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Measuring Cocoa Agricultural Productivity: A Spatio-Temporal Econometric Approach

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Abstract. A significant increase of 50.5 percent in the national production of cocoa was registered between 2011 and 2015 in Colombia. Nevertheless, 5,890 tons were imported in 2015 to supply domestic demand. Unlike other crops, the production of cocoa has made a significant contribution to the income of approximately 38,000 families of which 90 percent are small farm-producers with very little capital. Facilitating credit for investment is one of the main strategies of the national government to increase cocoa productivity. Correspondingly, the impact of the credit for investment on the cocoa agricultural productivity and if those investments have a spillover effect is studied in 584 municipalities in Colombia. I use a yearly municipal agricultural assessment combined with municipality socioeconomic variables and georeferenced data from 2007 to 2017 to measure this impact and spatial interactions, based on a fixed effect and a spatial autoregressive model - SAR. Overall, the results suggest a positive relationship of credit for investment on agricultural productivity. Similarly, I found positive and significant agricultural productivity spillover. My results suggest that access to credit for investment is fundamental in cocoa agricultural productivity but the impact is larger when spatial interactions are accounted for, which provides a rationale for the national government to increase the offer of credit for investment for the development of a regional economic agglomeration.

Keywords. Spatial-temporal analysis, Agricultural productivity, Access to credit

1. Introduction

The population in the countryside in Colombia represents 22 percent of the total population and approximately 38,000 low-income families in rural areas depend on cocoa production for their sustenance. Cocoa farming activity contributed positively to 2 percent of the agricultural income in 2014 (Finagro, 2014). This contribution to the development of the agricultural sector is explained by an increase of public investments in the rural area and a broad portfolio of credit services created by the national government for the development of the farming activity. This is a sustainable government farming development strategy that is typically associated with agricultural productivity. Consequently, the public fund Finagro was established in the 1990s to provide a greater dynamic to the crop production and achieve immersion of small/medium farmers into the credit system. A credit policy should focus on improvement in modern infrastructure and sustainable technology beyond the use of working capital. There is evidences that technology generates higher added value to production in comparison to working capital.

Agricultural productivity is also measured from the impact of spillover effect. The literature suggests that spillover effect generate a positive and significant impact on agricultural production (Ulimwengu & Sanyal, 2013; Githiomi et.al, 2019). However, some studies state that spillover effect could have an adverse effect on agricultural productivity (Parker & Munroe, 2007). In Colombia, the Ministry of Agriculture and Rural Development is the national government entity responsible for formulating the policy related to rural development, agricultural, fisheries, and forestry. Its purpose is to contribute to the improvement of the living conditions of the farmers (Minagricultura, n.d.). Consequently, the national ministry designed a unique annual municipal agricultural assessment in the early 1970s for analysis of agricultural supply and outcomes.

My empirical study makes use of this municipal agricultural assessment – EVA (Spanish acronym) from 2007 to 2017 to evaluate the economic impact of the national policy of access to credit for investment. This unique assessment reports a total of 585 municipalities cocoa producers spread in the six economic regions of Colombia. However, I included 99.8[1] (584) percent of contiguous municipalities cocoa producers which is a representative sample population. Also, I used data from additional sources. One of them, the EVA which includes

[1] I dropped out one municipality of the sample because to estimate a spatial analysis it is not possible with an island. In other words, the municipalities have to share least the border or vertex.

information of farming activity outputs, for instance, cocoa total planting (ha), harvesting (ha), production (ton) and, yield (ton/ha). In addition, I utilized data from Finagro, a source that reports information about municipality credit granted by year. Finally, I employed geographic information contained in a shapefile to capture spillover effect on agricultural performance and municipal socioeconomic data to build additional control variables. The sources were provided by national entities such as Minagricultura, IGAC, DANE, and DNP.

Accordingly, I am interested in answers to the following questions: Does access to credit for investment correlate with cocoa agricultural productivity? And, do those investments have a spillover effect?. To address those questions, this paper posits two different estimation techniques to measure the causal relationship between credit for investment and agricultural productivity, and also spillover effect as a result of spatial interactions. The first research question was answered using a fixed-effect panel data model. This estimation technique was utilized to address the concern of endogeneity because of unobservable variables. However, the second question was addressed using a spatial autoregressive model - SAR which is global spatial model.

Overall, the results suggest a positive correlation between credits for investment on agricultural productivity. Similarly, I found positive and significant credit for investment spillover effect on agricultural productivity. Spillover effect which has a larger impact on agricultural productivity. Those results provide a rationale for the national government increase the offer of credit for investment for the development of a regional economic agglomeration.

Summarizing, the main contributions of my study are defined as follows: i) a greater contribution to the literature by answering the questions more broadly, ii) a novel identification strategy which has been unused to address the same research questions, iii) a reference for local, regional, and national government to understand the role of spatial interactions in the development of regional economic clusters, and iv) to introduce to the national government the result of an empirical analysis as reference for the assessment of other crops.

The remainder of the paper is structured as follows: section II introduces a brief review of the literature which involves empirical findings of theory related to the following: the market structure of farming credit in Colombia, access to credit, structural change, and, the spatial dependence effect. Section III contains the study area and data description; section IV presents the methodological approach and estimation technique. Section V discusses the empirical findings; and finally, section VI explains the conclusion and policy implications.

2. Literature Review

2.1 Access to Credit and Agricultural Productivity Connection

Cocoa farming represents one of those activities that are most developed by small/medium farmers and are globally and locally acceptable. An area of 127,988 hectares (ha) of cocoa was cultivated in Colombia in 2009, equivalent to only 2 percent of world cultivation, (Minagricultura, n.d.) but according to the study reported by UPRA in 2017, the country contains 19.2 million ha of land suitable for cocoa production[2]. This is equivalent to 16.8 percent of the continental territory of the country. The total of remaining lands, 68.7 percent, are non-suitable and 14.5 percent have legal restrictions.

As one of the most striking features of the cocoa productive system in Colombia, 90 percent of the cocoa productive system consists of small farmers, corresponding to approximately 38,000 low-income families in rural areas. The average cocoa production units of these small farmers is 3.3 hectares. These farms use traditional and low-tech modes for planting, maintenance, and harvesting, which leads to a low quantity and quality of the product. The price of the grain and the investment of resources for the maintenance of the plantations are the main determinant for the cultivation of cocoa. There are also business crops larger than 50 ha, corresponding to 5 percent of the area sown and 16 percent of production (UPRA, 2017).

In addition, 60 percent of the labor employed is the family type. According to Minagricultura (2005), family farming tasks are related to harvest (44%) and control of weeds (28%). Fertilization tasks represent 0.6 percent of the workforce, but it is not highly applied in the cocoa cultivation. Pruning is the only farming task where the labor is contracted because a good productive capacity depends on technical knowledge (UPRA, 2017). The lack of capital for investment constitutes a barrier to the development of cocoa production. The rural

[2] Of the total suitable land, a 4.1 percent corresponds to high suitability (A1), 8.5 percent to medium (A2), and 4.2 percent to a low (A3).

capitalization index[3] registered 17 percent in 2014 (UPRA, 2017), a fraction which is low in comparison with other agricultural activities. Consequently, the national government has designed different mechanisms to facilitate access to credit for investment for producers of different size and origin. One of them, it is an incentive for the production granted through a special line of credit which involve projects such as planting, renovation, and maintenance of new hectares, acquisition of machinery and equipment, and the improvement of infrastructure to achieve high level of productivity.

Productivity focuses on the quality of production more than quantity (Drucker, 1999), as well, it considers production efficiency and effectiveness. Several studies that linked agriculture productivity and access to credit in developing countries have been conducted. Most of them are consistent in their argument that access to credit has a positive and significant indirect impact on agriculture outcomes Awotide et al. (2015). For example, many studies have found that access to credit has a positive influence on technologies adoption in agricultural, increased capital for farm investment, hired labor, and improved household welfare (health care and better nutrition). Consistently, the credit could be considered as an important element in the agriculture system Feder et al. (1990). It permits farmers to have the working capital needed to increase the production cycle as well as provide resources to invest. Working capital provides the monetary resource to acquire the inputs and raw material, hire labor, and replace fixed assets Banrep (n.d).

The influence of credit for investment on agriculture has been studied broadly beyond the impact of working capital. Researchers have mainly focused on investment because of its providing more added value to the productivity of the sector. Thus, scholars mostly have concluded that access to credit may raise allocative efficiency in agriculture e.g., farmers with access to credit are enabled to invest in capital-intensive methods of production. In other words, i.e. improved technology results in technical efficiency (Hazarika & Alwang, 2003). Therefore, the differences in the volume of productions between credit constrained farmers and unconstrained, it is explained by the relationship between access to credit and the level of efficiency of crop production (Saldias & Von Cramon-Taubadel, 2012)

[3] The rural capitalization index is a deposit to the credit made by Finagro to reduce the balance of this, recognizing a percentage of the value of new investments. Finagro recognizes a 30 percent under the investment to small-farmers, 20 percent to medium-farmers, and 10 percent to large-farmers.

Consequently, the absence of credit service constitutes one of the most important constraints for agricultural development because improving farm productivity could be achieved through better access to agricultural credit (Sossou et al., 2014). Specifically, the authors empathize that those farm production operations are correlated with credit investment in crop production, the adoption of new technologies, and proper processing and storage. Along with the conclusive theory that credit contributes to improving agricultural outcomes. The theory has determined that the agricultural credit can be defined into institutional and non-institutional sources. However, the sources of non-institutional credit cannot significantly contribute to agricultural development because the amount of money that a farmer can borrow is minimum compared to what they can receive from the formal institution (Olomola, 1999; cited in Chandio et al., 2017). Therefore, non-institutional credit can decrease farmer constraint, but it does not provide the required total amount of money to operate.

In the context of the market structure of credit for farming purpose in Colombia, credit for investment in agriculture is associated with farming performance in Colombia because it permits equal access to the market to small-size, medium-size, and large-scale producer. (Marin-Usuga et al., 2016). Similarly, Estrada et al. (2011) conclude that access to credit and adequate financial services are the main components to improve the competition in the agricultural sector in Colombia. That is, it is fundamental to generate the economic conditions of production and the basic supply of food which help to improve the living conditions of the rural population. Furthermore, Marulanda et al. (2010) suggest that saving, credit, transfer, payment, and insurance permit the producers and micro-enterprises to compensate the effect of adverse shocks that decrease their income and deteriorate their living standards. In addition, Echavarria et al. (2017) suggest that credit has a positive and significant effect on yield (between 3 percent and 28 percent), which is mainly explained by the impact on seasonal cycle crops.

All the above-mentioned studies are unanimous in the conclusion that access to credit has a positive and significant indirect impact on agriculture outcomes. In addition, there is a generalized perception that worldwide the structure of the credit market and strategies that are available to rural households are extremely variable (Conning & Udry, 2005) and constitute the main strategy adopted by the local government to farming support in developing countries.

However, several studies had found no effect of credit on farm productivity for market-oriented farmers in the short-term (Reyes et al., 2012) and farmer efficiency (Kochar, 1997).

Referring to the estimation technique adapted to capture the causal relationship between access to credit and agricultural productivity several studies have used the endogenous switching regression model (ESRM), propensity score matching technique, and stochastic frontier model. The literature acknowledges that access to credit is endogenous to agricultural productivity because of self-selection (Awotide et al., 2015, Saldias & Von Cramon-Taubadel, 2012; and Reyes et al., 2012), i.e. the credit is voluntary and there are farmers in better position. In addition, access to credit mays theoretically endogenous to agricultural productivity because reverse causality, unobserved characteristics, and measurement error. I believe that access to credit for investment is endogenous to agricultural productivity for this research particularly, because of unobserved characteristics. This arguments is further defined in the model specification. Therefore, the type of estimation technique used depends on the type of data and the period of analysis, e.g. cross-sectional or panel study that use observational or experimental data.

2.2 Spatial Dependence Effect Theory

The concept of "spatial econometrics" is a term which is relatively new and consists of a subfield of econometric estimation techniques that combine the treatment of spatial interactions (spatial autocorrelation) and spatial structure (spatial heterogeneity) in regression models for cross-sectional and panel data. This notion of spatial econometrics is attributed to Paelinck & Klaassen (1979). However, it was improved by Anselin in 1988 who took the concept and introduced it formally into econometric estimation and specification techniques (Anselin, 1999; Dabbert, 2013). In spite of recent applications on econometric analysis, this concept has been widely used on empirical studies such as international economics, labor economics, public economics, local public finance, and agricultural and environmental economics (Anselin, 1999, Lippert et al., 2009, Breustedt & Habermann, 2011, Lewis et al., 2011).

Referring to the effect of spatiotemporal factors that could influence agricultural productivity. Thünen (1910, Cited in Dabbert, 2013) is recognized as the creator of agricultural location theory. He correlated the agricultural activities with locational factors, i.e. crop activities and animal breeding are strategically located near the consumer. (O'kelly & Bryan, 1996 and

Dabbert, 2013). In addition, Bichler et al. (2005) concluded that geographical features and location have an impact on farmers' decisions and agriculture outcomes. This is called spillover effect as a situation in which the dynamics in a certain area directly or indirectly influence the pattern of neighboring local economies (Boncinelli et al., 2015).

This argument is supported by Schmidtner et al. (2012) who developed the concept of agglomeration effects on their analysis and determined that there are spillover effects that may influence the spatial distribution of organic farming in the county level. A spillover effect that is driving by spatial interaction of economic factor among regions, for instance, exchange of labor, capital, and other resources can be promoted among each other (Jin et al., 2018). Nevertheless, Wollni & Andersson (2014) highlight that farmers who have access to information from their neighborhood networks are more likely to adopt organic agriculture and new technology. This is because the spatial agglomeration of agricultural innovation given the influence of knowledge spillovers (Läpple et al., 2016). New adopters that are more often found within the neighborhoods of each other's and of earlier adopters (Nyblom et al., 2003).

However, Parker & Munroe (2007) suggest that spillover effect could generate negative externalities as well. This because incompatible production processes among farming systems may lead to spatial conflicts and production losses between neighboring farms, and the magnitude of such losses may depend not only on the scale of each activity but also on patterns of land use. Such conflicts can be classified as "edge-effect externalities"—spatial externalities whose marginal impacts decrease as the distance from the border generating the negative impact increases. For instance, Deininger et al. (2015) found a positive spillover effect of large-farms located within 0-50 km radius on small-farms' adoption of traditional agricultural practices and input, but not on cultivated land, non-farm occupation, output market participation, access to credit or, for farms growing the same crop measured on yields.

In the context of Colombia and after conducting a search for related studies, it does not exist related studies for the county which measured global and local spatial autocorrelation in agricultural productivity among neighbor municipalities. Most studies exist to explain the challenges, land tenure reforms, and issues that face the agricultural sector. Two studies noted here relate to the spatial correlation effect. The first one explored whether different groups of regions will react differently to a labor market impulse (Diaz, 2015). The author found that spatial effects are relevant factors when interpreting municipal disparities in unemployment rates in Colombia. The second one analyzes whether the geographical separation of markets constitutes a factor that helps explain the dynamics of agriculture price (Iregui & Otero, 2012). The scholars found that distance (and thus transportation costs) is a factor that helps explain the speed at which prices adjust to shocks in other locations (Iregui & Otero, 2012).

Consistent with the above theory cited, the concept of spatial econometrics is incorporated in the analysis of the impact of access to credit for investment because allow making econometric inferences that what occurs in a certain municipality, it could impact positively or negatively neighbor municipalities. For instance, it has been evidenced that in the agricultural sector in Colombia there are several types of spatial interaction among neighboring municipalities; such as, sharing: i) labor and transfer knowledge from one to another, ii) infrastructure for the development of agricultural activities or implement new infrastructure based on the neighbors, iii) technology that supports the production of their neighbor, and iv) adverse effects such as conflict in the area, dry season, environmental issues, etc. that could affect in greater or less proportion the closest municipalities.

Summarizing the above-mentioned theories, the literature related to access to credit consistently concludes that access to credit has an indirect and significant effect on agriculture productivity. It also suggests that agricultural performance can be explained by regional economic interactions that generate spillover effects. Therefore, I consider those theories to test the null hypothesis: 1) there is no impact of access to credit for investment on cocoa agricultural productivity, and 2) agricultural productivity spillover is not the rationality behind credit for investment, i.e. there is no spillover effect.

3. Study Area and Data

3.1 Study Area

Colombia has 19.2 million ha of land suitable for cocoa production[4]. However, a 4.1 percent corresponds to high suitability (A1), 8.5 percent to medium (A2), and 4.2 percent to a low (A3) (UPRA, 2017). Cocoa production is concentrated in four agro-ecological zones principally, as

[4] The identification of land suitable to cocoa involved 22 criterions of which 9 are physicals, 5 bio-geophysical, and 8 socioeconomic.

follows: i) Santandereana mountain, which represents about 50% of national production; ii) dry inter-Andean valleys; ii) tropical humid forest, and iv) marginal coffee zone low. This study focuses on a total of 584 municipalities that growing cocoa. This represents more than 50 percent of the total municipalities in the country. Cocoa production is scattered in all regions: Centro Oriente (127), Eje Cafetero (109), Pacifico (105), Centro Sur (100), Caribe (81), and Llano (62) [Figure 1].

3.2. Data Description and Measurement of Variables

3.2.1 Observational Data

This study uses observational panel data which was provided by several ministry offices in Colombia. The agricultural data was obtained from the Ministry of Agriculture and Territorial Development (Spanish acronym, Minagricultura). This is a unique annual municipal agricultural assessment that compiles production outputs of all crops. The assessment is performed for more than 270 crops in each of the 1,001 municipalities. It includes 10 special districts in a total of 32 departments in the country. The information is collected in partnership with other agricultural offices. This methodology was implemented in early 1970s. However, it was disaggregated to the municipal level in 2007. The data period ran from 2007 to 2017, for a total of 187,335 registers[5]. The rationale for using this data is that it provides the farming activity outputs which permitted the building of additional indicators. The planting and harvesting outputs are measured in total hectares, the production outputs in tons, and yield corresponds to tons over hectares. The panel data was created on 584 cocoa producing municipalities from 2007 to 2017 for a total of 6424 register.

I measure the impact of access to credit for investment and spillover effect on agricultural productivity from the perspectives of quality, i.e. by the ability of each municipality to generate high-value farming activity (yield and production value). The building of outcome-variables also implied the use of additional sources. For instance, production value is defined as cocoa valuation production (price) times the municipality's total ton produced divided by total hectares. I used observational data from DANE and Minagricultura. Overall, Yit represents the agricultural productivity in depth of each municipality at time t.

[5] The data was desegregated to departmental level in 1987 and municipal level in 2007

The control variables that help to explain the causal impact on agricultural productivity of cocoa are defined in the methodology. I used datasets from different sources. One of them corresponds to the data provided by Finagro. Finagro provided data related with access to credit for investment by municipalities and type of crop. Land use per km^2 was created by using data from Minagricultura and IGAC. It is defined as total cocoa hectare by kilometer.

Georeferenced data contained in a shapefile was used to localize the six regions in Colombia. The shapefile was provided by IGAC. As a result, indicator variables were defined. Data of infrastructure to farming is also provided by IGAC. This is a georeferenced data that defined the percentage of aqueduct coverage (water supply) by municipalities. Finally, additional information of energy coverage, fiscal revenue and labor were provided by DNP. A descriptive statistic table of the control variables and outcome variables is reported in the [Table 1].

3.2.2 Spatial Data.

The literature acknowledges that addressing impact evaluations on the agricultural sector constitutes a real challenge due to the geographical dependence and factors such as crop cycles, seasonality, context variables, spillover effects, implementation changes, sequencing of interventions in integrated projects, national-level interventions, and self-selection (Farley et. al, 2012; Goldstein, 2018; Winters et. al, 2010; IEG, 2011). Therefore, spatiotemporal analysis captures those effects by creating and managing spatial-weighting matrices to analyze spatial interaction. Spillover effects that could occur in three dimensions: a) The value of the outcome variable (Yit) in a region might impact the value of Yit in a neighboring region (b) the value of the treatment variable (X's) in a region might affect the value of Yit in a neighboring region, and (c) the residuals ε might impact the residual in a neighboring region (spatial heteroskedastic).

The Spatio-temporal analysis make use of the panel data created on 584 cocoa municipalities' producer from 2007 to 2017. However, the analysis involved additional stages. In the first stage I used a shapefile provided by IGAC to create a new shapefile for the 584 municipalities that farm cocoa. The following steps were involved in the process: 1) creating a geodatabase in ArcGIS 10.6 that included a shapefile with the total municipalities in Colombia and a database in CSV format in excel with registers of cocoa for the 584 producer municipalities, 2) joining the databases using a unique id that is defined on each source of data, 3) using the selection tool that permitted me to draw a map for the 584 municipalities, and 4) using the option export data to store a new shapefile for the 584 municipalities.

In the second stage I used the generated shapefile for the 584 cocoa producing municipalities to define a contiguity queen. (This captures neighboring municipalities that share the same border and vertex) spatial-weighting matrix and lag matrices which are included in the estimation. The assumption of this selection is that unobserved features not specified in the regression of a closer neighbor has greater impact than a far one. Creating the contiguity queen spatial-weighting matrix, I followed the instruction defined by Drukker et al. (2013). I also used Stata version 13.0 in conjunction with R version 3.5.1 and ArcGIS 10.6. The steps are as follows: 1) importing the shapefile into Stata format, 2) creating contiguity queen spatial-weighting matrix from geospatial data, 3) standardizing the contiguity queen spatial-weighting matrix, and 4) banding the contiguity queen spatial-weighting matrix.

The final stage involved a Spatio-temporal correlation diagnostic. The contiguity queen spatial-weighting matrix and the outcomes variables were used to test the null hypothesis which is - there is not spatial or temporal auto-correlation between the observed data, i.e., the distribution is random (Baumbach et al., 2018).

4. Method

4.1 Methodological Approach

The literature concludes that access to credit has an indirect impact on productivity, but this impact is greater on credit beneficiaries than non-beneficiaries (Feder et al., 1990; Hazarika & Alwang, 2003; Saldias & von Cramon-Taubadel, 2012, and Awotide et al., 2015). It also acknowledges that spatial interaction of neighboring regions has influence on economic development Jin et al. (2018), i.e. the regional development depends significantly of how the regions are interrelated to each other (Schmidtner et al., 2012). Controlling for municipality level individual effect, I defined the following typical regression model based on the literature which is focused on the fixed-effect variant beyond the random-effect variant (Hughes et al., 2017):

$$Y_t = X_t\beta + \mu + \tau + u_t, \tag{4.1}$$

$$\mu = Z_u\mu + \nu_t, \tag{4.2}$$

$$\nu_t = \lambda M\nu_t + \varepsilon_t. \tag{4.3}$$

Where Y_t denote a N_t *x 1* vector of agriculture productivity. X_t is an N_T *x K* matrix of the explained variables including credit for investment, fiscal revenue, water coverage, energy coverage, labor, and land use. β is *K x 1*. The vector μ is N_t *x 1* which is assumed to be independently distribute. ν_t is a vector of N_T *x 1* of individual effects for each municipality which is assumed be independent and identically distributed – i.i.d. (0, $\sigma^2_\mu I_{NT}$). The error component Z_u is $\iota_T \otimes I_N$ denoting the selector matrix *N x 1* random vector of individual effects μ which is assumed to be i.i.d (0, $\sigma^2_\mu I_N$). ι_T is a vector of ones of dimension *T* and I_N is an identity matrix of dimension *N*. μ and ν is assumed, they are independent of each other and the regressor matrix *X*. τ denotes the time effect (Baltagi & Liu, 2011, and Hughes et al., 2017).

The rationale to treat the individual fixed effect is that I assume that this variable is correlated with the control variables defined on the right-hand side of the regression. In addition, it is assumed that this variable is roughly fixed over time for each municipality within the sample. It permits to correct for omitted variables bias given the possibility of the fixed effect is correlated with the independent variables, such as; unobservable geographic characteristics, abrupt climate change, economic liberalization, change of the agricultural policy, and insecurity in the area. Omission which would increase my concern of endogeneity. Therefore, I control for fixed effect for demean the data as a static effect (Burnett et al., 2013).

An additional contribution of this paper is to measure how spatial interaction among neighboring municipalities may have an impact on agricultural productivity. I define spatial interaction effect by including a contiguity queen weighting matrix (W_N) into the regression. W_N is an N x N positive matrix that consist of 584 cross-sectional units (584 contiguous municipalities) with at least one neighbor, with about 4.6 contiguous units on average. The weighting matrix is defined to the model as

$$W_N = I_T \otimes W_N \tag{4.4}$$

To get W = is $I_T \otimes W_N$, Baltagi & Liu (2011) suggest that one sort the data first by time ($t = 1 \dots T$) and then by individual units ($i = 1 \dots N$), where the $N\ x\ N$ spatial weighty matrix W_N is binary matrix with zero elements in its diagonal and is row-normalized with its entries usually declining with distance. In addition, the authors argue that because endogeneity is present include in spatial-temporal analysis, i.e. a spatial lagged dependent variable Wy that is correlated with the disturbance u is included in the model and the explained variable that interact with the matrix is endogenous. The Ordinary Least Squares estimator will be biased.

Kelejian & Robinson (1993) and Kelejian & Prucha (1998) (cited in Anselin et al., 2008) suggest that endogeneity issues of the spatially lagged dependent variable is solved through an instrumental variable strategy in which the spatially lagged (exogenous) explanatory variables WX are used as instruments. Consequently, Anselin et al., 2008 argue that this applies directly to the spatial lag in the pooled model, where the instruments would be $(I_T \otimes W_N)X$ with X as a stacked $N_T \times (K-1)$ matrix, excluding the constant term. An additional, identification was introduced by Kelejian & Piras (2012) when it is not possible to find a strong instrument. It theoretical reasonable lagged the explanatory variable one-period to achieve exogeneity in the variable as well in the weighting matrix.

Consequently, I tested the four type of spatial-temporal panel estimations to determine which fit better in my data: the spatial autoregressive model (SAR), Spatial Durbin model (SDM), Spatial Autocorrelation Model (SAC or SARAR), or spatial error model. The basic representation of the spatial autoregressive model – SAR can be defined as

$$Y_t = \rho W Y_t + X_t \beta + \mu + u_t \qquad t = \cdots, T, \tag{4.5}$$

where ρ is the coefficient of the spatial autoregressive model. μ is a vector of parameter to be estimated in the fixed effect. The standard assumption that $u_t \sim N(0, \sigma^2_u)$ and $E(u_{it}\ u_{js})=0$ for $i \neq j$ and/or $t \neq s$ apply in this case (Hughes et al., 2017).

The spatial Durbin model - SDM, on other hand, can be defined on its generalized form as

$$Y_t = \rho W Y_t + X_t \beta + W Z_t \theta + \mu + u_t \tag{4.6}$$

The spatial Durbin model is considered a generalization of the SAR model because besides including a spatially weighted explained (W_y), it defines spatially weighted regressor variables (W_z) as explanatory variables. It is assumed that $Z_t \neq X_t$. As it was defined above, ρ is the coefficient of the spatial autoregressive model (Hughes et al., 2017).

Otherwise, the spatial autocorrelation model – SAC or SARAR, as a combination of SAR and SEM is defined as

$$Y_t = \rho W Y_t + X_t \beta + \mu + v_t \tag{4.7}$$
$$v_t = \lambda M v_t + u_t \tag{4.8}$$

where M is a matrix of spatial weights which may or may not be equal to W (Hughes et al., 2017). ρ is the coefficient of the spatial autoregressive model and λ is the coefficient of the spatial autocorrelation of the error term.

Finally, the spatial error model – SEM is defined as

$$Y_t = X_t \beta + \mu + v_t \tag{4.9}$$
$$v_t = \lambda M v_t + u_t \tag{4.10}$$

The spatial error model focuses on spatial autocorrelation in the error term. This could be a special case of the SAC as well of the SDM (Hughes et al., 2017). As I mentioned above, λ is the coefficient of the spatial autocorrelation of the error term.

For those dynamic models defined above, it incorporates bias corrected Quasi-Maximum Likelihood (QML) estimators defined by Yu et al. in 2008, which treat the lagged dependent variables as exogenous regressor (Hughes et al., 2017). In order to stablish a diagnostic test to determinate if the model should reduce to a spatial lag model or a spatial error model (Burnett et al., 2013). This paper follows the suggested by LeSage & Pace (2009) and Elhorst (2010) of begin with spatial Durbin model as general estimation and test for alternative specifications as follow:

$$\text{Ho: } \rho = 0 \tag{4.11}$$
$$\text{Ho: } \rho + Z * \beta = 0 \tag{4.12}$$

where the first hull hypothesis define if the SDM must be simplified to the spatial autoregressive model and the second null hypothesis define if it must be correspond instead of a spatial error model. If the two null hypothesis are rejected, it indicates that the spatial Durbin model offer the best fit for the data (Burnett et al., 2013 and Hughes et al., 2017). Finally, after regression estimation and the diagnostic is carried out following the LeSage & Pace (2009) the direct and indirect is calculated in order to interpret the coefficient on the spatial autocorrelation to test the secondary research question if spatial spillover effect helps to explain agricultural productivity.

4.2 Empirical estimation

This paper examines the relationship between access to credit for investment and cocoa agricultural productivity by extending the standard productivity defined as yield. In addition, the production value is incorporated as a secondary perspective to analyze whether credit for investment generates high-value to the farming activity. Consequently, I test the impact of access to credit for investment on agricultural productivity of municipality i in time t as is defined in equation 4.13.

$$lnY_{it} = \beta_0 + \beta_1 \ln(I_{it}) + X_{it}'\beta + m_i + \tau_t + u_{it}; \qquad i = 1, \dots, N, \qquad t = 1, \dots, T \tag{4.13}$$

where Yit is agriculture productivity and measured from depth impact (yield and output value per hectare), t indicates different years (e.g. 2007-2017), i identifies the 584 municipalities, β denote the fixed effects regression coefficients, m municipality fixed effect and t time fixed effect. The control variables in the model are credit for investment (lnI), fiscal revenue (lninc), aqueduct coverage (aqued), water coverage (Energ), land use (LU), and labor (L). With this regression I expected to test the null hypothesis of there is not impact of access to credit for investment in agricultural productivity.

I recognize that credit for investment is potentially endogenous to agricultural productivity. For instance, unobservable characteristics like governance, municipality capacity, and so on. It could influence farming productivity and access to credit for investment. Endogeneity also occurs by reverse causality between access to credit for investment and agricultural productivity. In other words, the literature suggests the access to credit is determined by the capacity to generate revenue as a result of the economic activity. Likewise, it concludes that access to credit has a positive impact on agricultural productivity. However, the national policy of access to credit for the agricultural sector in Colombia, it is not linked to agricultural performance and the capacity for generating income. The national government has implemented an inclusive system of credit of which the offer depends on the aim prioritized by in each sector. Thus, small-size and medium-size famers have equal possibility to access to credit that large-size farmer but under different conditions and incentives.

Particularly, cocoa farmer can apply for working capital or investment. Nevertheless, the national government offers an incentive if the credit is for investment in infrastructure and technology. The strategy is to increase the rural capitalization index to achieve a higher level of competitiveness. There are 585 cocoa producing municipalities identified in the Minagricultura's assessment. This study analyzed the impact access to credit in agricultural productivity for 584 municipalities of which an 86 percent of the municipalities were granted at least one credit for investment between 2007 and 2017. Municipalities which has different socioeconomic conditions. Therefore, there is no reason to believe that agricultural productivity has influence over the access to credit for investment for this particular situation. I assume that access to credit is exogenous for measure agricultural productivity.

Nevertheless, I use a fixed effect estimation described previously in this section to correct for endogeneity. The advantages of use fixed effect model is it provide an alternative solution to the endogeneity issue without using instrumental variables. In addition, it removes any time invariant regressor after the first differencing which make the OLS estimates unbiased and consistent.

I analyze also the relationship between access to credit for investment and cocoa agricultural productivity by testing whether investment spillover has an effect on agricultural productivity. The rationality for and approaches to estimating spillover effect is based on three dimensions supported in the contexts of how the farming activity is developed in Colombia. First, the credit for investment may generate knowledge spillover in farming activity because it intensifies employment options and improves labor skill in the zone. In addition, investment may influence information and technology exchange and collaboration cross-border and cross-farming activity.

The second dimension is production spillover. The intuition is that access to credit for investment boosts innovation in new infrastructure and the adoption of technology in neighbor municipality. The result is increasing agricultural productivity, higher profit, and competitiveness in the region. In addition, this investment may also influence private and government in the area and the generation of new enterprises. The final dimension is network spillovers. Credit for investment may lead the creation of cluster as result of economic exchanged. Furthermore, as result of investment in the zone, it improves living condition of the communities close each others.

I capture spatial spillover effect that may affect agricultural productivity by using a spatial-autoregressive with spatially spatial autoregressive model – SAR explained in the past section. I therefore treat investment spillover in the agricultural productivity equation as specified in the following equation:

$$lnY_{it} = \rho W lnY_{it} + \beta_1 \ln(I_{it}) + X'_{it}\beta + m_i + \tau_t + u_{it}; \quad i = 1, \dots, N, \quad t = 1, \dots, T \tag{5.14}$$

Where W is the spatially weighted regressors. p is the spatial coefficient. The rest of variables remain similar as was defined in the previous section. With this regression I expected to test the null hypothesis of there is not spatial spillover effect.

6. Empirical Findings.

6.1 Descriptive Tables

The descriptive statistics show that on average municipalities were granted 132 million COP by year which represents an 86 percent in the data. However, 14 percent of municipalities were not granted credit for investment in the equivalent period. Municipalities generate also fiscal revenue by tax collections for investment in any sector. On average, municipalities gather 7,841.04 million COP by year. Analyzing other production factors, on average, municipalities have 0.51 hectares per km2 for cocoa production. Labor represents 61.09 percent of the total population on average. Municipalities have limited coverage of the aqueduct, on average municipalities' water supply represent 58.42 percent. However, municipalities' energy coverage represent 88.09 percent on average. Finally, the result shows that on average, municipalities achieve a yield of 0.54 (ton/ha) and the value of the production is 150049.3 COP (ton/ha).

6.2 Impact of Credit for Investment on Agricultural Productivity

Table 2 introduces estimates of the effect of access to credit for investment on cocoa agricultural productivity defined as yield. The table includes the result of OLS, municipality fixed effect, and time fixed estimations for comparison purposes. The results are consistent across different estimations and indicate that increasing access to credit for investment significantly improve cocoa yields. The results suggest the importance of investment in infrastructure and technology to achieve development in the area, competitiveness, and increase food security. Other statistical significant to determinate cocoa yield. This is expected because the high dependence of labor in the production process.

Estimating heterogeneity cocoa agricultural productivity across regions, table 3 shows a significant effect variability in the region of Centro Oriente. This result indicates that municipalities that access to credit for investment in this region differ from one another in the amount of credit for investment granted and its impact on cocoa yield. Result that it is expected due to the region of Centro Oriente is where is concentrated on large-scale cocoa production. The region of Centro Oriente tend to be homogenous in relation to the labor use in cocoa production. However, the heterogeneous effect of credit for investment on cocoa yield across time remain positive and significant in Centro Orient but negative and significant in the region of Caribe which is expected given the physical, bio-geophysical, and socioeconomic characteristics of the area for the development of the cocoa farming. Heterogeneous effect of labor on cocoa yield remain positive and significant in the region of Eje Cafetero, Centro Oriente, Centro Sur y Pacifico [see table 4].

Table 5 presents estimates impact of access to credit for investment on cocoa output value per hectare, estimated using a similar approach to the analysis of impact on yield. The outcomes strength the previous result by indicating across estimation credit for investment affect cocoa production value. Impact that is positive and statistically significant. Similarly, Labor and fiscal revenue is associated with output value per hectare. Analyzing heterogeneity cocoa output value by hectare across regions, table 6 indicates that there is variability in the production value in regions such as Eje Cafetero, Centro Oriente, and Llanos. This is expected due to geographical separation of markets constitutes a factor that helps explain the dynamics of agriculture value. All region has a positive and significant effect on output value which is reasonable because the availability of labor post-harvest vary across regions. Also, the investment of income revenue in the farming activity in the area for achieve productivity. Across time, a positive and significant heterogeneous effect on production value is observed in the region of Centro Oriente. However, the region of Caribe has a negative and significant heterogeneous effect on output value per hectare.

6.3 Credit for Investment Spillover effect on Agricultural Productivity

Table 9 shows that there are strong spillover effect in cocoa yield. The coefficient of the spatial lagged dependent variable (rho) is highly significant but with positive sign for explain the effect on yield. Therefore, analyzing the indirect and indirect effect, table 10 indicates that the direct and total effects of credit for investment, energy coverage, and labor on yield has a positive and significant global effect in neighboring municipalities. Marginal indirect effect that remain positive and significant to explain yield. The intuition behind is that credit for investment and labor on one's own municipalities has on positive effect on Cocoa productivity. Nevertheless, when credit for investment increase in a neighbor municipality, this investment attract labor and decrease the availability of labor in municipalities where investment is no longer execute. In addition, when investment on infrastructure and technology are developed in a specific municipality, it generates production spillover which incentive to neighbor municipalities implement the same innovation. Therefore, the industrialization of the process could generate positive externalities, e.g. economic clusters. This affect globally all the municipalities close each other.

Analyzing, credit spillover effect on cocoa output value per hectare, table 11 shows also a high level of spillover effect in cocoa production value. The coefficient of the spatial lagged dependent variable (rho) is positive and significant across municipalities, and remain positive across time. Therefore, table 12 indicates a significant and positive direct, indirect, and total spillover effect of credit for investment, fiscal revenue, and labor on average over all municipalities. Nevertheless, energy coverage spillover effect is not significant across time. A reasonable explanation is that investment from access to credit may influence information and technology exchange and collaboration cross-border and cross-farming in the short-run. Conversely, when the region is balanced, it is no reasonable expect this exchanged. The intuition of labor is statistical significant across municipality time is that labor is require in all the stage of cocoa farming. Exchanged of labor in neighbor municipalities that have an indirect effect due to when the harvest occur on one municipality, the labor emigrate from one municipality to another, generating adverse effect on the rest of region.

The local interaction of spatial association - LISA cluster map provide some evidence of spatial heterogeneity. I found evidence of spatial grouping. A cluster of municipalities with high agricultural productivity, as well as neighbors with high agricultural productivity. This "municipality core" of high agricultural productivity is also implicated surrounding municipalities with low agricultural productivity, but high-agricultural productivity neighbors. In addition, there are clusters of low-agricultural productivity municipalities, surrounded by other municipalities with low agricultural productivity. The no significant municipalities indicate spatial randomness (It means the absence of any pattern) of values is equally likely as any the other spatial pattern [see figure 9 and 10].

7. Conclusion and Policy Implications.

Credit for investment has been included in the agenda of the national government of Colombia as a strategy to boost the agricultural sector. Cocoa farming is one of those farming activities that represent an opportunity for development in the country. The high demand of cocoa in the national and international market combined with a low-tech production process have influenced offers of incentives and flexible credit by the government. These conditions have created a general demand for credit for investment by municipalities in Colombia. I utilized two different approaches to measuring the effect of access to credit for investment in cocoa agricultural productivity: 1) fixed effect model; and 2) spatial autoregressive model. The fixed effect estimation model captures the average effect across individuals and time. The spatial autoregressive model captures the credit for investment spillover effect.

My empirical findings are consistent with the conclusions in the literature that access for credit for investment has positive and indirect impact on agricultural productivity. In addition, my findings suggests that the contribution of labor in cocoa agricultural productivity is greater than credit for investment. Findings that are consist where spillover is measured. The use of a spatial-autoregressive with spatially autocorrelated model (SAR) helped to capture the dimension of credit for investment spillover on yield and production values as a proxy for agricultural productivity. The result suggests a global positive and negative effect, but this negative effect is indirect. Comparing, the result from the fixed effect estimation and SAR estimation permits a conclusion that credit for investment affects agricultural productivity. However, this impact is larger when spillover effect is measured.

The policy implication of my findings advocates by a credit for investment allocation in municipalities located in strategies regions. In other words, the aim of investment in a specific area has to be considered in the development of a regional economic integration and the creation of economic clusters that strengthen the farming activity, increase the living condition, and generate a collaborative system of cross-border and cross-farming activity. Thus, the contribution of this paper beyond adding to the literature is to create a new method of evaluation and design of agricultural public policy.

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Appendix

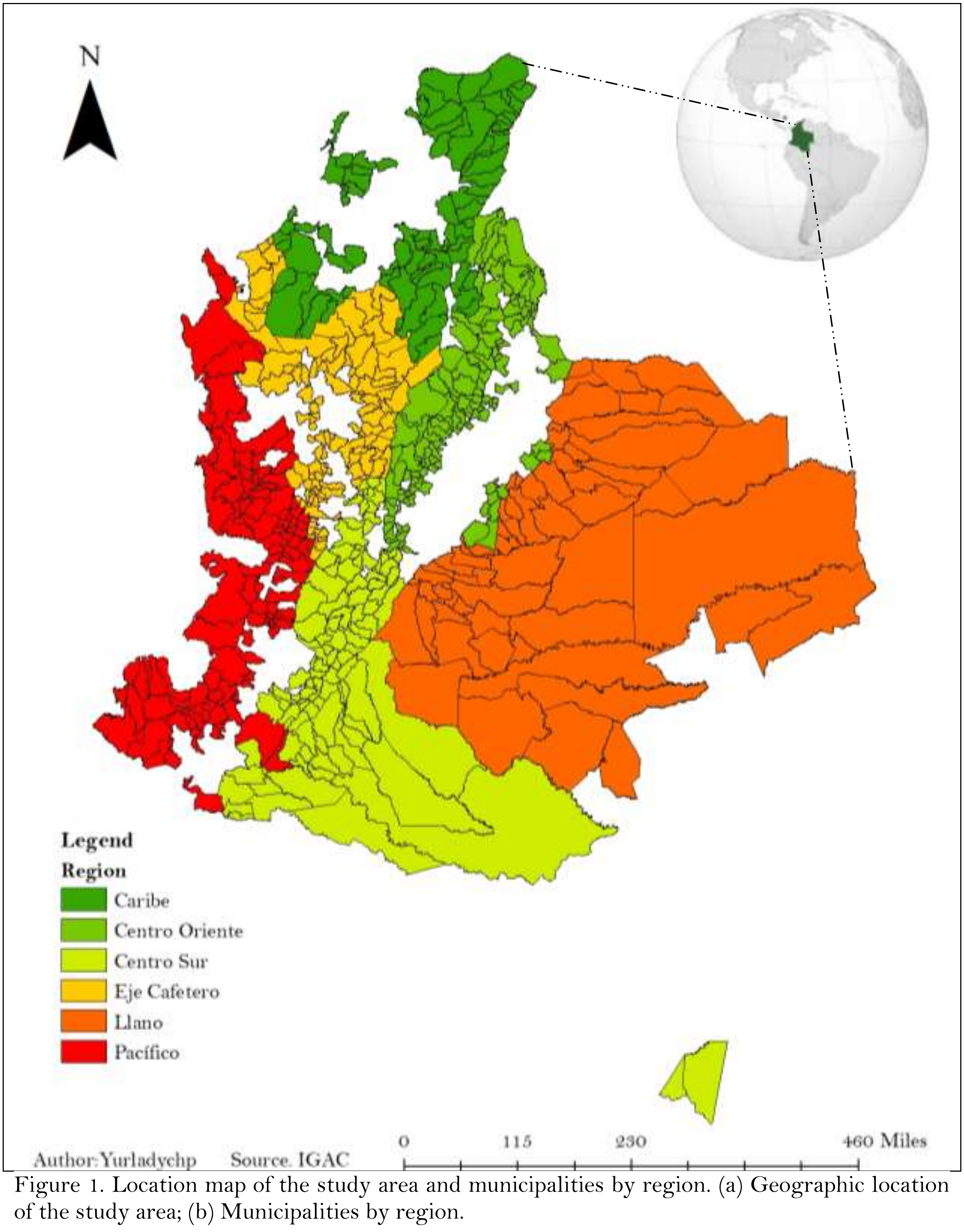

Figure 1. Location map of the study area and municipalities by region. (a) Geographic location of the study area; (b) Municipalities by region.

Table 1: Summary Statistics
---Means with Standard Deviations in Parentheses---

Agricultural Productivity: Outcomes	**Abbreviation**	**Units**	**Obs.**	**Mean**	**Std. Dv.**	**Min.**	**Max.**
Yields	Y_{d1}	ton/hectares	6424	0.54	0.22	0.00	1.52
Output value per hectare	Y_{d2}	($Price*ton)/hectare	6424	150049.30	66575.52	0.00	506725.70
Agricultural Performance: Covariance	**Abbreviation**	**Units**	**Obs.**	**Mean**	**Std. Dv.**	**Min.**	**Max.**
Investment	I	000 Col Pesos	6424	132000	474000	0.00	14800000
Fiscal Revenue	Inc	000 Col Pesos	6424	7841	43339	0.00	1163338
Land use	LU	Land used in agriculture	6424	0.51	1.12	0.00	19.82
Labor	L	Percentage	6424	61.09	4.23	0.00	74.47
Aqueduct Coverage	Aqued	Average	6424	58.42	29.82	0.00	100.00
Energy Coverage	Energ	Average	6424	88.09	17.14	0.00	100.01
Region: Eje Cafetero	R_1	Dummy	6424	0.19	0.39	0.00	1.00
Region: Caribe	R_2	Dummy	6424	0.14	0.35	0.00	1.00
Region: Centro Oriente	R_3	Dummy	6424	0.22	0.41	0.00	1.00
Region: Centro Sur	R_4	Dummy	6424	0.17	0.38	0.00	1.00
Region: Pacifico	R_5	Dummy	6424	0.18	0.38	0.00	1.00
Region: Llano	R_6	Dummy	6424	0.11	0.31	0.00	1.00

Note. A total of 584 municipalities is studied over the period 2007 – 2017. This represents the 99.9 percent of cocoa producer.

Table 2: Cocoa Agricultural Productivity
Dependent Variable: [lnYield (ton/he)]
- - - OLS, Municipality and Year Fixed Effect - - -

Variables	(1)	(2)	(3)
Ln(Credit for Investment)	0.00452***	0.00164**	0.00137*
	(0.000546)	(0.000618)	(0.000623)
Ln(Fiscal Revenue)	-0.00847*	0.00206	-0.00774
	(0.00343)	(0.00744)	(0.00868)
Land use	-0.000196	-0.00758	-0.00637
	(0.00271)	(0.00834)	(0.00831)
Labor	0.0139***	0.0357***	0.0339***
	(0.00173)	(0.00525)	(0.00827)
Aqueduct Coverage	-0.000514**	0.0000916	0.000176
	(0.000163)	(0.000161)	(0.000159)
Energy Coverage	0.00186***	0.000800*	0.000664
	(0.000279)	(0.000362)	(0.000367)
Constant	-1.596***	-2.918***	-2.726***
	(0.0957)	(0.294)	(0.514)
Municipality FE	No	Yes	Yes
Year FE	No	No	Yes
N	6424	6424	6424
R-sq	0.052	0.616	0.623

OLS Robust Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

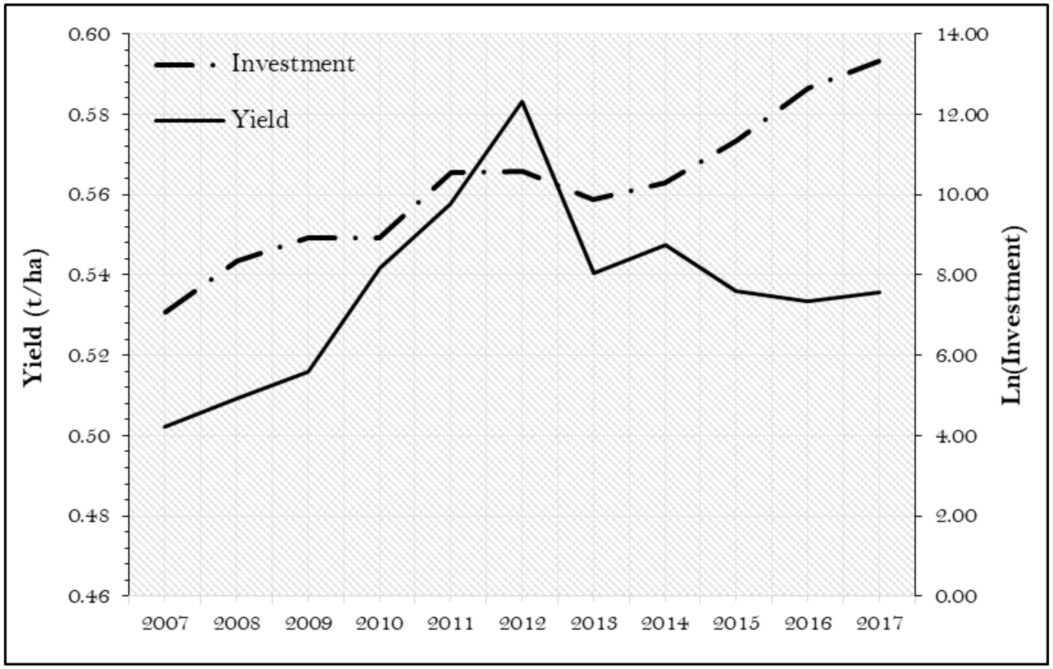

Figure 2. Temporal Trends in Yield and Credit for Investment for 584 Cocoa Municipalities Producer in Colombia over the Periods of 2007-2017

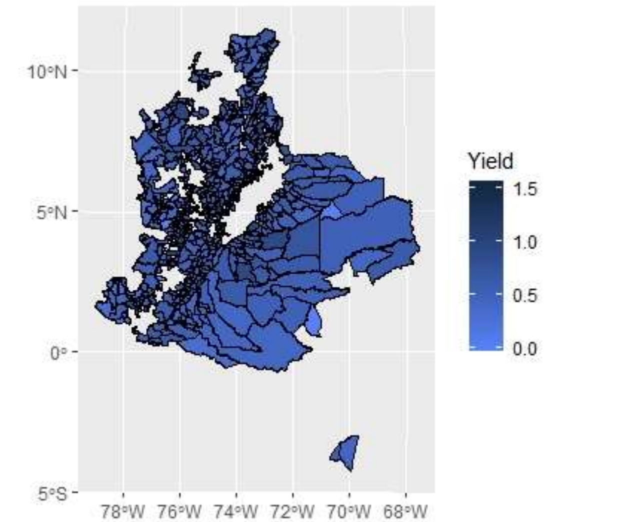

Figure 3. Cocoa Yield in Colombia averaged over the 2007–2017 period

Figure 4. Access to Credit for Investment in Colombia averaged over the 2007–2017 period

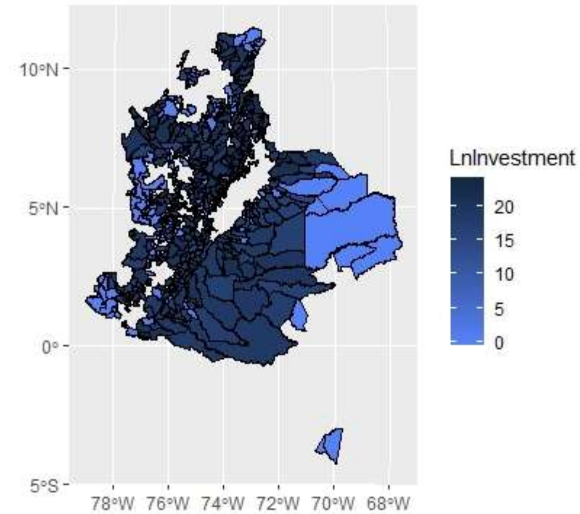

Table 3: Heterogeneity in Cocoa Agricultural Productivity Effect by Region
Dependent Variable: [lnYield (ton/he)]
- - - OLS, Municipality Fixed Effect - - -

Variables	(1) Eje Cafetero	(2) Caribe	(3) Centro Oriente	(4) Centro Sur	(5) Pacifico	(6) Llano
Ln(Credit for Investment)	0.00244	-0.00260	0.00557***	0.000873	-0.00135	0.00201
	(0.00138)	(0.00137)	(0.00160)	(0.00106)	(0.00144)	(0.00173)
Ln(Fiscal Revenue)	0.0463*	0.0291*	-0.0195	-0.0688**	-0.00371	0.0727***
	(0.0207)	(0.0137)	(0.0174)	(0.0209)	(0.0170)	(0.0209)
Land use	0.0288	-0.0594	0.00378	-0.0463*	-0.0186**	0.0201
	(0.0377)	(0.0644)	(0.0130)	(0.0224)	(0.00656)	(0.0128)
Labor	0.0899***	-0.0293*	0.0109	0.0787***	0.0757***	-0.0182
	(0.0147)	(0.0122)	(0.0120)	(0.0110)	(0.0112)	(0.0191)
Aqueduct Coverage	-0.000210	0.000466	0.0000378	0.000121	0.000286	-0.0000667
	(0.000461)	(0.000338)	(0.000342)	(0.000321)	(0.000350)	(0.000589)
Energy Coverage	0.00177	-0.000500	0.000757	0.00447***	0.00184*	-0.00232**
	(0.00152)	(0.000689)	(0.000821)	(0.000851)	(0.000892)	(0.000729)
Constant	-6.803***	0.941	-1.194	-5.308***	-5.526***	0.0859
	(0.846)	(0.666)	(0.669)	(0.589)	(0.655)	(1.069)
N	1199	891	1397	1100	1155	682
R-sq	0.603	0.645	0.596	0.412	0.702	0.472

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Heterogeneity in Cocoa Agricultural Productivity Effect by Region
Dependent Variable: [lnYield (ton/he)]
- - - OLS, Municipality and Year Fixed Effect - - -

Variables	(1) Eje Cafetero	(2) Caribe	(3) Centro Oriente	(4) Centro Sur	(5) Pacifico	(6) Llano
Ln(Credit for Investment)	0.00200	-0.00356**	0.00541***	0.00118	-0.00180	0.000216
	(0.00146)	(0.00136)	(0.00162)	(0.00110)	(0.00142)	(0.00165)
Ln(Fiscal Revenue)	-0.000696	0.0490**	-0.00490	-0.0499*	-0.00853	0.0154
	(0.0252)	(0.0152)	(0.0187)	(0.0252)	(0.0195)	(0.0256)
Land use	0.0269	-0.0434	0.00497	-0.0393	-0.0178**	0.0193
	(0.0380)	(0.0613)	(0.0129)	(0.0238)	(0.00650)	(0.0161)
Labor	0.0576**	0.0356	0.0575**	0.118***	0.0537*	-0.0381
	(0.0182)	(0.0261)	(0.0186)	(0.0160)	(0.0232)	(0.0250)
Aqueduct Coverage	-0.000263	0.000803*	0.000136	0.0000602	0.000312	-0.0000898
	(0.000468)	(0.000326)	(0.000343)	(0.000319)	(0.000350)	(0.000581)
Energy Coverage	0.00150	-0.000174	0.000538	0.00446***	0.00180*	-0.00310***
	(0.00161)	(0.000712)	(0.000844)	(0.000869)	(0.000885)	(0.000806)
Constant	-4.393***	-3.142*	-4.146***	-7.849***	-4.139**	1.799
	(1.149)	(1.569)	(1.144)	(0.990)	(1.469)	(1.521)
N	1199	891	1397	1100	1155	682
R-sq	0.609	0.669	0.611	0.429	0.709	0.514

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Cocoa Agricultural Productivity
Dependent Variable: Output value per hectare [ln(ton/he)*Price]
- - - OLS, Municipality and Year Fixed Effect - - -

Variables	(1)	(2)	(3)
Ln(Credit for Investment)	0.0370***	0.00402***	0.00122
	(0.00319)	(0.000679)	(0.000629)
Ln(Fiscal Revenue)	0.125***	0.107***	-0.00829
	(0.0202)	(0.00842)	(0.00879)
Land use	0.0282**	-0.00688	-0.00666
	(0.00970)	(0.00857)	(0.00812)
Labor	0.00374	0.151***	0.0327***
	(0.00627)	(0.00575)	(0.00836)
Aqueduct Coverage	-0.00527***	-0.0000807	0.000182
	(0.000923)	(0.000176)	(0.000161)
Energy Coverage	-0.00333*	0.000926*	0.000597
	(0.00135)	(0.000388)	(0.000370)
Constant	10.56***	1.372***	9.475***
	(0.330)	(0.320)	(0.519)
Municipality FE	No	Yes	Yes
Year FE	No	No	Yes
N	6424	6424	6424
R-sq	0.043	0.986	0.988

OLS Robust Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

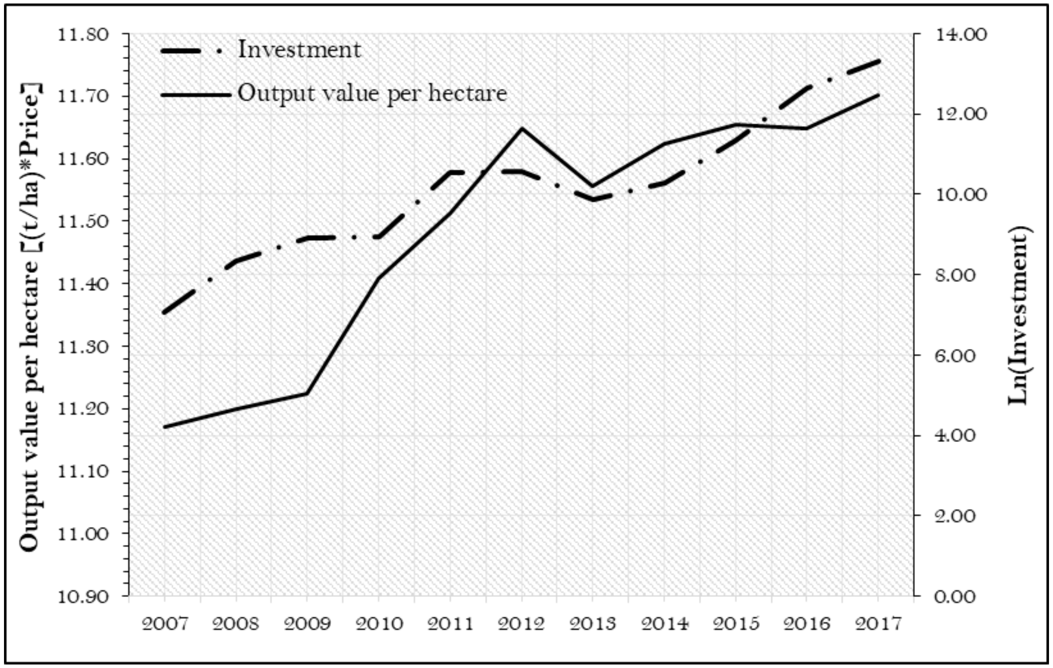

Figure 5. Temporal Trends in Output value per hectare and Credit for Investment for 584 Cocoa Municipalities Producer in Colombia over the Periods of 2007-2017

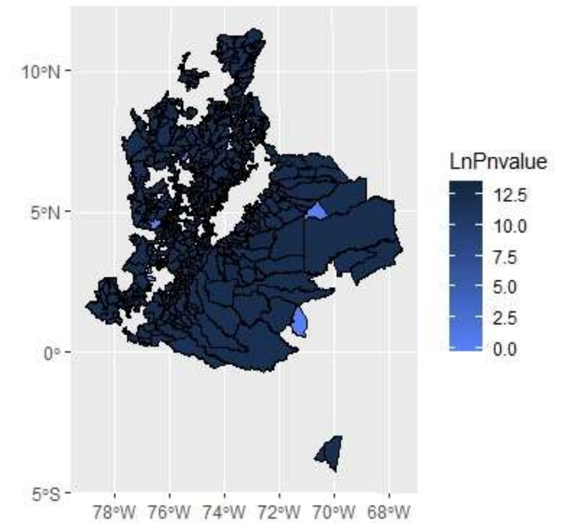

Figure 6. Cocoa Output value per hectare in Colombia averaged over the 2007–2017 period

Figure 7. Access to Credit for Investment in Colombia averaged over the 2007–2017 period

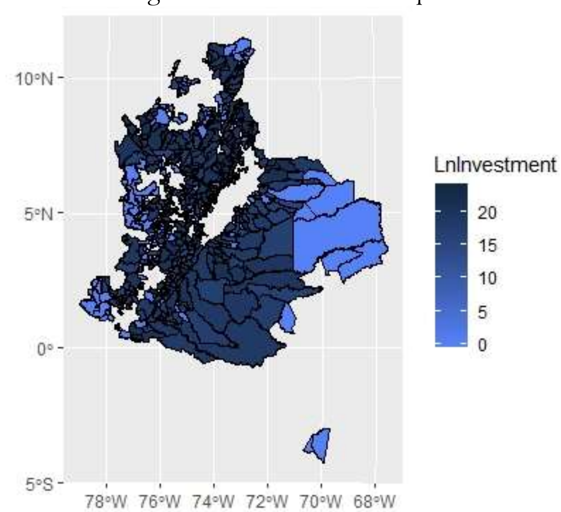

Table 6: Heterogeneity in Cocoa Agricultural Productivity Effect by Region
Dependent Variable: Output value per hectare [ln(ton/he)*Price]
- - - OLS, Municipality Fixed Effect - - -

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Eje Cafetero	Caribe	Centro Oriente	Centro Sur	Pacifico	Llano
Ln(Credit for Investment)	0.00501***	-0.00116	0.00775***	0.00242*	-0.000260	0.00540**
	(0.00150)	(0.00142)	(0.00176)	(0.00123)	(0.00159)	(0.00191)
Ln(Fiscal Revenue)	0.220***	0.0871***	0.0995***	0.0728**	0.0476**	0.204***
	(0.0260)	(0.0149)	(0.0182)	(0.0231)	(0.0181)	(0.0252)
Land use	0.0212	-0.0308	0.00402	-0.0394	-0.0184**	0.0267*
	(0.0410)	(0.0683)	(0.0139)	(0.0251)	(0.00622)	(0.0127)
Labor	0.202***	0.107***	0.106***	0.183***	0.207***	0.0850***
	(0.0170)	(0.0133)	(0.0127)	(0.0120)	(0.0119)	(0.0215)
Aqueduct Coverage	0.00000972	-0.000229	-0.000670	0.000174	0.000268	0.000245
	(0.000473)	(0.000382)	(0.000375)	(0.000344)	(0.000395)	(0.000671)
Energy Coverage	0.00281	-0.000458	0.00100	0.00509***	0.00156	-0.00279**
	(0.00169)	(0.000706)	(0.000898)	(0.000896)	(0.000944)	(0.000865)
Constant	-3.056**	4.446***	4.117***	-0.213	-2.079**	5.009***
	(0.974)	(0.725)	(0.712)	(0.642)	(0.690)	(1.191)
N	1199	891	1397	1100	1155	682
R-sq	0.980	0.992	0.990	0.542	0.989	0.985

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Heterogeneity in Cocoa Agricultural Productivity Effect by Region
Dependent Variable: Output value per hectare [(ton/he)*Price]
- - - OLS, Municipality and Year Fixed Effect - - -

Variables	(1) Eje Cafetero	(2) Caribe	(3) Centro Oriente	(4) Centro Sur	(5) Pacifico	(6) Llano
Ln(Credit for Investment)	0.00184	-0.00333*	0.00516**	0.00118	-0.00232	0.000491
	(0.00147)	(0.00136)	(0.00165)	(0.00110)	(0.00144)	(0.00165)
Ln(Fiscal Revenue)	0.00315	0.0488**	-0.00412	-0.0499*	-0.0101	0.00779
	(0.0253)	(0.0155)	(0.0190)	(0.0252)	(0.0196)	(0.0267)
Land use	0.0264	-0.0468	0.00522	-0.0393	-0.0175**	0.0184
	(0.0380)	(0.0618)	(0.0128)	(0.0238)	(0.00617)	(0.0156)
Labor	0.0647***	0.0336	0.0501**	0.118***	0.0575*	-0.0482
	(0.0182)	(0.0261)	(0.0190)	(0.0160)	(0.0233)	(0.0255)
Aqueduct Coverage	-0.000217	0.000683*	0.0000278	0.0000602	0.000397	0.0000596
	(0.000466)	(0.000331)	(0.000346)	(0.000319)	(0.000358)	(0.000595)
Energy Coverage	0.00128	-0.000157	0.000628	0.00446***	0.00155	-0.00309***
	(0.00162)	(0.000716)	(0.000859)	(0.000869)	(0.000888)	(0.000826)
Constant	7.333***	9.047***	8.331***	4.676***	7.469***	14.57***
	(1.147)	(1.573)	(1.163)	(0.990)	(1.478)	(1.554)
N	1199	891	1397	1100	1155	682
R-sq	0.983	0.993	0.992	0.626	0.991	0.989

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

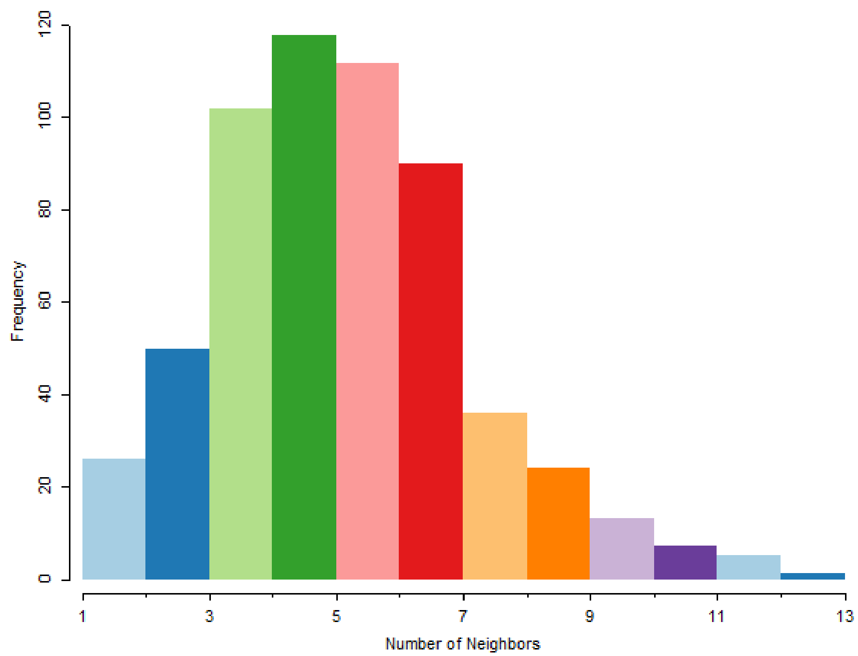

Table 8. Summary of Spatial-Weighting Object W

--- Contiguity Queen Weighting-Matrix ---

Matrix	Description
Dimensions	584 x 584
Stored as	584 x 584
Links	
Total	2702
Min	1
Mean	4.627
Max	12

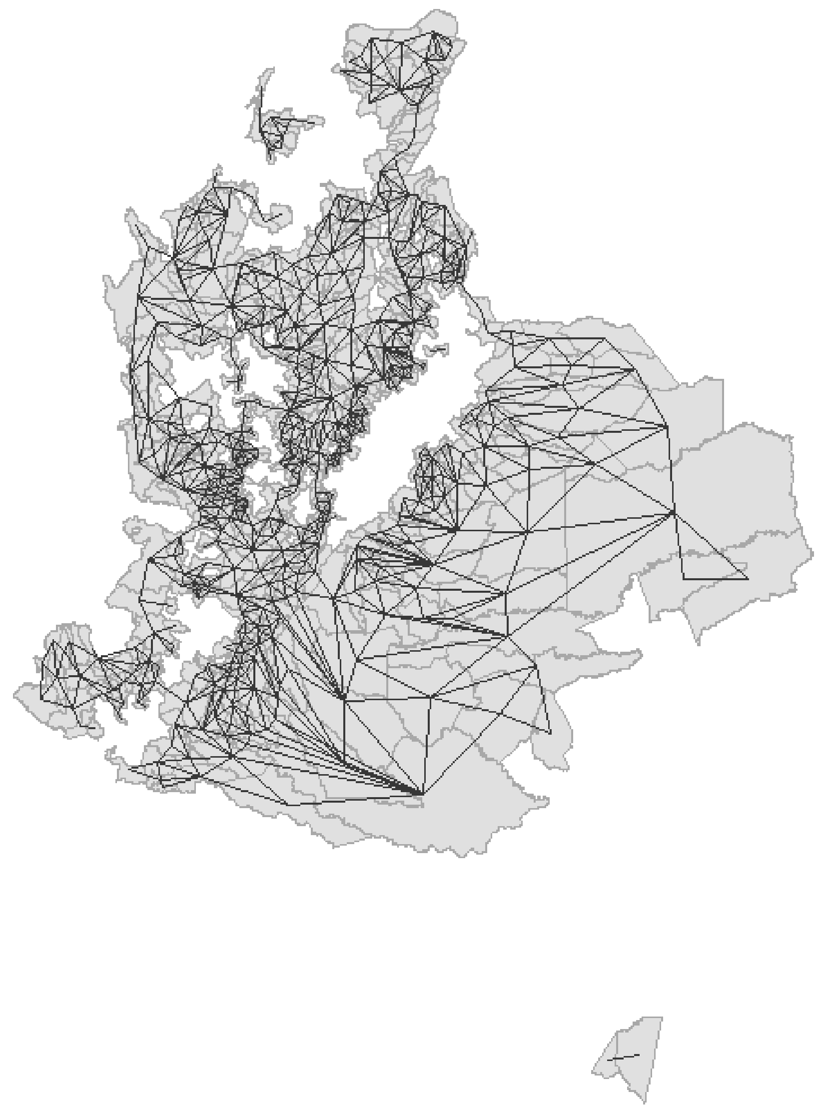

Figure 8. Summary of the Contiguity Queen Weighting Matrix. (a) Histogram; (b) Connectivity Graph.

Table 9. Estimation Results for the Spatial-Autoregressive Model (SAR)
- - - Dependent Variable: [lnYield (ton/he)] - - -

Main	(1) OLS	(2) SAC with spatial fixed-effects	(3) SAC with spatial and time fixed-effects
Ln(Credit for Investment)	0.00452***	0.00137**	0.00123*
	(0.000546)	(0.000522)	(0.000530)
Labor	0.0139***	0.0332***	0.0366***
	(0.00173)	(0.00478)	(0.00709)
Energy Coverage	0.00186***	0.000684*	0.000590
	(0.000279)	(0.000305)	(0.000307)
Spatial			
rho		0.190***	0.166***
		(0.0160)	(0.0164)
Variance			
sigma2_e		0.0518***	0.0512***
		(0.000917)	(0.000906)
Log-lik		368.03	408.63
Obs	6424	6424	6424
R^2_w		0.018	0.017
R^2_b		0.052	0.051
R^2	0.052	0.037	0.036
AIC	5213.71	-720.1	-801.3
BIC	5261.09	-665.9	-747.1

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10. Direct, Indirect and Total Effect for the Spatial-Autoregressive model (SAR)
- - - Dependent Variable: [lnYield (ton/he)] - - -

Main	(1) SAR with spatial fixed-effects			(2) SAR with spatial and time fixed-effects		
	Ln(Credit for Investment)	Labor	Energy Coverage	Ln(Credit for Investment)	Labor	Energy Coverage
Long-run direct effect	0.00137**	0.0334***	0.000686*	0.00123*	0.0366***	0.000591
	(0.000518)	(0.00477)	(0.000311)	(0.000525)	(0.00709)	(0.000312)
Long-run indirect effect	0.000307*	0.00750***	0.000155*	0.000235*	0.00701***	0.000114
	(0.000122)	(0.00130)	(0.0000730)	(0.000106)	(0.00157)	(0.0000624)
Long-run total effect	0.00167**	0.0409***	0.000841*	0.00146*	0.0436***	0.000704
	(0.000637)	(0.00589)	(0.000383)	(0.000628)	(0.00848)	(0.000373)

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 9: Spatial Heterogeneity in Cocoa Agricultural Productivity Effect by Municipality
- - - Dependent Variable: [lnYield (ton/he)] - - -

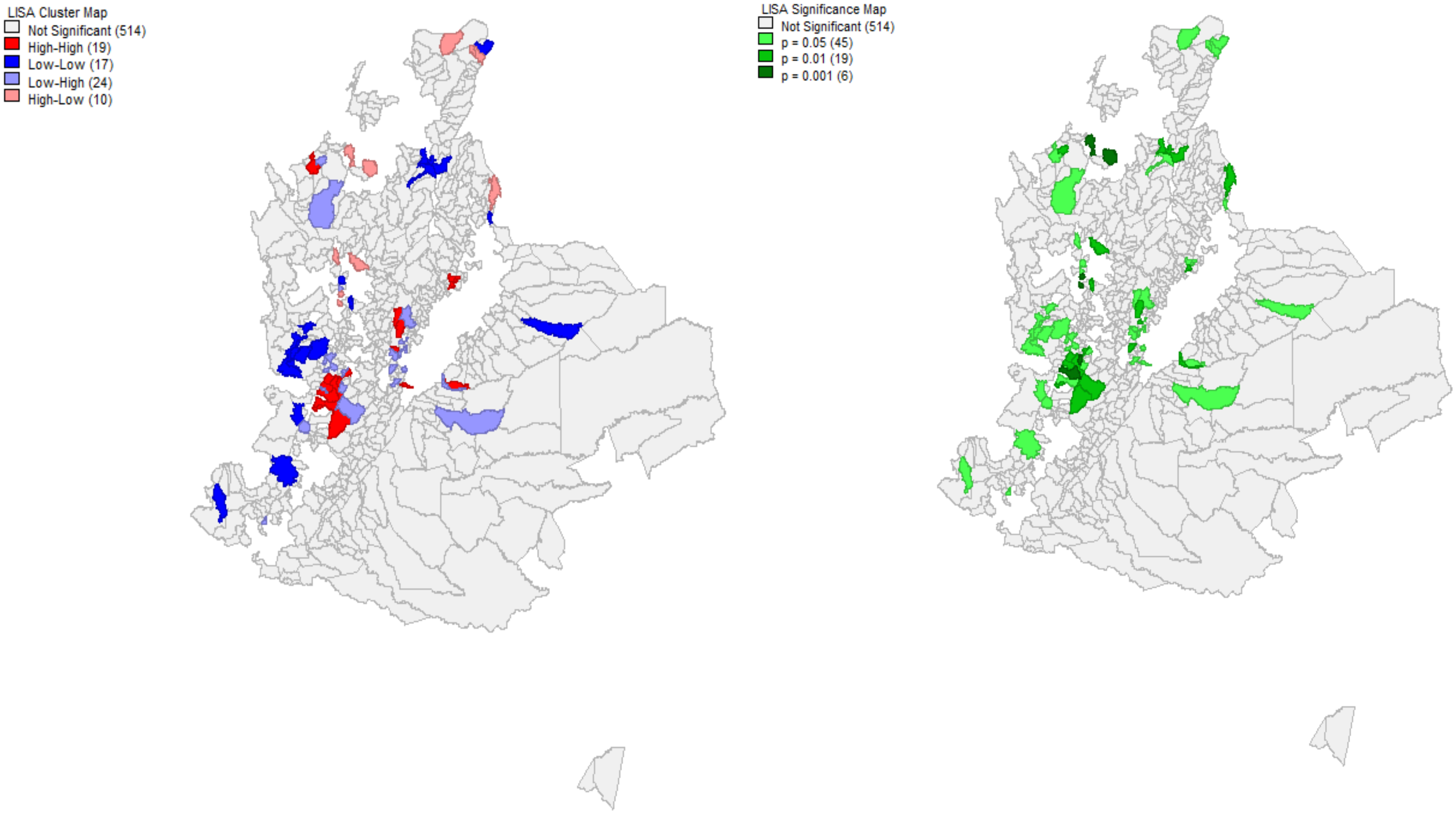

Table 11. Estimation Results for the Spatial Autoregressive Model (SAR)
- - - Dependent Variable: Output value per hectare [ln(ton/he)*Price] - - -

	(1)	(2)	(3)
Main	OLS	SAC with spatial fixed-effects	SAC with spatial and time fixed-effects
Ln(Credit for Investment)	0.0370***	0.00252***	0.00108*
	(0.00319)	(0.000548)	(0.000537)
Labor	0.00374	0.103***	0.0355***
	(0.00627)	(0.00529)	(0.00719)
Energy Coverage	-0.00333*	0.000652*	0.000539
	(0.00135)	(0.000319)	(0.000311)
Spatial			
Rho		0.373***	0.154***
		(0.0134)	(0.0164)
Variance			
sigma2_e		0.0567***	0.0526***
		(0.00101)	(0.000930)
Log-lik		-12.02	328.10
Obs	6424	6424	6424
R^2_w		0.306	0.247
R^2_b		0.003	0.001
R^2	0.043	0.006	0.002
AIC	27760.6	40.03	-640.2
BIC	27807.95	94.18	-586.1

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12. Direct, Indirect and Total Effect for the Spatial Autoregressive Model (SAR)
- - - Dependent Variable: Output value per hectare [ln(ton/he)*Price] - -

Main	(1) SAR with spatial fixed-effects			(2) SAR with spatial and time fixed-effects		
	Ln(Credit for Investment)	Labor	Energy Coverage	Ln(Credit for Investment)	Labor	Energy Coverage
Long-run direct effect	0.00260***	0.107***	0.000673*	0.00107*	0.0354***	0.000539
	(0.000560)	(0.00535)	(0.000335)	(0.000531)	(0.00718)	(0.000316)
Long-run indirect effect	0.00140***	0.0576***	0.000363*	0.000190	0.00626***	0.0000958
	(0.000312)	(0.00367)	(0.000183)	(0.0000990)	(0.00147)	(0.0000582)
Long-run total effect	0.00400***	0.165***	0.00104*	0.00126*	0.0417***	0.000635
	(0.000865)	(0.00804)	(0.000517)	(0.000628)	(0.00847)	(0.000373)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 10: Spatial Heterogeneity in Cocoa Agricultural Productivity Effect by Municipality
--- Dependent Variable: Output value per hectare [ln(ton/he)*Price] ---