422.89	5208.60	8422.89	2677.40	6701.77	4329.72	6701.77	3072.59	14421.05	6791.49	14421.05
Extension	0.091	-	-	-	-	-	-	-	-	-	-	-	-
Credit	0.134	-	-	-	-	-	-	-	-	-	-	-	-
Travel time	4.541	4.58	3.56	3.49	3.56	4.79	5.51	5.53	5.51	4.24	4.71	4.69	4.71
Colombia													
Value of production	5449.37	5245.33	6170.83	4861.84	6170.83	5245.33	6475.64	4982.06	6475.64	5253.66	6385.48	4857.10	6385.48
Extension	0.102	-	-	-	-	-	-	-	-	-	-	-	-
Credit	0.144	-	-	-	-	-	-	-	-	-	-	-	-
Travel time	2.971	3.20	1.94	1.93	1.94	3.2	2.49	2.50	2.49	3.04	1.88	1.87	1.88

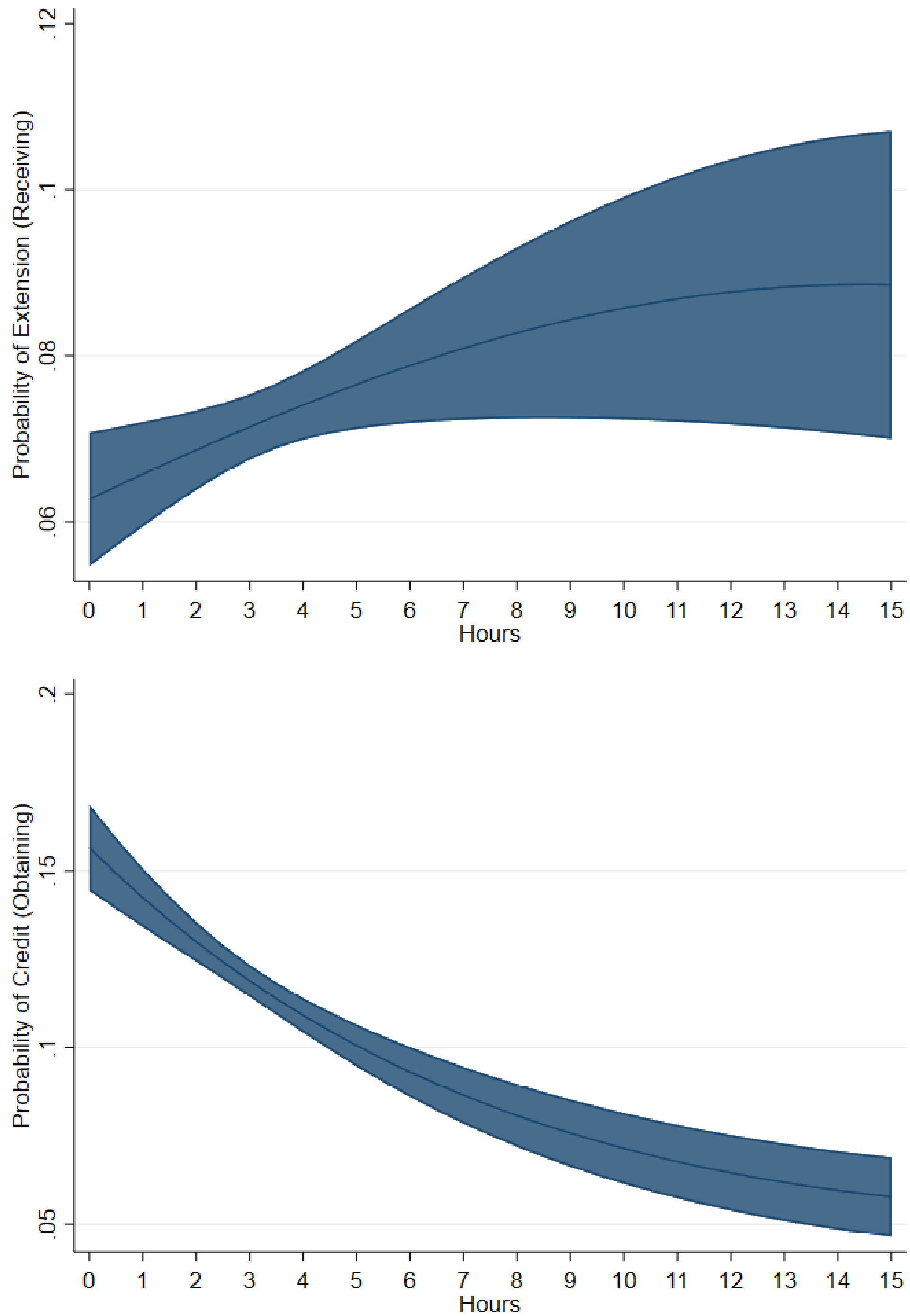
Note: In addition to these variables, we included state fixed effects and farm size. For Peru and Bolivia, we also included producer's gender, education, and age. For the matched sample, a test of means confirmed that the means of the treated and control groups are statistically the same.

Table 5.2 Average treatment effect on the treated – ATET for rural extension services and credit on value of agricultural production (USD) for Bolivia, Peru, and Colombia

	Bolivia	**Peru**	**Colombia**
	PSM for access to extension		
No extension services	2659.82	4329.72	4982.06
Extension services	3280.44	6701.78	6475.64
ATET (Extension effect)	*620.62*	*2372.06*	*1493.58*
	PSM for access to credit		
No credit	3362.40	5208.60	4861.84
Credit	4288.66	8422.89	6170.83
ATET (Credit effect)	*926.25*	*3214.29*	*1308.99*
	PSM for access to credit & extension		
No credit & extension services	5088.77	6791.48	4857.10
Credit & extension services	6999.62	14421.05	6385.48
ATET (Credit & extension effect)	*1910.85*	*7629.56*	*1528.38*

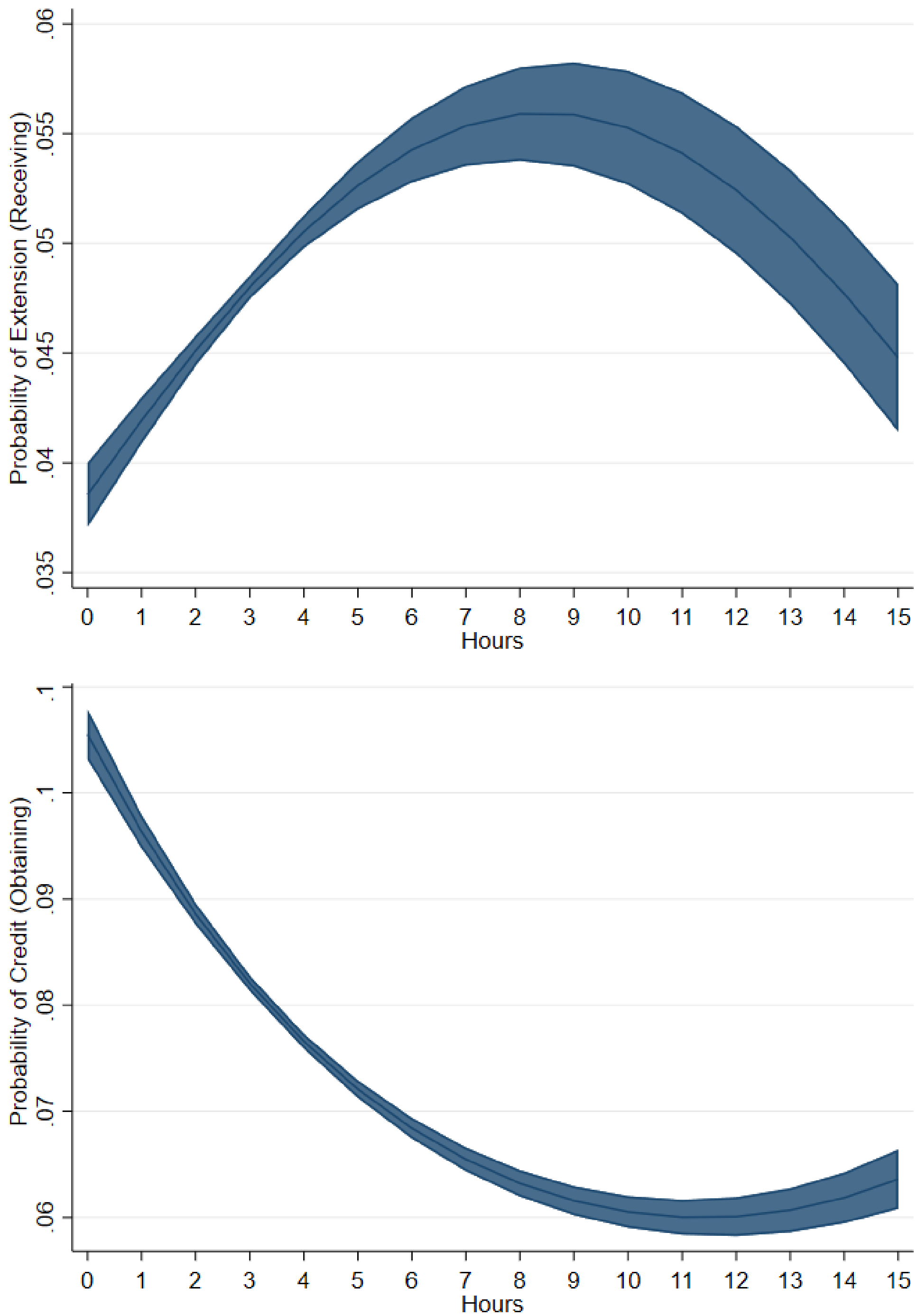
Note: All treatment effects are significant at 1%.

Figure 5.1 Prediction of the probability of obtaining extension services (top panel) and credit (bottom panel) over travel time (in hours) for Peru



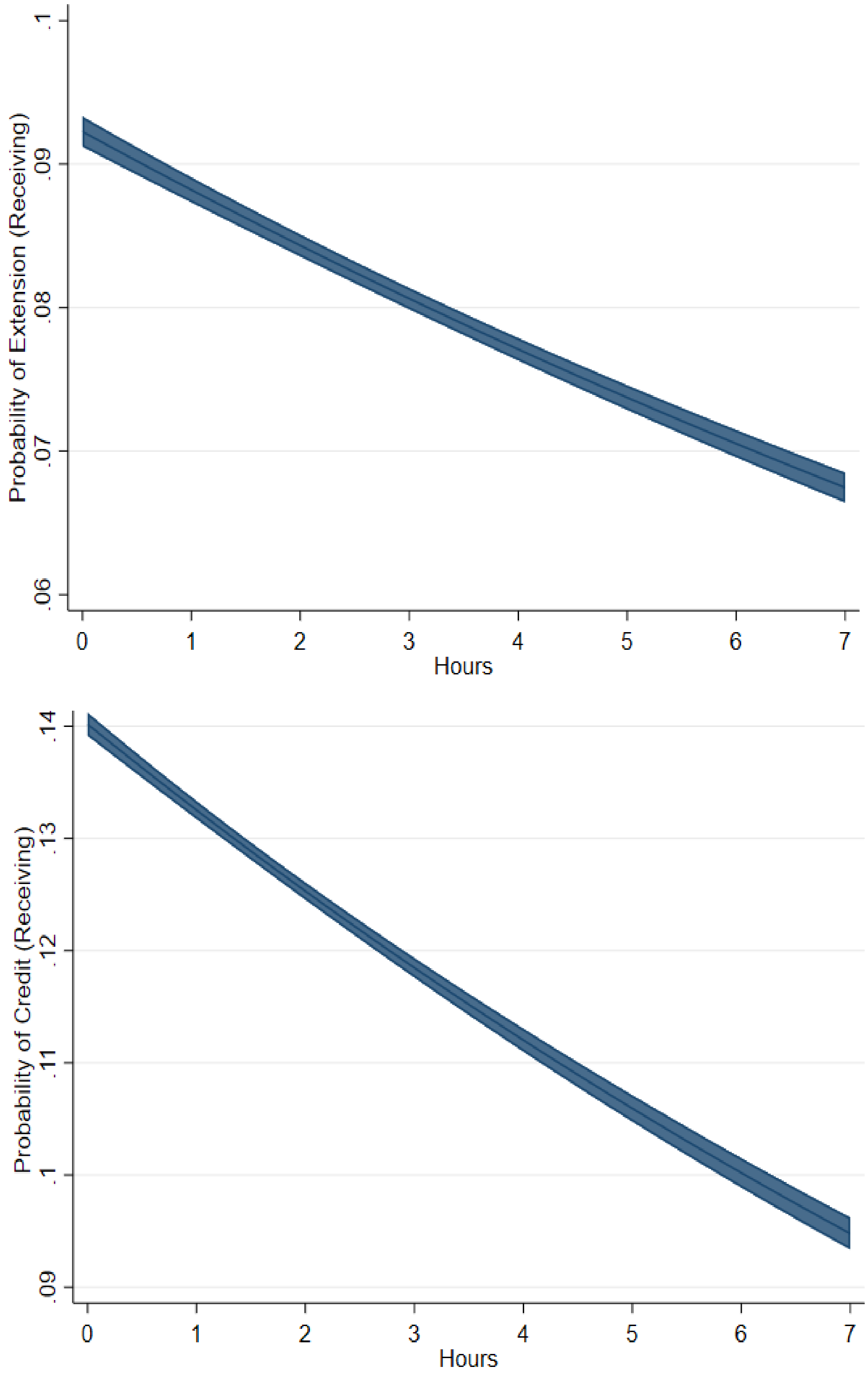
Note: Line of best fit represents estimation and shaded area represents the confidence interval.

Figure 5.2 Prediction of the probability of obtaining extension services (top panel) and credit (bottom panel) over travel time (in hours) for Bolivia



Note: Lines of best fit represents estimation and shaded areas represents the confidence interval.

Figure 5.3 Prediction of the probability of obtaining extension services (top panel) and credit (bottom panel) over travel time (in hours) for Columbia



Note: Lines of best fit represents estimation and shaded areas represents the confidence interval.

Appendix

Tables of logit estimates (PSM first step) for Peru, Bolivia, and Colombia

Table A.1 Logit estimates for access to rural extension services and credit in Peru

Access to	Rural extension		Credit		Extension & credit	
	Coef.	SD	Coef.	SD	Coef.	SD
Schooling:						
Basic education	0.232 NS	0.540	0.506 NS	0.423	0.898NS	0.806
Primary (incomplete)	0.468***	0.137	0.610***	0.115	0.901***	0.291
Primary (complete)	0.651***	0.142	0.849***	0.119	1.078***	0.296
Secondary (incomplete)	0.762***	0.152	0.991***	0.126	1.387***	0.305
Secondary (complete)	0.758***	0.150	1.016***	0.123	1.464***	0.302
High (incomplete)	0.959***	0.242	1.113***	0.193	1.181***	0.446
High (complete)	1.116***	0.185	0.966***	0.154	1.520***	0.347
Higher (incomplete)	1.474***	0.250	1.042***	0.227	1.453***	0.469
Higher (complete)	0.886***	0.194	0.955***	0.158	1.483***	0.349
Gender	-0.189***	0.071	-0.124**	0.054	-0.260**	0.118
Experience	0.001 NS	0.003	0.003 NS	0.002	0.003 NS	0.005
Age	-0.005*	0.003	-0.021***	0.002	-0.014***	0.005
Timemean_hours	0.0566**	0.028	-0.131***	0.018	-0.042 NS	0.036
Timemean_hours^2	-0.00195***	0.001	0.003***	0.001	0.000 NS	0.001
Pop. density	-0.000004 NS	0.0001 NS	0.00002 NS	0.0001	-0.00003 NS	0.0002
Farm size classes:						
5 to 10 hectares	0.466***	0.094	0.683***	0.068	0.594***	0.179
10 to 50 hectares	0.854***	0.081	1.091***	0.060	1.721***	0.140
50 to 100 hectares	1.131***	0.117	1.193***	0.094	2.206***	0.181
100 to 500 hectares	1.215***	0.119	1.269***	0.101	2.410***	0.191
500 to 1000 hectares	1.499***	0.257	1.647***	0.226	3.066***	0.348
>1000 hectares	0.584 NS	0.545	0.507 NS	0.486	3.233***	0.515
Constant	-5.534***	0.623	-2.113***	0.263	-6.234***	0.710
Dummies at municipality level	Yes		Yes		Yes	

Source: Own elaboration.
Note: *** significant at 1%, ** significant at 5%, * significant at 10%, NS = not significant.

Table A.2 Logit estimates for access to rural extension services and credit in Bolivia

Access to	Rural extension		Credit		Extension & credit	
	Coef.	SD	Coef.	SD	Coef.	SD
Elementary school	-0.071***	0.018	-0.019 NS	0.013	-0.306***	0.0315
High school	-0.031 NS	0.027	0.172***	0.018	-0.094**	0.0470
Gender	0.194***	0.015	0.193***	0.012	0.259***	0.0336
Age	-0.001**	0.0004	-0.021***	0.0003	-0.016***	0.0009
Timemean_hours	0.098***	0.008	-0.120***	0.005	0.025NS	0.0176
Timemean_hours^2	-0.006***	0.0004	0.005***	0.0003	0.001 NS	0.0012
Pop. Density	0.001***	0.00004	-1.78e-05 NS	0.00003	0.0002**	0.0001
Energy	0.555***	0.013	0.790***	0.011	1.403***	0.0316
Farm size classes:						
5 to 10 hectares	0.423***	0.022	0.677***	0.017	1.064***	0.0382
10 to 50 hectares	0.495***	0.025	0.960***	0.019	1.438***	0.0412
50 to 100 hectares	0.596***	0.052	1.223***	0.036	1.781***	0.0684
100 to 500 hectares	0.466***	0.081	1.098***	0.056	1.313***	0.1190
500 to 1000 hectares	-0.0003 NS	0.352	0.605**	0.240	0.191 NS	0.7190
>1000 hectares	0.495 NS	0.540	0.590 NS	0.451	2.063***	0.5530
Constant	-3.601***	0.058	-2.590***	0.057	-4.949***	0.1460
Dummies at province level	Yes		Yes		Yes	

Source: Own elaboration.
Note: *** significant at 1%, ** significant at 5%, NS = not significant.

Table A.3 Logit estimates for access to rural extension services and credit in Colombia

Access to	Rural extension		Credit		Extension & credit	
	Coef.	SD	Coef.	SD	Coef.	SD
Timemean_hours	-0.051***	0.002	-0.077***	0.002	-0.062***	0.005
Timemean_hours^2	0.0002***	0.00004	0.001***	8.44E-05	-0.001***	0.0003
Pop. density	-4.96e-05***	0.00001	-0.0002***	1.53E-05	-0.0002***	0.00002
Farm size classes:						
5 to 10 hectares	0.195***	0.013	0.169***	0.010	0.253***	0.018
10 to 50 hectares	0.081***	0.013	0.184***	0.010	0.123***	0.018
50 to 100 hectares	-0.145***	0.036	0.110***	0.026	-0.185***	0.055
100 to 500 hectares	-0.286***	0.044	-0.049^{NS}	0.032	-0.661***	0.080
500 to 100 hectares	-0.215*	0.119	-0.063^{NS}	0.095	-1.144***	0.304
>1000 hectares	-0.621***	0.181	-0.604***	0.161	-1.344***	0.450
Constant	-2.141***	0.013	-2.089***	0.013	-2.960***	0.020
Dummies at departmental level	Yes		Yes		Yes	

Source: Own elaboration.
Note: *** significant at 1%, ** significant at 5%, * significant at 10%, NS = not significant.