

WORKING PAPER IDB-WP-01906

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Abstract

Colombia has favorable agroecological conditions but continues to face low agricultural productivity. This paper examines total factor productivity (TFP) between 2015 and 2023 using stochastic frontier analysis on household- and municipal-level panel data. We decompose productivity growth and assess the effects of climate shocks, access to credit, rural public investment, and the peace agreement with FARC. Results show that output growth has been driven mainly by input expansion, with TFP increasing by less than 1% annually. Rural road infrastructure and low-interest credit are consistently linked to productivity gains, while input delivery and service programs show no measurable impact. Climate variability remains a major source of productivity fluctuations, highlighting sectoral vulnerability. The 2014 ceasefire with FARC produced heterogeneous effects: household-level productivity rose in previously affected areas, but municipal-level averages declined possibly due to land expansion into less productive zones. Findings underscore the need to shift from input-based support to connectivity, rural finance, and climate-resilient investments.

JEL Codes: Q10, Q12, Q18

Key Words: Total Factor Productivity (TFP), Agriculture, Latin America, Rural Development

1. Introduction

Agricultural productivity growth is a central driver of rural development, food security, and environmental sustainability. In Latin America and the Caribbean, which account for 16% of the world's agricultural land and are major suppliers to global markets, past productivity gains have supported rising demand, rural incomes, and poverty reduction. Today, however, this role is challenged by three interconnected imperatives: ensuring food security for a growing population, raising agricultural incomes while building resilience to climate change, and safeguarding the environment (De Salvo et al., 2025). Addressing these challenges simultaneously requires advancing productivity in ways that are both economically viable and environmentally sustainable.

Strengthening agricultural productivity has become a central objective in the policy agendas of countries across the region. In Colombia, agriculture has historically been one of the country's most important productive sectors. Its rich endowment of natural resources, tropical climate, and strategic geographic location position it as a critical contributor to both domestic food supply and global agricultural trade. Despite this potential, the sector's relative contribution to national GDP has declined over time, falling from 17% in 1990 to 9% in 2024. While part of this reflects structural transformation and the rise of services (OECD, 2022), it also points to persistently low productivity.

Understanding the evolution of agricultural productivity and the factors shaping it is critical for designing policies that can unlock the sector's potential. This study contributes to this understanding by analyzing total factor productivity (TFP) in Colombian agriculture from 2015 to 2023. Using stochastic frontier analysis (SFA) on both household- and municipal-level panel data, we estimate total factor productivity growth (TFPG) and decompose it into technical change, technical efficiency, scale efficiency, and weather effects. We also use impact evaluation methods to assess how credit access, public expenditure on agriculture through targeted contracts, and the 2016 FARC ceasefire have shaped productivity, providing new insights to guide agricultural policy.

Previous research indicates that Colombia's agricultural TFP has lagged behind the Latin American average, with an annual growth rate of 0.6% between 2001 and 2016, compared to 1.8% regionally (Parra-Peña et al., 2021). Labor productivity shows a similar gap, with rural labor output in 2021 remaining 59% below the national average, a disparity that has persisted since 2005 (OECD, 2022). Several factors have been identified as contributing to this persistent gap. Prolonged armed conflict in rural areas has exacerbated unequal land access, generated forced displacement, weakened local institutions, and discouraged long-term investment (Arias et al., 2019; Fernandes-Tavares et al., 2024; Ibáñez Londoño & Moya Rodríguez, 2006). Infrastructure limitations further constrain productivity: only 25% of rural roads are paved (MADR, 2018), and the poor condition of tertiary networks leaves farms, on average, five hours from the nearest municipal center, with just 2.9% of rural areas located within one hour of a major market (Lozano-Espitia & Restrepo-Salazar, 2015). In addition, limited innovation and technology adoption, scarce financing and investment, and inefficient resource allocation have also been identified as major constraints to productivity growth (Jiménez et al., 2019).

Climate change represents another critical challenge for Colombian agriculture. From 1971 to 2020, average national temperatures rose by 0.22 °C per decade (World Bank, 2021), a trend expected to continue, altering rainfall patterns and increasing the frequency and intensity of extreme events. The country's vulnerability to climate variability, particularly during El Niño and La Niña episodes, was underscored during the most recent event, the 2014-2016 El Niño, which

caused agricultural losses of approximately USD 525 million (2016 prices) and affected 1,185,763 hectares across 20 departments (Unidad Nacional para la Gestión del Riesgo de Desastres, 2016). By 2050, climate change is projected to impact up to 14 % of agricultural GDP, posing serious risks to food security and rural development (World Bank, 2021).

We analyze agricultural productivity using two levels of analysis. At the household level, we rely on the *Encuesta Longitudinal Colombiana de la Universidad de los Andes (ELCA)*, available for 2010, 2013, and 2016, with respective sample sizes of 2,291, 2,305, and 2,222 households. At the municipal level, we employ the *Evaluaciones Agropecuarias Municipales (EVA)*, which provide annual data for 2007-2023 across municipalities nationwide. These datasets are complemented with satellite data on temperature and precipitation to capture the effects of climate shocks. We also use administrative data on agricultural credit from the *Fondo para el Financiamiento del Sector Agropecuario (FINAGRO)*, a second-tier public bank that provides loans under special conditions and channels a large share of the country's rural credit, to assess the effect of credit access. In addition, we draw on government procurement data from the Electronic Public Procurement System (SECOP), to evaluate the impact of targeted public spending on road infrastructure, inputs delivery, agricultural services, and machinery provision. Finally, to estimate the effect of the FARC peace agreement, we use data on exposure to armed groups provided by the Violent Presence of Armed Actors in Colombia (ViPAA). Together, these sources allow us to link TFP dynamics to both structural constraints and key policy interventions.

This paper contributes to the existing literature in two main ways. First, most previous studies estimating TFP growth in Colombia have been conducted in multi-country frameworks and rely on aggregate national-level agricultural data. By contrast, our study employs stochastic frontier analysis (SFA) to estimate and decompose TFP growth using both municipal- and household-level data. Municipal-level information provides wide coverage across time and space, allowing us to capture broad patterns and long-term dynamics of agricultural productivity. However, such data are limited in terms of input information and may mask within-municipality heterogeneity. Household-level surveys, by contrast, offer richer information to construct more precise productivity measures and, because they track the same farmers over time, reduce biases from selection effects arising when new farmers enter or exit under changing conditions, although their coverage is restricted to a subset of regions and periods. By integrating both perspectives, we exploit the strengths of each dataset -coverage versus detail- and provide a more comprehensive understanding of productivity dynamics. Second, while various structural and contextual factors have been identified as constraints to Colombian agriculture, few studies measure their impact on productivity. Our analysis addresses this gap through a complementary analysis that estimates the effects of these factors on agricultural output using OLS regressions controlling for production inputs, rather than relying on the previously estimated TFP. Drawing on novel data sources, this analysis offers new insights into the mechanisms shaping the sector's performance over nearly a decade and provides evidence that can directly inform policy design.

We find that agricultural TFP in Colombia grew at a modest average annual rate of 0.65% between 2015 and 2023. Most output growth stemmed from increased input use rather than productivity improvements. Among policy drivers, not all types of public investment proved equally effective: public goods, particularly rural road infrastructure, caused positive and sustained productivity gains, while input or service transfers had negligible effects. Access to subsidized credit was also associated with productivity improvements. Finally, the effect of the FARC ceasefire on agricultural productivity varied with the scale of analysis: at the household level, farmers in communities previously affected by FARC presence experienced significant gains, whereas

municipal-level data suggest a decline in average productivity, likely due to land expansion into lower-yielding areas and the entry of less productive producers.

This analysis highlights the importance of prioritizing investments in public goods, particularly rural infrastructure for enhancing technical efficiency and promoting technological adoption. Expanding access to rural credit and promoting efficient land use in post-conflict areas are also important. These efforts must be accompanied by the development of adaptive practices that support sustainable and climate-resilient agricultural growth at the national level.

2. Literature

2.1 Total Factor Productivity

Research on agricultural productivity in Colombia has been relatively limited, with most analyses embedded within broader multi-country studies that rely on aggregate data for cross-country comparisons and employ diverse methodologies, providing limited insight into the country's productivity dynamics over the past several decades.

Early works, such as Fulginiti et al. (1998) and Bravo et al. (2004), employed growth accounting and Malmquist indexes, estimating annual TFPG of around 1.4-1.5% during the latter half of the twentieth century. Extending the analysis, Ludeña (2010) applied Data Envelopment Analysis (DEA) and reported a slightly higher rate of 2.1% between 1961 and 2007. Focusing on the period 1975-2013, Jiménez et al. (2018) provided one of the few studies dedicated exclusively to Colombia. Using alternative econometric production functions (Cobb-Douglas, CES, Translog), they estimated TFP by deriving input elasticities directly from the data and measuring TFP as the share of output growth not explained by inputs. Their results suggest annual productivity growth of 0.8% to 1.3%, driven mainly by productivity gains in the livestock sector. They emphasize that changes in agricultural productivity in Colombia were strongly dependent on policy regimes and economic circumstances.

At the regional scale, Nin-Pratt et al. (2015) analyzed TFP trends from 1981 to 2012 in Latin America using both growth accounting and DEA. For Colombia, they found an average annual TFP growth of 1%, explained by technological progress of 1% per year, partially offset by a 0.1% decline in efficiency. Their results indicated that Colombia's productivity growth lagged behind the regional average by approximately two percentage points.

More recently, Salazar et al. (2025) analyzed agricultural productivity in 25 Latin American countries over the period 1961-2021. For Colombia, they found that agricultural output grew at an average annual rate of 2.4%, primarily driven by TFP growth (1.5%), a rate similar to the Latin American average (1.7%) and the Andean group average (1.5%). This relatively weak performance reflects a pattern of marked volatility, with TFP growth peaking in the 1970s, experiencing sharp declines in the 1980s and 2000s, and only a moderate recovery in the period 2011-2020, still falling short of the levels observed in earlier periods.

Fewer studies have applied frontier-based approaches. Lachaud (2025) analyzed TFP trends in ten Latin American countries between 1981 and 2012 using a stochastic production frontier model and FAOSTAT data, reporting an average annual TFP growth rate of 1.44% for Colombia, slightly above the sample average of 1.40%. Technological progress, averaging 1.57% per year, emerged as the main driver of productivity gains.

A common feature of previous studies is that they are conducted within the framework of multi-country analyses and differ in their methodologies, with the growth accounting approach being the most prevalent, despite relying on strong assumptions. Additionally, these studies are based on country-level aggregated data, which have been subject of criticism due to inconsistencies and incompleteness, limiting the ability to produce harmonized and comparable time series across countries and over time (Bravo-Ureta et al., 2021). This reliance on aggregated information also overlooks the heterogeneity of agricultural households, which is central to understanding productivity dynamics (Bravo-Ureta et al., 2022). Ignoring such variation risks drawing misleading conclusions about the drivers of growth and the effectiveness of policy interventions.

Another significant limitation is the lack of inclusion of climate variables in the models used to estimate TFPG, thereby neglecting the direct impact of climate on agricultural productivity. Lachaud et al. (2017) pioneered the integration of climate variability into TFP decomposition, which allowed to isolate weather-related factors influencing productivity.

Building on these limitations, we adopt a SFA framework, which allows us to decompose productivity growth into components with straightforward economic interpretation. Unlike most previous research, our analysis focuses on the most recent decade and relies on household- and municipal-level data, enabling the capture of heterogeneity across producers and production environments.

2.2 Credit

Access to credit and its relationship with agricultural performance have been widely examined in the literature, reflecting the central role of credit as a catalyst for rural development. Credit can facilitate technology adoption (Wang et al., 2025; Makate et al., 2019), encourage the uptake of climate-smart agricultural practices (Ali & Awume, 2025; Ehiakpor et al., 2021), improve risk-management strategies (Bohórquez-Peñuela et al., 2025), and enable the acquisition of inputs and productive infrastructure. These mechanisms underscore the potential of financial inclusion to enhance agricultural productivity.

Numerous studies have quantified the productivity impacts of agricultural credit across countries, evidence generally points to a positive relationship between credit access and productivity (Akudugu, 2016; Haryanto et al., 2023; Guirking & Boucher, 2008). Seven and Tumen (2020) using a panel of 104 countries for 1991-2014, finds that doubling agricultural credit is associated with a roughly 4% increase in labor productivity at the aggregate level. The high marginal product of capital observed in developing countries is indicative of pervasive credit constraints (Banerjee & Duflo, 2010). These constraints are particularly salient in rural areas, where large numbers of smallholder farmers face limited access to formal financial services. Evidence from Peru suggests that alleviating such constraints could increase output per hectare by 26% (Woutersen et al., 2024). Similarly, Haryanto et al. (2023), studying Indonesia, find that while both formal and informal credit positively affect agricultural productivity, the impact of formal credit is generally stronger.

In Colombia, Echavarría et al. (2017) evaluates the effect of credit access on coffee producers and finds that it boosts productivity by increasing the cultivated area, raising the share of coffee within the farm, and significantly reducing the age of the coffee plants. Evidence from cattle production further indicates positive effects of credit, with spatial spillovers across regions (Mejía Tejada et al., 2024).

2.3 Public Investment

The rationale for public investment in agriculture rests on two main pillars. First, it seeks to correct market failures, such as incomplete markets and information asymmetries, that limit the development and adoption of agricultural technologies. Second, it aims to reduce social inequities, as rural populations, who depend heavily on agriculture, often receive fewer goods and services than their urban counterparts (Mogues, Fan, & Benin, 2015). Through these mechanisms, agricultural public spending can enhance agricultural performance (Anríquez et al., 2016).

Theory suggests that public investment can stimulate growth, but its effect is not guaranteed: it depends on whether it creates complementarities and positive externalities or, alternatively, substitutes and crowds out private investment (Fournier, 2016). Because public support can take many forms, including direct subsidies to producers, higher output prices, consumer subsidies, investment in public goods, empirical evidence on its effects varies across types of investment.

A large strand of the literature focuses on subsidies, as they represent a significant share of agricultural spending worldwide. More than half of total government support is directed to producers, while only a smaller fraction is allocated to public goods (Amaglobeli et al., 2024). Evidence on their effectiveness is far from conclusive. Arague and Balié (2021) show that input subsidies can raise output and welfare more effectively than commercialization policies, though mainly in the short run, while Zafar et al. (2023) argue that subsidies in India contribute more to productivity than public investment. Carter et al. (2021) show that temporary input subsidies in Mozambique promote adoption of Green Revolution technologies and generate long-term benefits, largely through positive learning spillovers among farmers and their social networks. Nguyen et al. (2023) find in a meta-analysis that well-targeted subsidy programs improve yields and household income. On the other hand, a large body of research finds limited or even negative effects (Latruffe & Desjeux, 2016; Zhu & Milán Demeter, 2012; Rizov et al., 2013), often attributing them to distortions in farmers' incentives, such as reduced effort or changes in risk behavior that undermine efficiency and long-term productivity growth.

In contrast, investments in public goods, such as agricultural research, extension services, rural roads, and irrigation, consistently show higher and more sustainable returns. Some studies underline that shifting resources away from subsidies and private transfers toward public goods generates stronger impacts on sectoral performance (Mogues & Benin, 2014; Amaglobeli et al., 2024). In Latin America and the Caribbean, Anríquez et al. (2016) find that increasing total agricultural spending alone has only modest effects on sectoral income. However, when spending composition shifts toward public goods, the gains in agricultural value added per capita are substantial. Similarly, evidence from India shows that while subsidies once played a role in technology adoption during the Green Revolution, in more recent decades they have yielded very low returns, whereas public spending on research, education, and infrastructure has been the most effective in promoting agricultural growth and poverty reduction (Gulati & Narayanan, 2003).

Evidence for Colombia aligns with this broader debate. The *Agro Ingreso Seguro* program, which provided subsidies for working capital, productive capital, and irrigation, showed only limited aggregate impacts and weak capacity to offset foreign competition (Arguello & Valderrama, 2014). Castro Rodríguez et al. (2024) evaluate the impact on green paddy rice producers of the *Colombia Siembra* program, which subsidized agricultural credit for targeted crops. Their results show that the program largely benefited the milling industry, the main buyer, rather than producers themselves. In contrast, Lozano-Espitia and Restrepo-Salazar (2015) finds that public

investment in irrigation and drainage significantly improves yields, especially in rice, while rural road infrastructure contributes to expanding cultivated and harvested areas.

2.4 Conflict

An internal armed conflict has affected Colombia for more than half a century. It began in the mid-1960s with the emergence of left-wing guerrilla groups, most notably the Revolutionary Armed Forces of Colombia (FARC) and the National Liberation Army (ELN). The FARC eventually became the largest guerrilla group in the country, with an estimated 16,000 combatants (Centro Nacional de Memoria Histórica, s.f). The Colombian conflict, deeply rooted in disputes over land, left more than 8.5 million people formally registered with the state as victims (Prem et al., 2018). Over five decades of armed struggle, rural areas were the main stage of the conflict, experiencing widespread violence, land dispossession, capital destruction, and forced displacement. These dynamics created long-lasting structural barriers to agricultural development and productivity.

In 2012, formal peace negotiations began in Cuba between the Colombian government, under President Juan Manuel Santos, and the FARC. After several rounds of dialogue, a bilateral ceasefire was announced in December 2014, marking a crucial milestone as it represented the first concrete step toward de-escalating violence and building trust between the parties. These negotiations culminated in the signing of the Peace Agreement in November 2016.

Empirical evidence shows that armed conflict has profound effects on agricultural performance (Nillesen, 2016; Odozi & Uwaifo Oyelere, 2021; Gonzalez & Lopez, 2007). Conflict affects productivity through two main channels. First, a direct destruction channel, where attacks generate losses of physical and human capital, disrupt market transactions, and immediately reduce output. Second, an uncertainty channel, in which producers make decisions under risk even in the absence of direct violence, limiting efficiency and constraining productive investment (Arias et al., 2019).

Evidence shows that households respond to these conditions by adjusting their agricultural strategies. For example, Rockmore (2020) shows that in Uganda, conflict does not necessarily push households out of agriculture but leads them to adjust their crop and livestock choices toward less profitable but safer activities, thereby reducing the sector's productive potential. Similarly, Arias et al. (2019) show that rural households in Colombia adapt to armed conflict by shifting production toward short-term and subsistence activities, which helps them cope with risk in the short run but ultimately constrains income growth and long-term agricultural development. In general, in contexts of violence, producers' decisions are altered in ways that reduce productivity or even lead to displacement (Engel & Ibáñez, 2007).

The transition toward peace in Colombia, particularly the ceasefire with the FARC, offers a unique natural experiment to examine how a potential de-escalation of violence can alter agricultural dynamics. By reducing both direct threats and uncertainty, the ceasefire may influence farmers' decisions regarding resource allocation, investment timing, labor use, input application, and access to markets and credit, potentially reshaping agricultural patterns in the affected regions.

Recent evidence highlights post-conflict adjustments in agricultural activity. Niño (2022) finds that farm investment in areas previously affected by the armed group more than doubled, largely due to a shift from annual to perennial crops. Similarly, Cristhancho (2022) shows that in municipalities with FARC presence, the share of cultivated land relative to potential agricultural area rose by 28% after the bilateral ceasefire and by 15% following the signing of the peace agreement.

3. Overview of the Agricultural Sector in Colombia

Colombia has historically been a country with significant agricultural potential. Its variety of climate zones and topography provide optimal natural conditions to produce a wide range of agricultural products. The agricultural frontier encompasses 43 million hectares, corresponding to 38% of the country (UPRA, 2024). However, only about one-fifth of this frontier is under cultivation, while the majority is devoted to cattle ranching—an activity associated with high environmental costs and lower returns (Agronet, 2021). This disparity underscores the potential for expanding productive capacity and fostering rural development, positioning Colombia as an important global food producer (FAO, 2019).

Although the sector's share of GDP has declined in recent decades, agriculture remains a cornerstone of Colombia's economic activity. In 2024, it contributed 9.2% to GDP and grew by a notable 8%, well above the national average (Ministerio de Agricultura y Desarrollo Rural, 2025). The agricultural sector is the largest employer in rural areas, with approximately 4.8 million people employed in agriculture as of early 2025, representing 14% of total national employment (World Bank, 2023). The country's production spans both internationally demanded goods, such as coffee, bananas, oil palm, and flowers, and subsistence farming that sustains domestic food supply and food security. Between 2000 and 2021, agricultural and agro-industrial exports represented 37.3% of non-mining exports, growing at an average of 5.9% annually, with permanent crops, particularly coffee, leading this expansion (Bojacà, 2024).

Agricultural development is highly heterogeneous across the country. Colombia is organized into 32 departments and its capital district, and it is divided into six natural regions: Caribbean, Coffee Region, Pacific, South-Central Amazonia, Central-Eastern Region, and Eastern Plains (See Figure 1). Each region has distinct characteristics of climate, soil, and agricultural dynamics.

Figure 1. Geographic distribution of Colombia's regions



Note: The Caribbean Region includes the departments of Atlántico, Bolívar, Cesar, Córdoba, La Guajira, Magdalena, San Andrés, and Sucre. The Coffee Region comprises Antioquia, Caldas, Quindío, and Risaralda. The Pacific includes Cauca, Chocó, Nariño, and Valle del Cauca. South-Central Amazonia includes Amazonas, Caquetá, Huila, Putumayo, and Tolima. The Central-Eastern Region comprises Bogotá, Boyacá, Cundinamarca, Norte de Santander, and Santander. The Eastern Plains Region includes Arauca, Casanare, Guainía, Guaviare, Meta, Vaupés, and Vichada.

The Caribbean region, which accounts for 12% of Colombia's agricultural production units (UPAs), benefits from fertile soils, proximity to ports, and a tropical climate that support crops such as bananas, maize, cassava, and rice for both domestic consumption and export. The Eastern Plains region, by contrast, holds some of the country's greatest unexploited agricultural potential. The region has extensive land, diverse ecosystems, and abundant water resources. Yet only 14% of its arable land is effectively cultivated, while the remaining hectares are predominantly devoted to cattle ranching (Medrano Acosta, 2018). Although the region contributes substantially to national production palm oil, sugarcane, plantain, and rice, its full development remains constrained by weak road infrastructure, limited market integration and persistent uncertainty surrounding land tenure (Puyana, et al., 2025).

The Pacific region, despite its geostrategic location, is characterized by high rainfall, low soil fertility, and a history of conflict that has constrained agricultural development. Within the region, however, production systems differ markedly. In the fertile valleys, large-scale farms specialize in sugarcane cultivation, while in the surrounding mountains, family farmers grow potatoes and other tubers. In contrast, vast forested areas remain largely devoted to traditional subsistence crops, primarily oriented toward local markets. Similarly, the South-Central Amazonia region combines family farming with agro-industrial crops such as rice, cotton, and coffee. Agricultural production here coexists with environmental and social challenges, including mining, illicit crops, and the persistence of armed conflict.

The Coffee Region accounts for around 600,000 tons of food production and hosts 9.4% of UPAs (RAP Eje Cafetero, 2021). Its economy has long been shaped by coffee cultivation, which contributes nearly 20% of the sector's national value added and remains present in almost every municipality (PNUD & Red ORMET, 2014). The activity continues to employ about one-fifth of the country's coffee-growing population (RAP Eje Cafetero, 2021). Yet, despite its historical significance, the sector has been in decline, facing stagnant productivity, reduced yields, limited generational renewal, climate pressures, and slow technological adoption. In recent years the region has experienced an expansion of fruit crop cultivation with export potential, although this process remains at an early stage of development.

Finally, in the Central-Eastern Region, altitudinal diversity allows for a broad agricultural basket, including rice, plantain, cocoa, oil palm, and panela cane. This region is particularly important for national food supply: Cundinamarca alone contributes nearly half of the products arriving at Colombia's largest wholesale market.

In general, the agricultural sector has contributed to the development of all regions of the country. However, a series of structural conditions have limited its ability to reach full productive potential. Among them, the armed conflict and land inequality stand out as some of the most critical. Rural areas bore the brunt of violence, dispossession, and displacement, while land tenure became increasingly unequal: 1% of holdings concentrate more than 80% of arable land, whereas farms smaller than 10 hectares represent 81% of all holdings but occupy less than 5% of the area (Díaz Díaz & López Bayona, 2021). These dynamics eroded productivity, disrupted labor availability, and undermined trust in rural institutions and markets.

In response to these historical challenges, Colombia undertook peace negotiations with the FARC between 2012 and 2016. The signing of the Final Peace Agreement in November 2016 represented a turning point for rural policy, as it placed agricultural development at the heart of peacebuilding. The *Reforma Rural Integral*, the first point of the agreement, proposed a profound transformation of the countryside. Its main pillars include the democratization of land access; the

provision of infrastructure, social services, and productivity incentives through national sectoral plans; targeted interventions in regions most affected by conflict and poverty; and the strengthening of food security. Despite these ambitions, the implementation of the peace agreement encountered significant challenges. Several former combatants (“dissidents”) either abandoned the process or never fully committed, resuming or continuing armed activities. Coupled with the expansion of coca cultivation and the state’s limited capacity to establish territorial control, these dynamics reignited conflict in rural areas during the early 2020s (UNODC-SIMCI, 2025).

The limited level of agricultural public spending has been identified as another constraint for the sector (Misión para la Transformación del Campo, 2015). Between 2020 and 2022, producer support accounted for 6.1% of gross farm receipts, well below the OECD average and 25% lower than in the early 2000s. Most of this support was concentrated in Market Price Support (83.5% of the PSE), while direct budgetary transfers to producers represented 16.5%, mainly through subsidies for inputs, credit, and insurance. While public spending on general services for the sector remained particularly low, averaging just 1.1% of production value, well below the OECD benchmark (OECD, 2023).

This distribution of support is reflected in the policy instruments implemented in the country, which have relied heavily on price support mechanisms, such as the Andean Price Band System (SAFP) and Price Stabilization Funds (FEPs), as well as on direct transfers to producers. The latter have operated through programs such as *Desarrollo Rural con Equidad* and the *Fondo de Fomento Agropecuario* (FFA), designed to provide subsidies or co-finance inputs and productive projects. However, the emphasis of these schemes has been limited in the provision of public goods such as rural infrastructure, research, innovation, and extension services, which has reduced their overall impact on the sector’s productivity and resilience.

Overall, Colombia’s agricultural sector reflects a paradox of abundance and constraint. Despite its natural endowments and its key role in employment, food security, and exports, structural inequalities, decades of armed conflict, rising climate pressure, and a policy framework that has often prioritized short-term support over long-term development, have hindered its full potential.

4. Data

To analyze agricultural productivity trends in Colombia over recent decades and their relationship with potential determinants, the study is conducted at two levels: household and municipal. The following section describes the scope of each dataset, presents descriptive statistics at both levels, and details the complementary data employed to examine the drivers of productivity.

4.1 Agricultural Data

4.1.1 Household Level Data: Colombian Longitudinal Survey from the Universidad de Los Andes (ELCA)

The household-level analysis relies primarily on the ELCA, a longitudinal survey conducted by the Center for Studies on Economic Development (CEDE) at Universidad de Los Andes, which tracks more than 10,000 urban and rural households. This survey, the first of its kind in the country, was carried out in three rounds: 2010, 2013, and 2016. For this study, only the rural sample is used, which initially included 4,800 rural households from 17 municipalities. The rural sample is representative for small holders in four regions: *Atlántica*, *Altiplano Cundi-boyacense*,

Eje Cafetero, and *Centro-Oriental*. These regions were selected because, while all have a strong presence of small farmers, they differ markedly in their overall productive structure.

The ELCA includes an agricultural module that tracks the productive characteristics of rural households, identifying planted area and output per crop, as well as the livestock products raised or sold in the last year of each round. It also records detailed information on production costs, allowing for the identification of input use. Taken together, these components provide a characterization of the households' productive activity.

We restrict the rural sample to households that report owning land dedicated to agricultural production and that engage in agricultural or livestock activities in at least one of the three survey rounds. We then construct a panel tracking household heads over time, excluding households that change municipality of residence and those reporting zero production value. We then construct a panel tracking household heads over time, excluding households that change municipality of residence and those reporting zero production value. For households observed in all three rounds, we retain the observations corresponding to the modal municipality and discard inconsistent rounds.

For the TFP decomposition, we use a balanced panel that follows the same household head over time to analyze the evolution of productivity. This results in a sample of 2,291 households in 2010, 2,305 in 2013, and 2,222 in 2016. Because the survey round in which a household reports a different municipality is dropped, the panel is not perfectly balanced across years. For the analysis of productivity determinants, we instead use an unbalanced panel to maximize sample size.

Some questions in the first survey round (2010) differ in format from those in subsequent rounds. Appendix A1 details the harmonization procedures applied to construct variables that are comparable across rounds.

a) Summary Statistics at household level (ELCA)

Table 1 presents the descriptive statistics of the variables included in the estimation of the production function. During the 2010-2016 period, households in the sample cultivated between 1.6 and 2 hectares, with moderate growth in output value and significant changes in the use of inputs, within a context of climate variability. In particular, the value of agricultural production increased over the three rounds, with an overall growth of 33%. Input value and hired labor costs increased by 38% and 80%, respectively, while the use of family labor decreased by 5%. These suggests that much of output growth may have been absorbed by higher costs. There was also increased investment in livestock assets (animal capital) and a notable rise in machinery rental value between 2010 and 2013, followed by a decline in 2016.

Climate conditions shifted toward higher temperatures and drier weather. This can be explained by the occurrence of the El Niño phenomenon between 2014 and 2016, one of the most intense and prolonged events since 1950. In Colombia, El Niño is associated with reduced rainfall and increased temperatures, especially in the Caribbean and Andean regions (UNGRD, 2016). This is reflected in the temperature anomaly variable, which is positive for all three years analyzed, reaching its highest value in 2016, indicating abnormally warm conditions. Similarly, the precipitation anomaly shows that 2016 was a significantly drier year than the historical average, coinciding with the peak of the El Niño episode.

Table 1. Descriptive statistics at household level (2010-2016)

Variable	2010	2013	2016
Production value (\$US)	2,790	3,389	3,734
Cultivated area (Ha)	1.6	2.1	2.0
Family labor index	3.4	3.4	3.2
Cost of purchased inputs (\$US)	993.6	1187.2	1367.1
Cost of hired labor (\$US)	255.9	442.5	460.9
Capital stock of animals (\$US)	761.1	1027.4	1124.7
Machinery rental value (\$US)	24.7	76.5	54.7
Average monthly temperature (°C)	22.1	22.3	22.6
12-month average cumulative monthly precipitation (mm)	181	137.9	129.4
Average temperature anomaly (°C)	1.3	1.9	2.8
Average precipitation anomaly (mm)	2.0	-0.2	-0.6
Households Number	2,291	2,305	2,222

Note: Values are in constant 2010 dollars. Purchased inputs include expenditures on seeds, fertilizers, pesticides/fungicides/herbicides, breeding stock, feed, vaccines, veterinary medicines, and vitamins.

4.1.2 Municipal Level Data

a) Agricultural Production Data: Evaluaciones Agropecuaria Municipales (EVA)

Municipal-level estimates rely primarily on the EVA database, the main source of information on agricultural produce at the municipal level in Colombia. EVA provides publicly available data for the period 2007-2023, covering 239 crops across 1,122 municipalities and including key variables such as cultivated area, production, and yield for both temporary and permanent crops nationwide. Nevertheless, it lacks information regarding the use of agricultural inputs. Since input data comes from an additional source that begins in 2015, the period for the empirical analysis is 2015-2023.

Data collection follows a semiannual scheme. In the first semester, information on temporary crops is gathered for a sample of key municipalities, while in the second semester data are collected for all municipalities, completing and updating the annual records.

EVA's methodology is based on a consensus-driven data collection process that involves various local entities, including the Departmental Secretariats of Agriculture, *Unidades Municipales de Asistencia Técnica Agropecuaria (UMATA)*, and other stakeholders in the agricultural sector (MADR, 2016). This collaborative approach enhances representativeness. However, because it relies on informed consensus rather than statistical sampling methods, the resulting measurements may lack precision.

Since the analysis includes multiple crops, we converted their production into monetary values. This requires sourcing price data for major agricultural products from institutions such as the Colombian Mercantile Exchange, the National Manufacturing Survey by DANE, the Ministry of Agriculture and Rural Development (MADR), and various agricultural associations. Prices are aggregated into a single database and reported by AGRONET, the information and communication network for Colombia's agricultural sector. However, this database provides

prices for only 29 crops, making it necessary to incorporate a second data source: the Agricultural Sector Price Information System (SIPSA), which records wholesale prices of agricultural products traded in the country.

Using SIPSA data, annual prices for each crop are calculated as the average of monthly prices in the country's main wholesale markets. A discount factor, commonly used by government authorities, is then applied to convert wholesale prices into producer prices. Ultimately, the municipal panel covers 90 crops, accounting for 98.5% of total agricultural production.

b. Agricultural Input Data

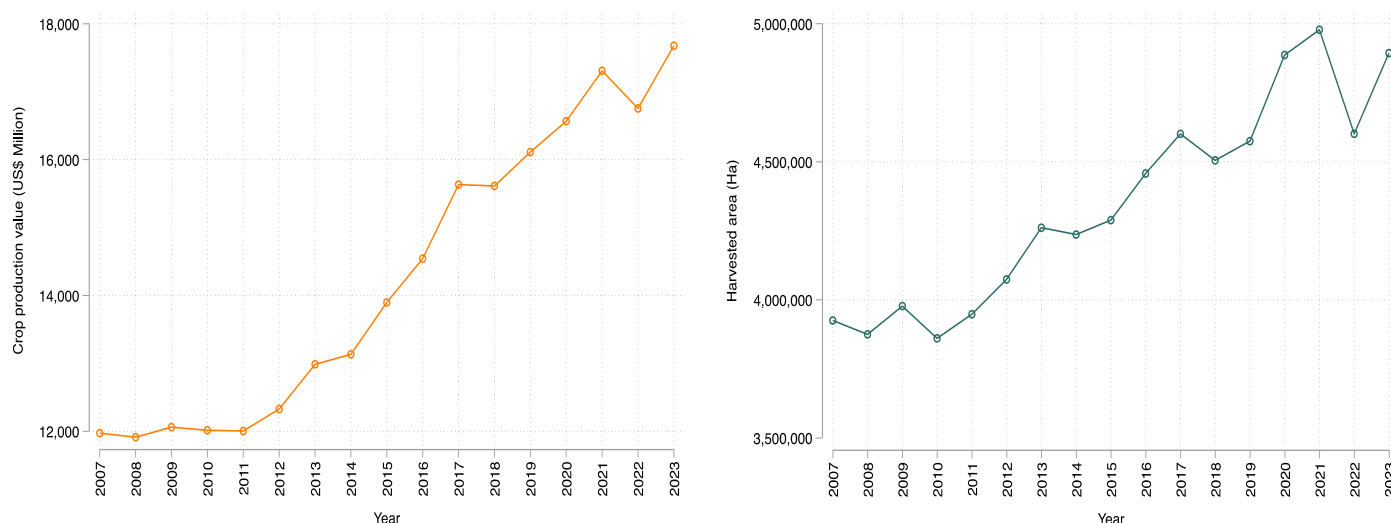
In Colombia, every legally authorized public freight company must issue a manifest for each road freight transport service. Information on agricultural inputs covering transported volumes of fertilizers, seeds, and tractors, is drawn from cargo manifests registered with the Ministry of Transport since 2015. This mandatory and enforceable document includes details about the goods transported, their origin, and destination, enabling the tracking of input flows to different areas of the country. This information is aggregated at the municipality of destination by summing the volumes of each input received each year.

This information captures most of the agricultural inputs that arrive in each municipality. Some volumes may, however, be omitted or wrongly attributed, for instance, when inputs are initially registered as arriving in one municipality but are later transported informally to a neighboring one, or when shipments are handled entirely by private companies using their own logistics systems.

c. Summary Statistics

The EVA dataset offers broad temporal and geographic coverage, enabling the analysis of long-term trends in both agricultural production and harvested area in the whole country. Figure 2 displays annual trends in crop production value and harvested area between 2007 and 2023. Table 2 summarizes these patterns over four multi-year periods, as well as the evolution of average agricultural input volumes since 2015.

Figure 2. Evolution of crop production value and harvested area (2007-2023)



Note: The graphs report the national totals of production value and harvested area, obtained by summing municipal-level data for each year. Crop production value is expressed in US\$ million in constant 2013 dollars.

As shown by Figure 2 and Table 2, from 2007 to 2014, growth in both production value and cultivated area was modest and broadly proportional. The period 2015-2023 marked an acceleration in the growth of production value, interrupted only by a temporary dip between 2021 and 2022, consistent with the 0.8% contraction in agricultural GDP reported for that year (Pardo & Orbegoza, 2024), before rebounding in 2023. A parallel pattern is observed for harvested area, which expanded steadily, with a decline in 2022, primarily due to a reduction in non-perennial crops. Overall, production value grew more than proportionally compared to harvested area: while land under cultivation expanded by roughly one quarter, the value of production rose by almost half. This indicates a substantial growth in land yields over this period.

Regarding input trends, the volume of all inputs increased between 2015 and 2023, indicating a growing use of inputs. Fertilizer volumes rose by about 35%, while seed volumes increased by roughly 9%.

Table 2. Descriptive statistics at municipal level (2007-2023)

Variable	2007-2010	2011-2014	2015-2019	2020-2023
Production value (\$US)	10,967,724	11,513,260	13,776,111	15,556,066
Land (Ha)	3,577	3,770	4,077	4,410
Production value / Ha (\$US)	3,006	3,108	3,496	3,625
Rural population	9,859	9,979	10,276	10,791
Seeds (Kg)			64,264	69,943
Tractors (Kg)			2,198,093	2,983,764
Machinery (Kg)			56,194	120,762
Municipalities	1,099	1,098	1,105	1,099

Note: Values are in constant 2013 dollars. Data on rural population is sourced from the CEDE Municipal Panel.

4.2 Climate Variables

Temperature and precipitation data come from the Climate Research Unit of the University of East Anglia (CRU TS v4.08). The dataset provides monthly climate information from 1901 to 2023 on high-resolution $0.5^\circ \times 0.5^\circ$ grids. These gridded data are aggregated at the municipal level, using area-weighted averages based on the geographic boundaries of each municipality.

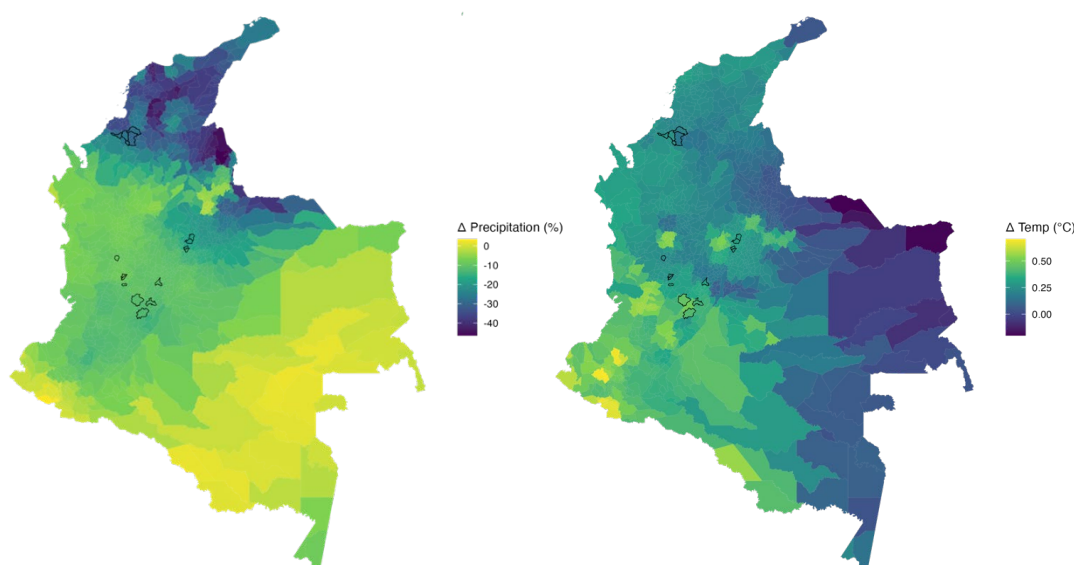
We calculate annual averages from the monthly data to obtain average temperature and precipitation values. We also construct temperature and precipitation anomalies, defined as deviations from the country's long-term mean divided by the long-run standard deviation, following Barrios et al. (2010). The long-run reference period is defined as 1950-2000.

a. Summary Statistics

Figure 3 illustrates the distribution of changes in temperature and precipitation between the periods 2007-2011 and 2019-2023. Only a few municipalities experienced a decline in temperature levels, with the most significant increases concentrated in the southwest of the

country, particularly in some municipalities in the departments of Nariño, Cauca, and Valle del Cauca. In contrast, precipitation decreased by an average of 11% at the national level, with the sharpest decline observed in the northern region of the country. Figure B1 complement this spatial perspective by showing the evolution of temperature and precipitation anomalies, calculated as the municipal average for the period 2007-2023. Over this period, the average temperature increased by 0.61 °C, with a peak of 22.14 °C in 2015, coinciding with a strong El Niño event. By contrast, average national precipitation fell by 11%, with the sharpest decline in the northern region. El Niño years (2015-2016) show relatively low precipitation, whereas 2011, a La Niña year, recorded substantially higher rainfall.

Figure 3. Changes in precipitation (%) and temperature (°C) between 2007-2011 and 2019-2023



Note: Municipalities outlined in black indicate the municipalities covered by the ELCA survey.

4.3 Additional Data on TFP Determinants

The selection of factors that may influence the dynamics of agricultural productivity in the country is based on three main criteria: (i) the contextual relevance and structural characteristics of the national agricultural sector, (ii) empirical evidence documented in the literature on the determinants of productivity, and (iii) the availability and quality of data at both the territorial and temporal levels. Specifically, we examine how violence, agricultural credit, and publicly funded interventions, such as rural road infrastructure, technical assistance, input delivery, and machinery provision affect agricultural productivity. Below we describe the additional data sources used in this analysis and the variables constructed from them.

4.3.1 The Electronic Public Procurement System (SECOP)

Data on publicly funded interventions are drawn from the Electronic Public Procurement System (SECOP), Colombia's official platform for managing public procurement information. All contracting entities are required to publish the complete documentation of their procurement

processes on SECOP, regardless of their legal regime, public or private status, or institutional affiliation.

SECOP has two versions: SECOP I and SECOP II. SECOP I, created in 2007, is a platform for registering and publishing procurement information, but the actual procurement process occurs outside the platform. In contrast, SECOP II, implemented in 2015, is a fully digital and transactional platform that manages all stages of procurement online, from planning to contract liquidation. It also allows for real-time interaction between government entities and suppliers. While SECOP II is now the standard, some entities still use SECOP I due to internet connectivity issues, leading to a gradual migration to SECOP II.

The platform allows the identification of various characteristics of contractual processes, such as start, execution, and completion dates, the municipality of execution, contract status, value, awardee, among other details. Contract data from SECOP I are extracted using web scraping, while SECOP II data are obtained from the *Datos Abiertos de Colombia* platform provided by the *Agencia Nacional de Contratación Pública (Colombia Compra Eficiente)*. Contracts are classified according to the United Nations Standard Products and Services Code (UNSPSC). Table C1 lists the specific groups, segments and families used to categorize the contracts associated with each type of public investment analyzed. A keyword-based filtering process was then applied to identify and retain only those contracts explicitly targeted to the agricultural sector.

For analytical purposes, the filtered contracts are grouped into four operational categories used throughout the study:

1. Road Infrastructure: Contracts related to the construction, maintenance or improvement of rural transportation infrastructure, including roads, bridges, *placa huella* (reinforced concrete roads used in slippery steep slopes), and other complementary works aimed at improving mobility and connectivity in rural municipalities.
2. Inputs Delivery: Contracts for the provision of agricultural inputs such as fertilizers, seeds, and agrochemicals, designed to directly support producers with essential inputs for agricultural activities.
3. Agricultural Services: Contracts related to the hiring of specialized professionals, such as technical advisors, agronomists, or veterinarians, as well as specific contracts for technical assistance and agricultural extension services.
4. Machinery Delivery: Contracts involving the supply or rental of agricultural machinery, tools, and equipment.

Appendix A2 provides a detailed description of the filtering criteria applied to each category, along with a list of the types of contracts included in each.

4.3.2 Fondo para el financiamiento del sector agropecuario (FINAGRO)

Total agricultural credit in Colombia consists of two main sources: (i) preferential loans provided by financial intermediaries under special conditions, and (ii) loans disbursed directly by banks under standard terms. The first type is managed by the *Fondo para el Financiamiento del Sector Agropecuario (FINAGRO)*, the country's rural development bank, which operates as a second-tier financial institution. FINAGRO channels resources through supervised lenders—banks, financial corporations, trust companies, and cooperatives—to provide rural and agricultural

producers with loans at preferential rates. Between 2010 and 2014, this mechanism supplied about 90% of total agricultural credit (McAllister-Harker et al., 2018).

Agricultural loans, channeled through FINAGRO, play a crucial role in supporting small and medium-sized producers in the country. These producers account for 97% of the total number of loans granted but receive only 40% of the total loan value. Credit has been used mainly for investment purposes, particularly in coffee, livestock, and other crops, but the share allocated to working capital has grown steadily, reaching 40% of the portfolio by 2023. Over the past decade, access to FINAGRO credit has expanded significantly: between 2010 and 2023, the number of loans more than doubled, rising from 249,000 to 533,000. Figure B2 shows how this growth unfolded across different producer sizes.

4.3.3 Violence

We use data from the *Violent Presence of Armed Actors in Colombia* (ViPAA) to identify the municipalities with FARC presence during the years leading up to the ceasefire (Osorio et al., 2019). This dataset provides information on violent events carried out by armed actors in Colombia at the municipality-year level, as well as the actor responsible, covering the period from 1988 to 2019.

We define FARC presence in each municipality based on the occurrence of violent events attributed to the group during the years preceding the ceasefire. Given that such groups often employ violence as a systematic tool of territorial and social control, violent actions serve as a reasonable proxy for active presence. This approach has been widely used in the literature (Acemoglu, 2013 Prem et al., 2020, 2022).

5. Measuring Agricultural Productivity Growth

This section outlines the methodological framework followed to estimate TFP growth and its components and reports the empirical results.

5.1 Methodology: Stochastic production frontier

We follow the frontier approach to measure TFPG. This approach assumes that production units operate under a common technology and that they reach the production frontier when they produce the maximum possible output given a set of inputs. Over time, units can either improve efficiency by catching up to the frontier, or the frontier itself may shift due to technological progress.

Among frontier methods, we apply a parametric approach, specifically the SFA. This method requires specifying a functional form for the production frontier and estimating parameters using econometric techniques. Unlike deterministic frontier models, which attribute all deviations from the frontier to inefficiency, SFA decomposes the error term into two components, a random noise term, which captures measurement errors and an inefficiency term, which reflects the shortfall in output due to technical inefficiency.

Specifically, we estimate the stochastic production function using a Cobb-Douglas functional form. This choice is motivated by its desirable properties, allowing us to decompose TFPG, as it globally satisfies nonnegativity and monotonicity. Unlike the Translog specification, it ensures that TFP measures are consistent with index number theory, particularly the transitivity property (O'Donnell, 2016).

We rely on two complementary data sources, EVA and ELCA, to estimate stochastic production frontiers at different levels of aggregation. EVA provides municipal-level data for the entire national territory. For this study, we focus on the 2015-2023 period, allowing us to analyze TFP trends over time and across municipalities. In contrast, ELCA offers detailed household-level data for the period 2010 to 2016, tracking the same producers over time and capturing a rich set of production inputs. Although ELCA's geographic scope is limited to specific regions and samples only smallholders, its longitudinal and micro-level detail makes it ideal to analyze within-farm TFP dynamics. This dual approach leverages the strengths of both datasets: ELCA's micro-level precision and EVA's broader temporal and spatial coverage.

The reference model we estimate is the following:

$$\ln y_{it} = \alpha_i + \sum_{n=1}^N \beta_n \ln x_{nit} + \sum_{j=1}^J \eta_j z_{jit} + \lambda t + v_{it} - u_{it} \quad (1)$$

Where y_{it} denotes the value of agricultural production for household/municipality i at time t . For the analysis at the household level, the vector of inputs x_{it} includes land, purchased inputs (seeds, fertilizers, pesticides, fungicides, herbicides, breeding stock, feed, vaccines, veterinary medicines, and vitamins), hired labor, family labor, capital stock of animals, and machinery rental. For the analysis at the municipality level, it includes the input vector includes land, rural population, and the declared volumes of fertilizers, seeds, and tractors.

z_{it} represents a vector of climate variables expressed in levels, including average monthly temperature and precipitation and their squares, as well as temperature and precipitation anomalies. t is a linear trend capturing technological progress. In the municipal-level estimation, regional dummies are interacted with the time trend, allowing technological progress to vary across regions (Caribbean, Coffee Region, Pacific, South-Central Amazonia, Central-Eastern, and Eastern Plains). Technical efficiency is modeled using the True Random Effects (TRE) model, which separates time-varying inefficiency from time-invariant unobserved heterogeneity specific to each unit. This unobserved heterogeneity is captured by α_i , while v_{it} is the idiosyncratic error term. The inefficiency term u_{it} is a non-observable and non-negative random error, and it is assumed to follow a truncated-normal distribution.

Appendix A3 displays a series of log-likelihood ratio tests that support key methodological decisions. These tests justify the use of the Stochastic Production Frontier (SPF) over the Ordinary Least Squares (OLS) production function, guide the choice of the appropriate distributional assumption for the inefficiency term, and indicate whether a Cobb-Douglas or a Translog functional form provides a better fit.

5.2 Methodology: TFP decomposition

TFP is defined as the ratio of aggregate output to aggregate input (Jorgenson & Griliches, 1967). More formally, the TFP of unit i in year t is:

$$TFP_{it} = \frac{Q_{it}}{X_{it}}$$

In our empirical analysis, we consider the case of one output (Q_{it}) and multiple inputs ($X_{it} = X(x_{it})$). Comparing the TFP of unit i in period t with that of unit s in period k yields the TFP index (TFPI), expressed as:

$$TFPI_{ksit} = \frac{Q_{it}/X_{it}}{Q_{ks}/X_{ks}}$$

We construct a multiplicative TFPI by aggregating inputs in the form:

$$X(x_{it}) = \prod_{n=1}^N x_{nit}^{b_n}$$

where b_n are weights that sum to one. Following Njuki et al. (2018), the weights are given by the elasticities estimated from equation (1), normalized by the sum of all elasticities, specifically,

$$b_n = \frac{\widehat{\beta}_n}{\sum_{j=1}^N \widehat{\beta}_j}, \text{ with } \widehat{\beta}_n \text{ denoting the estimated elasticity of input } n.$$

Using this formulation, the multiplicative TFP index takes the form:

$$TFPI_{ksit} = \frac{Q_{it}}{Q_{ks}} \times \left(\prod_{n=1}^N \left(\frac{x_{nks}}{x_{nit}} \right)^{b_n} \right) \quad (2)$$

Taking the exponential of equation (1) and substituting it into the TFP index in equation (2), through the ratio between the antilogarithm of observation i in period t and observation k in period s , gives the following decomposition of the TFPI:

$$TFPI_{ksit} = (e^{(\alpha_i - \alpha_k)}) \times \left(\prod_{n=1}^N \left(\frac{x_{nit}}{x_{nks}} \right)^{\beta_n - \frac{\widehat{\beta}_n}{\sum_{j=1}^N \widehat{\beta}_j}} \right) \times (e^{(\tau_t - \tau_s)}) \times \left(e^{\sum_{j=1}^J \eta_j (z_{jit} - z_{jks})} \right) \times \left(\frac{\exp(-u_{it})}{\exp(-u_{ks})} \right) \times \left(\frac{\exp(v_{it})}{\exp(v_{ks})} \right) \quad (3)$$

Following the approach of O'Donnell (2018), We decomposed TFP into the components of equation (3). The first term captures time-invariant unobserved heterogeneity (UH). The second term, scale efficiency (SE), measures the relative change in scale efficiency. The third term corresponds to changes in technological progress (TP). The fourth term reflects variations in weather effects (WE). The fifth term captures the relative change in technical efficiency (TE) as calculated by Jondrow et al. (1982); and the final term accounts for statistical noise (SN).

5.3 Results: Agricultural productivity dynamics at municipal level

5.3.1 Results: TFP decomposition at municipal level

Table 3 presents the results from the stochastic production frontier estimation (equation 1) at the municipal-level for the 2015-2023 period. As expected, all input parameters are positive and statistically significant. Moreover, the high significance of the weather-related parameters indicates that weather is a strong predictor of agricultural production. The value of the parameter λ , defined as the ratio of the standard deviation of the inefficiency term to that of the random noise, indicates that inefficiency plays an important role in explaining the total variation in agricultural output.

The decomposition results reported in Table 4 indicate that between 2015 and 2023, the value of agricultural production grew at an average annual rate of 2.46%. Approximately two-thirds of this growth was driven by increased input use, while less than one-third was due to gains in TFP. Average annual TFP growth was 0.65%, driven primarily by climate factors, followed by improvements in technical efficiency and technological progress.

Table 3. Coefficient estimates from the stochastic production frontier model at the municipal level

Dependent variable: Ln (Agricultural production value)	
Ln (Harvested Area in ha)	0.994*** (0.002)
Ln (Rural Population)	0.012*** (0.002)
Ln (Seeds in Kg)	0.009*** (0.002)
Ln (Fertilizer in Kg)	0.014*** (0.001)
Ln (Machinery in Kg)	0.003** (0.001)
Average Monthly Temperature (°C)	-0.142*** (0.001)
Average Cumulative Monthly Precipitation (mm)	0.0001** (0.00007)
Average Monthly Temperature (sq)	0.002*** (0.00003)
Average Cumulative Monthly Precipitation (sq)	-3.68e-07** (1.64e-07)
Temperature Anomaly	0.013*** (0.003)
Precipitation Anomaly	-0.011*** (0.003)
Trend * Caribbean	0.015*** (0.002)
Trend * Coffee Region	-0.005** (0.002)
Trend * Pacific	0.002 (0.002)
Trend * South-Central Amazonia	0.0002 (0.003)
Trend * Central-Eastern Region	-0.002 (0.002)
Trend * Eastern Plains	-0.002 (0.003)
σ_u	6.123 (0.052)
σ_v	0.157 (0.002)
λ	39.073 (0.053)
Observations	9,888
Number of municipalities	1,104

Note: To handle zeros in input factors, we follow Battese (1996) by replacing zeros with one and adding dummies for municipalities reporting zero values for each input. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

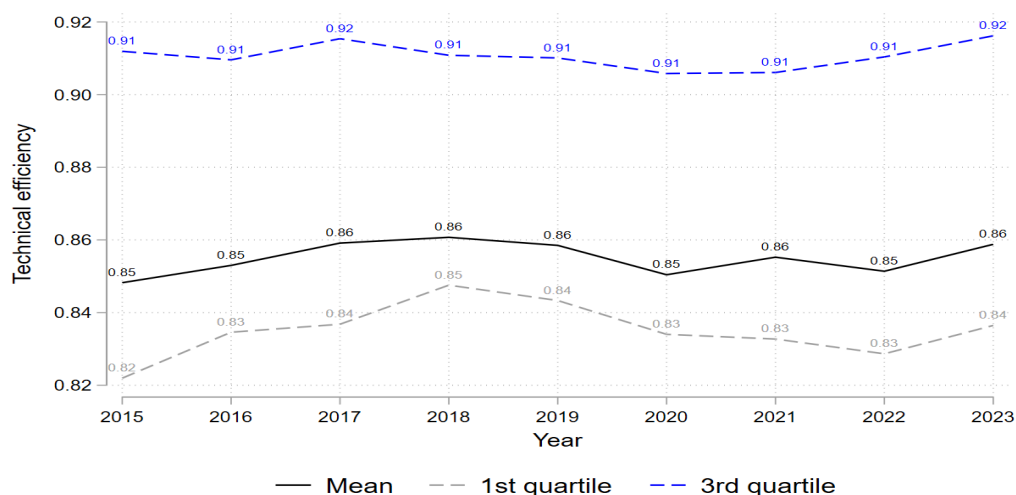
Table 4. Annual growth rates of output, inputs, TFP, and TFP components by region (%), 2015-2023

Region	Output index	Input index	TFP index	Scale efficiency index	Technical efficiency index	Technol. progress index	Weather effects	Statistical noise
Caribbean	5.84	3.62	2.14	0.12	0.47	1.56	0.22	-0.23
Coffee Region	1.22	0.97	0.25	0.03	0.15	-0.55	0.45	0.17
Pacific	2.63	1.62	0.99	0.05	0.33	0.16	0.33	0.12
South-Central Amazonia	1.04	1.15	-0.12	0.04	-0.06	0.02	0.42	-0.54
Central-Eastern	1.36	1.12	0.23	0.04	0.05	-0.20	0.53	-0.19
Eastern Plains	4.15	3.96	0.18	0.13	0.06	-0.18	0.30	-0.12
National	2.46	1.79	0.65	0.06	0.18	0.13	0.4	-0.12

Note: To compute the annual growth rate of TFP and its components, we first aggregate municipal indexes at the regional and national levels using a geometric mean for each year. Subsequently, the compound annual growth rate (CAGR) is calculated following the standard geometric growth rate formula.

Figure 4 shows the evolution of technical efficiency between 2015 and 2023, with an average efficiency level of 85% and no evidence of sustained improvement over time. The similarity between the mean and the first quartile reveals concentration in the distribution of efficiency between the median and lower part of the distribution.

Figure 4. Trends in technical efficiency by year (mean, 1st and 3rd quartiles)



The scale component remained stable over time, but because these estimations are at the municipality level it does not reflect the effect of scale at the farm level.

This national average masks substantial regional heterogeneity. Table 4 reports the annual growth rate of TFP and its components across Colombia's six regions. The Caribbean region

recorded the highest output growth and the largest increase in TFP, with an average annual growth rate of 2%, driven primarily by technological progress. Along with the Pacific region, it was the only one where TFP growth exceeded the national average between 2015 and 2023. By contrast, the remaining regions recorded TFP growth rates below the national average, with South-Central Amazonia being the only region that experienced a decline in productivity (-0.12%).

Climate emerges as the main driver of productivity growth, contributing the most to TFP gains across all regions, with the strongest effects in Central-Eastern, Coffee Region, and South-Central Amazonia. This pattern suggests a dependence on favorable weather conditions rather than on structural improvements in production processes, highlighting the vulnerability of productivity to climate variability.

Although technological progress at the national level was positive (0.13%), it remained weak and highly uneven across regions. Three of the six regions exhibit negative technological progress indices (Central-Eastern, Coffee Region, Eastern Plains) suggesting limited adoption of new technologies or productive innovations in large parts of the country, with major implications for the sustainability of long-term growth. The Coffee Region experienced the largest productivity losses due to limited technological progress, which significantly offsets the contribution of the other TFP components. In turn, improvements in technical efficiency were modest across regions, particularly in South-Central Amazonia, Central-Eastern, and Eastern Plains.

A small portion of the measured changes in productivity can be attributed to statistical noise, which encompasses a combination of functional form errors, omitted variable bias, measurement errors, and specification errors in included variables (O'Donnell, 2022). One source of noise in this study comes from the choice of functional form. Although the log-likelihood ratio test (Appendix A3) indicates that the Translog production function better explains the underlying production technology, a Cobb-Douglas specification was used to ensure consistency with the theoretical properties required for the TFP decomposition applied in this analysis.

Figure B3 presents departmental TFP growth levels, with Magdalena, Arauca, and Amazonas standing out for annual TFP growth rates above 3%, while Caquetá, Putumayo, and Guainía recorded the largest productivity declines.

5.3.2 Results: Land productivity

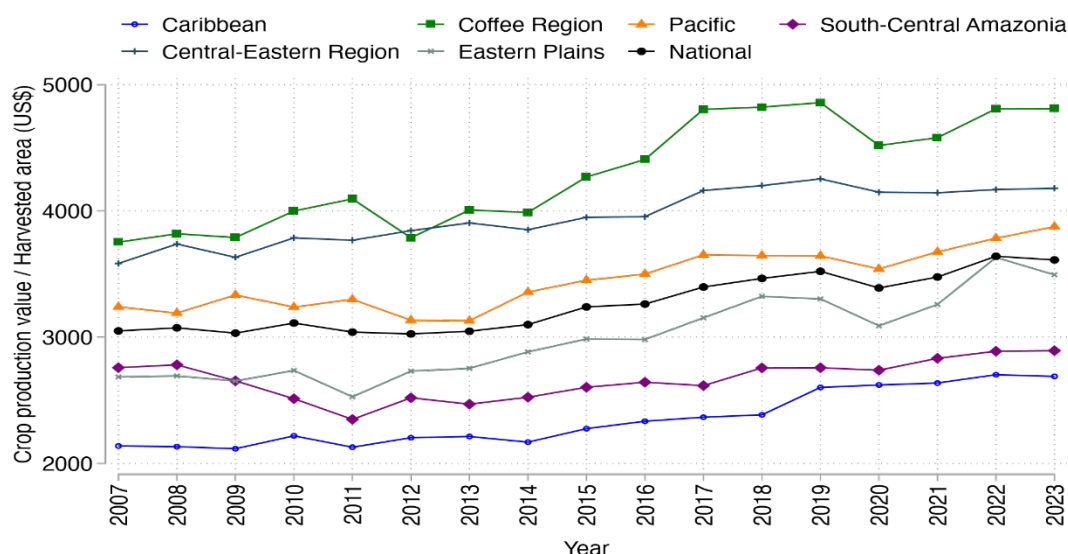
While TFP provides a comprehensive measure of productivity by accounting for all inputs, the value of crop production per harvested hectare provides a direct assessment of how much output is generated from land, the most fundamental agricultural input. This perspective highlights variations in the economic returns to land use across space and time, offering a straightforward benchmark to compare regional performance. Figure 5 presents the evolution of this measure between 2007 and 2015, both at the national level and disaggregated by regions.

While the national average of crop value per hectare shows a steady upward trend, regional disparities remain marked. Unlike in the TFP analysis, Coffee Region consistently outperforms all other regions, combining both the highest productivity levels and above-average growth, but also exhibiting the highest volatility. Eastern Plains exhibit the fastest growth rate (1.66% annually), yet their productivity levels remain below the national average. The region's historical reliance on extensive cattle ranching has kept land productivity low, and recent increases may reflect a catching-up process driven by a better use of land with agricultural potential. In contrast, South-

Central Amazonia lags behind, with the lowest productivity levels and a modest annual growth of 0.3%. Interregional gaps prove to be persistent, regions that lie above the national average remain in that position, despite fluctuations, while those below continue to lag behind.

Throughout the series, common trends can be observed across regions. In 2010-2011, many regions experienced a decline, which may be related to the 2010-2011 La Niña event. Another common shock occurred in 2019-2020, possibly linked to the disruptions caused by the COVID-19 pandemic, which hindered market access and affected supply chains and production overall. After the pandemic, yields recovered, but the intensity and stability of this rebound varied across regions.

Figure 5. Crop production value per hectare at the regional level, 2007–2023



Note: Regional and national series are obtained by aggregating municipal-level production value and harvested area by year and computing their ratio.

5.4 Results: TFP decomposition at household level

Table 5 presents the results of the stochastic production frontier estimation (equation 1) at the household level. These results are representative of small farmers across four rural micro-regions in Colombia: *Atlántica*, *Altiplano Cundi-boyacense*, *Eje Cafetero*, and *Centro-Oriental*.

Table 5. Coefficient estimates from the stochastic production frontier model at the household level

Dependent variable: Ln (Agricultural production value)	
Ln (Cultivated Area)	0.152*** (0.009)
Ln (Family Labor Index)	0.054 (0.033)
Ln (Capital Stock of Animals)	0.185*** (0.007)
Ln (Machinery Rental Value)	-0.025 (0.021)
Ln (Cost of Purchased inputs)	0.256*** (0.010)
Ln (Cost of Hired Labor)	0.178*** (0.014)
Time Trend	0.100*** (0.020)
Average Monthly Temperature (°C)	-0.266*** (0.083)
Average Cumulative Monthly Precipitation (mm)	-0.002 (0.003)
Average Monthly Temperature (sq)	0.006*** (0.002)
Average Cumulative Monthly Precipitation (sq)	5.45E-06 (8.24e-06)
Temperature Anomaly	-0.224*** (0.061)
Precipitation Anomaly	0.068*** (0.024)
σ_u	31.909 (0.02)
σ_v	0.671 (0.015)
λ	47.587 (0.025)
Observations	6,818
Number of households	2,307

Note: Specifications include household and year fixed effects. To address zeros in input factors, we follow Battese (1996) by replacing zeros with one and including dummies for households reporting zero values for each input. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Most input elasticities estimates are positive and statistically significant at the 5% level, except for machinery capital and the family labor index. A positive and significant time trend indicates the presence of technological progress over time, whereas the value of the λ parameter, shows that most of the unexplained variability in output is due to technical inefficiency rather than random noise.

Based on the estimated parameters, the decomposition of TFP was carried out. Table 6 presents the output and input index values as well as the average annual growth rate of TFP index and its components during the period analyzed. The evidence shows that TFP in the analyzed regions experienced a modest increase at an average annual rate of 0.38%. Meanwhile, input growth averaged an annual rate of 7.6% and accounted for approximately 95% of the total output growth

of 8.04%. This indicates that the increase in production in the sample was driven predominantly by expanded input use, with improvements in TFP contributing only marginally.

Table 6. Geometric means and annual growth rates of TFP and its components (2010-2016)

Year	Output Index	Input Index	TFP Index	Scale Efficiency Index	Technical Efficiency Index	Technol. Progress Index	Weather effects	Statistical Noise
2010	0.72	0.25	2.92	1.32	1.58	1.00	0.96	1.46
2013	1.20	0.46	2.63	1.17	1.79	1.35	0.75	1.25
2016	1.15	0.38	2.99	1.21	1.62	1.82	0.63	1.32
Growth Rate p.a. (%)	8.04	7.63	0.38	-1.46	0.46	10.49	-6.71	-1.62

Note: A geometric mean is used to aggregate households at the national level for each year.

Technological progress was the main driver of productivity growth, indicating a shift in the production frontier. In contrast, technical efficiency showed a moderate improvement, suggesting that the gap between actual output and the maximum possible output, given the available technology and inputs, slightly narrowed. Figure B4 shows the average technical efficiency along with the first and third quartiles for the three years analyzed. Efficiency levels remained relatively stable over time. There was a slight increase in 2013, but by 2016 they returned to 2010 levels. This pattern is also seen among the least efficient households, while the most efficient maintained constant levels throughout the period.

Gains in technological progress partially offset the decline in other components. Specifically, the percentage change in TFP due to scale efficiency decreased at an average rate of 1.46% per year, while the percentage change in weather effects, which captures TFP fluctuations caused by environmental factors, declined at an average rate of 6.71% per year.

It is worth highlighting that the strong negative influence of the climate component on TFP performance is largely associated with the occurrence of the El Niño weather event that occurred at the end of the study period. Although such events do not reflect average climate conditions, this finding highlights the vulnerability of the agricultural sector to these types of shocks, which are expected to become more frequent and intense under global climate change.

Even though the climate component negatively affected TFP growth in the household-level analysis, it contributed positively and emerged as the main driver of productivity gains at the municipal level. This contrast reflects the fact that the period analyzed at the household level coincided with a phase of extreme weather conditions, highlighting the sector's vulnerability to climate shocks, especially among small producers with limited adaptive capacity. Meanwhile, the municipal-level analysis spans a longer timeframe characterized by more stable climate conditions, which supported sustained productivity growth and further highlights the sector's sensitivity to weather variability.

Part of the observed changes in productivity reflect statistical noise rather than true variation, with one potential source stemming from inconsistencies in survey design. In particular, the 2010 round of the ELCA survey differs in some aspects from the later rounds in terms of the structure of the questionnaire and the scope of information collected. As detailed in Appendix A1, various

adjustments were necessary to harmonize this round with the rest of the dataset, which may have introduced measurement errors and added noise to the productivity estimates.

It is important to be cautious when interpreting and comparing results at the household and municipal levels, as there are differences between the two approaches. Household-level analysis captures microeconomic dynamics and individual heterogeneity among a sample of smallholders. In contrast, municipal-level analysis reflects aggregated trends and broader structural effects, which can include effects related to changes in the composition of farmers over time. Additionally, there are differences in the time periods covered, geographic scope, and the variables included in each dataset.

6. Potential Determinants of Agricultural Productivity: A Complementary Analysis

This section outlines the empirical strategy and methodological considerations used to estimate how civil conflict, credit and public investments relate to agricultural productivity.

6.1 Impact of credit access on productivity

We evaluated the effect of agricultural credit on productivity using both municipal-level (EVA) and household-level (ELCA) data. In both cases, a two-way fixed effects (TWFE) model of the following form is estimated:

$$\ln y_{it} = \alpha_i + \delta D_{it} + \sum_{n=1}^N \beta_n \ln x_{nit} + \sum_{j=1}^J \eta_j z_{jit} + \lambda_t t + v_{it} \quad (4)$$

where D_{it} measures credit exposure, λ_t and α_i correspond to time and municipality or household fixed effects, respectively, and v_{it} is an idiosyncratic error term. We control for the same inputs and climate variables (x_{it} and z_{it}) used in the production function estimated in Section 5.1. This specification allows the coefficient δ to be interpreted as capturing the relationship between credit and productivity. Standard errors in the estimation are clustered at the municipality level.

While equation 4 provides a unified empirical framework, the measurement of credit exposure and the identification strategy vary across levels of analysis, as described below.

6.1.1 Household-Level Analysis

At the household level, we estimate the effect of access to credit on agricultural productivity. Credit access, denoted by D_{it} in equation 4, is proxied by a binary indicator equal to one if the farm household had received any agricultural loan from a financial institution at the time of the interview. Since credit uptake is an endogenous decision that depends on household characteristics and unobserved factors potentially correlated with productivity, we address endogeneity through an instrumental variables (IV) approach with a two stage least squares estimation. Specifically, household access to credit is instrumented using the interaction between (i) the travel time from the household to the municipal capital, which proxies for physical access to financial services and (ii) the per-capita value of FINAGRO agricultural credit disbursed in the municipality, which captures the overall supply of credit. This instrument aims to exploit

exogenous variation in the availability and accessibility of credit across households, while remaining orthogonal to unobservable factors directly affecting productivity.¹

6.1.2 Municipal Level Analysis

Municipal credit exposure D_{it} is defined as the value of FINAGRO loans disbursed per rural capita. The use of administrative data allows us to construct annual credit flows for each municipality over 2015-2023. By incorporating municipality and year fixed effects, this TWFE specification identifies how within-municipality changes in credit supply correlate with agricultural productivity, net of persistent cross-sectional differences and common macroeconomic shocks. Figure B5 presents a municipal-level map illustrating the distribution of average per capita credit across municipalities during the study period.

6.2 Effect of the FARC ceasefire on agricultural productivity

We study the impact of the ceasefire with the FARC that took place in December 2014 on agricultural production value using both household-level (ELCA) and municipal-level (EVA) data. In both cases, we rely on a difference-in-differences (DiD) framework of the form:

$$\ln y_{it} = \beta_0 + \delta (FARC_i * POST_t) + \sum_{n=1}^N \beta_n \ln x_{nit} + \sum_{j=1}^J \eta_j z_{jit} + \phi_i + \lambda_t + \varepsilon_{it} \quad (5)$$

$FARC_i$ equals 1 for municipalities or households that experienced FARC presence in at least one year between 2010 and 2014, while $POST_t$ is an indicator for the period after the ceasefire. x_{it} and z_{it} correspond to inputs and climate variables, respectively. The coefficient δ captures the average effect of the ceasefire on productivity for areas previously exposed to FARC.

Below, we detail the estimation procedure and the measurement of treatment exposure at each level of analysis.

6.2.1 Household level analysis

The ELCA includes both household and community-level data. The information at the community level provides insights into various aspects including access to infrastructure, public services, agricultural markets, and allows us to determine whether a community had a presence of armed groups. This module is applied to at least two local leaders in communities with the presence of five or more agricultural households interviewed as part of the ELCA.

Our identification strategy leverages the timing of the permanent ceasefire announced by the FARC and the pre-ceasefire variation in FARC presence across communities. We compare changes in agricultural productivity after the ceasefire between communities with and without prior FARC presence. The post-ceasefire period is defined as 2016, the only ELCA round following the December 2014 ceasefire.

¹ Travel time to the municipal capital tends to correlate to many variables, however its interaction with FINAGRO credits is less subject to endogeneity. The effect of the interaction in the first stage regression might be negative if credit expansion benefits more the closest households, but it might also be positive if as credit expands in a municipality, it tends to provide access to the most isolated farmers (while the closest ones already had credits in greater proportions).

The sample is restricted to households that remain in the same community across survey rounds, and treated households are defined as those located in communities that reported FARC presence between 2010 and 2014. Because FARC presence is likely correlated with factors such as isolation or vulnerability that also influence productivity trends, we combine a difference-in-differences approach with matching techniques to improve comparability between treatment and control groups.

The matching procedure relies on pre-treatment characteristics of the communities. These include the total number of households in the community and travel time to the municipal administrative center. Also, economic conditions proxied by agricultural wages, cultivated area, and the value of agricultural output prior to the ceasefire; and security-related characteristics including perceptions of insecurity and reported incidents of homicides, kidnappings, and land disputes.

A nearest neighbor matching algorithm is employed. This procedure results in 19 treated communities and 41 control communities, encompassing 666 households in 2010, 692 in 2013, and 547 in 2016. The covariate balance results are shown in Figure B6, which illustrates that, after matching, observable characteristics that could have influenced the presence of FARC are more balanced between the treated and control groups

6.2.2 Municipal-level analysis

We use municipal-level data from the EVA survey spanning 2007 to 2023. As before, the analysis leverages the timing of the permanent ceasefire announced by the FARC, together with the spatial variation in FARC presence across municipalities prior to the ceasefire. Since the ceasefire occurred at the end of 2014 and data on agricultural inputs (seeds, tractors, and fertilizers) are only available from 2015 onward, it is not possible to include these inputs in the current analysis. Therefore, we consider the entire available EVA period (2007-2023) and estimate the effect on agricultural production, controlling for cultivated area and rural population.

The ViPPA data allows us to identify, for each year, violent acts committed by different armed groups at the municipal level. As in the household-level analysis, we recognize that the historical presence of the FARC may be correlated with other municipal characteristics that influence agricultural productivity trends over time. To enhance comparability and mitigate potential selection bias, we restrict the sample to municipalities that, according to ViPPA data, experienced at least one violent event perpetrated by any armed group between 2010 and 2014. This restriction ensures that we are comparing municipalities with a similar degree of conflict exposure, regardless of the specific perpetrator, under the assumption that shared exposure to violence leads to greater similarity in socioeconomic structure, historical vulnerability, and agricultural development constraints. Additionally, we exclude municipalities with more than 200,000 inhabitants, as these are predominantly urban, and were generally less exposed to the armed conflict.

Of the 499 municipalities under analysis, we identify as treated those that recorded violent acts by the FARC between 2010 and 2014.² We use this period because it corresponds to the first presidential term of Juan Manuel Santos, who led the peace agreement with the FARC, and the end of 2014 coincides with the FARC's unilateral ceasefire. Previous work estimating the effect of violence on agricultural outcomes in the country uses the same definition (Prem et al., 2018, 2023; Bernal et al., 2024).

² Violent events that occurred in 2014 after the ceasefire on December 20 are excluded from the analysis.

The final sample comprises 499 municipalities, of which 230 reported FARC presence during the specified timeframe, the rest belonging to the control group. Figure B7 presents a municipal-level map showing which municipalities were identified as having FARC presence, according to the criteria used in the analysis.

6.3 Public contracts in SECOP: Impact of road infrastructure, agricultural extension services, supply of agricultural inputs, and delivery or rental of agricultural machinery

We assess the impact of rural public investment at the municipal level by combining agricultural data from EVA with public contract information from SECOP³. Investments are classified into four categories, as detailed in Section A2: road infrastructure, input delivery, agricultural services, machinery provision.

Municipalities may receive more than one contract during the analysis period, and in some cases, multiple contracts within the same year. Figure B8 displays a municipal-level map indicating the year in which each municipality received its first contract in each spending category. The year is defined according to the completion date of the first contract. As shown, there is sufficient variation in the years when municipalities complete their first contract. Table 7 summarizes contract statistics by public investment category over the study period.

Table 7. Contracts summary by public investment category, 2015-2023

Type of public investment	Avg. number of contracts per municipality from 2015-2023	Avg. number of contracts per year	Average value of a contract per farm (\$USD)	Total number of contracts
Road infrastructure	8.59	3.16	103.2	3,075
Input delivery	5.85	1.95	44.73	3,312
Agricultural services	8.16	2.92	588.63	2,528
Machinery provision	2.26	1.18	74.93	463

Note: Only the contracts that remained after applying the filters are included: contracts worth less than 2 dollars per farm were removed, and only those in rural municipalities were retained.

We assess both intensive and extensive margin effects. First, we estimate a TWFE specification using the cumulative value of contracts per farm⁴ (in US\$) to evaluate the impact of cumulative investment value on agricultural TFP. Second, taking advantage of the staggered timing of contract allocations across municipalities, we implement a dynamic staggered difference-in-differences model. In this model, the treatment year for each municipality is defined as the year it receives its first contract in the relevant category, allowing us to trace the evolution of average treatment effects before and after initial exposure.

To quantify the impact of the value of public investment, we estimate the following specification:

³ This analysis is conducted only at the municipal level due to the limited temporal and geographic coverage of the ELCA data, which would greatly restrict the number of contracts that could be matched at the household level.

⁴ The number of farms in each municipality is taken from the 2014 Agricultural Census.

$$\ln y_{it} = \alpha_i + \delta D_{it} + \sum_{n=1}^N \beta_n \ln x_{nit} + \sum_{j=1}^J \eta_j z_{jit} + \lambda_t t + v_{it} \quad (6)$$

Where D_{it} denotes the cumulative value of contracts per farm in municipality i at time t . The coefficient δ measures the semi-elasticity of agricultural productivity with respect to additional investment, after accounting for unobserved heterogeneity, time-varying shocks common to all municipalities and weather shocks.

Additionally, to examine how the receipt of at least one contract affects productivity over time, we estimate:

$$\begin{aligned} \ln y_{it} = & \sum_{g=-s}^{-2} \delta_g \text{Lag}_{it}^g + \sum_{p=0}^P \theta_p \text{Lead}_{it}^p + \sum_{n=1}^N \beta_n \ln x_{nit} + \sum_{j=1}^J \eta_j z_{jit} + \\ & \phi_i + \lambda_t + \varepsilon_{it} \quad (7) \end{aligned}$$

Where Lag_{it}^g equals 1 if municipality i is in year t , which is g -years before the treatment year. Lead_{it}^p is a dummy equal to 1 if municipality i is in year t , which is p -years after the treatment year. All other variables are defined as above.

When treatment timing is staggered, the traditional TWFE tends to require unrealistic assumptions about constant treatment effects over time, frequently leading to inappropriate weightings (De Chaisemartin & d'Haultfoeuille, 2022; Goodman-Bacon, 2021). These limitations arise because the model fails to account for treatment effect heterogeneity and dynamic responses, potentially leading to biased estimates (Sun & Abraham, 2021). To overcome this issue, the analysis employs the estimator developed by Callaway and Sant'Anna (CS), which aggregates the cohort–time specific parameters (δ_g and θ_p) into an event-study framework. This approach accounts for heterogeneous treatment effects and avoids “forbidden comparisons” by allowing treated units to be compared with either not-yet-treated or never-treated controls. In our case, the control group consists of not-yet-treated municipalities, and the ATT is estimated using an outcome-regression DiD estimator based on OLS.

Since SECOP records the universe of public contracts executed in the country, many entries correspond to small-scale or low-value interventions with limited scope or economic significance. As these contracts are unlikely to generate meaningful changes in agricultural productivity, the analysis is restricted to contracts exceeding US\$ 2 per farm, thereby focusing on investments of sufficient magnitude to plausibly affect municipal-level TFP.

Likewise, the analysis is restricted to predominantly rural municipalities, defined as those with a rural index of 70% or higher, in order to enhance comparability between treated and control units, reduce structural differences in baseline characteristics, and support the plausibility of the parallel trends assumption. The resulting municipal-level panel spans the period 2015-2023 and includes 380 municipalities. Table C2 presents the number of treated and control municipalities for each type of intervention during 2015-2023 period.

7. Results: Impact of Policy Drivers on Agricultural Productivity

7.1 Municipal-level results

Table 8 presents the estimated effects of municipal-level policy interventions on agricultural productivity using TWFE models. The analysis distinguishes between two periods: the 2015-2023 window for agricultural credit and public investment, and the 2007-2023 panel for assessing the impact of the FARC ceasefire.

Table 8. Average impact of agricultural determinants on municipal-level productivity

Dependent variable: Ln (Agricultural production value)	Credit value (US\$, per capita)	Road infrastructure (US\$1000/far m)	Input delivery (US\$1000/far m)	Agricultural services (US\$1000/far m)	Machinery provision (US\$1000/far m)	Post Conflict indicator
D_{mt}	0.014** (0.006)	0.007*** (0.002)	-0.007 (0.009)	0.003 (0.002)	-0.004 (0.004)	-0.041* (0.022)
Ln (Harvested Area in ha)	1.023*** (0.020)	0.997*** (0.029)	0.996*** (0.029)	0.996*** (0.029)	0.996*** (0.029)	1.001*** (0.014)
Ln (Rural Population)	0.015 (0.019)	-0.037 (0.040)	-0.037 (0.040)	-0.035 (0.040)	-0.036 (0.040)	0.021 (0.027)
Ln (Seeds in Kg)	0.011** (0.006)	0.022 (0.014)	0.022 (0.014)	0.022 (0.014)	0.022 (0.014)	
Ln (Fertilizer in Kg)	0.006 (0.004)	0.005 (0.006)	0.005 (0.006)	0.005 (0.006)	0.005 (0.006)	
Ln (Machinery in Kg)	0.002 (0.004)	-0.004 (0.008)	-0.004 (0.008)	-0.004 (0.008)	-0.004 (0.008)	
Average Monthly Temperature (°C)	-0.013 (0.101)	0.186 (0.171)	0.192 (0.170)	0.193 (0.17)	0.195 (0.170)	-0.084 (0.096)
Average Cumulative Monthly Precip. (mm)	-0.001** (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Average Monthly Temperature (sq)	0.001 (0.001)	0.004** (0.002)	0.003** (0.002)	0.004** (0.002)	0.004** (0.002)	-0.003** (0.001)
Average Cumulative Monthly Precip. (sq)	0.001 (0.001)	1.06E-06 (9.29e-07)	9.30E-07 (9.28e-07)	9.96E-07 (9.30e-07)	9.82E-07 (9.30e-07)	1.98E-07 (4.46e-07)
Temperature Anomaly	-0.011 (0.044)	-0.109 (0.077)	-0.111 (0.077)	-0.112 (0.077)	-0.112 (0.077)	0.038 (0.044)
Precipitation Anomaly	0.024** (0.011)	0.013 (0.019)	0.012 (0.019)	0.012 (0.019)	0.012 (0.019)	0.008 (0.012)
Observations	9,885	3,420	3,420	3,420	3,420	8,483
Municipalities	1,101	380	380	380	380	499
Period	2015-2023	2015-2023	2015-2023	2015-2023	2015-2023	2007-2023

Notes: All models include municipality and year fixed effects. Credit is measured as the value of agricultural loans per capita (IHS transformed). Road infrastructure, input delivery, agricultural services, and machinery provision are measured as the cumulative value of public contracts per farm in thousands of USD. FARC ceasefire is a dummy equal to one for municipalities with prior FARC presence after 2016. Standard errors clustered at the municipal level (in parentheses) **p<0.01, *p<0.05, p<0.1

The results reveal a positive and statistically significant relationship between per capita agricultural credit and municipal agricultural productivity. A 1% increase in credit per capita is associated with a 0.014% increase in TFP. However, this association must be interpreted with caution. Municipalities with more dynamic agricultural sectors may also exhibit stronger institutional frameworks that enhance both the variation in productivity and access to credit over time. These institutions, in turn, support a more developed financial system, facilitating the allocation of credit to agricultural producers. Or alternatively, households in municipalities with a

more dynamic agriculture may seek more credit. Therefore, the observed relationship may reflect a joint determination rather than a strictly causal effect.

Public investment in rural road infrastructure also shows a significant and robust association with productivity gains. Specifically, an additional US\$ 1,000 per farm in cumulative infrastructure investment is linked to a 0.75% increase in TFP. In contrast, investments in input delivery, machinery provision and, to some extent, agricultural services do not exhibit statistically significant effects on productivity. A significant share of rural development policies has focused on input transfers; however, the results suggest that on average, such interventions do not lead to sustained improvements in productivity. This result may stem from distorted production incentives, imperfect targeting, or weak complementary conditions -such as limited input supply, poorly trained extension services, inadequate infrastructure, low connectivity, and low technological adoption. These factors may reduce the effectiveness of input-based interventions in increasing productivity.

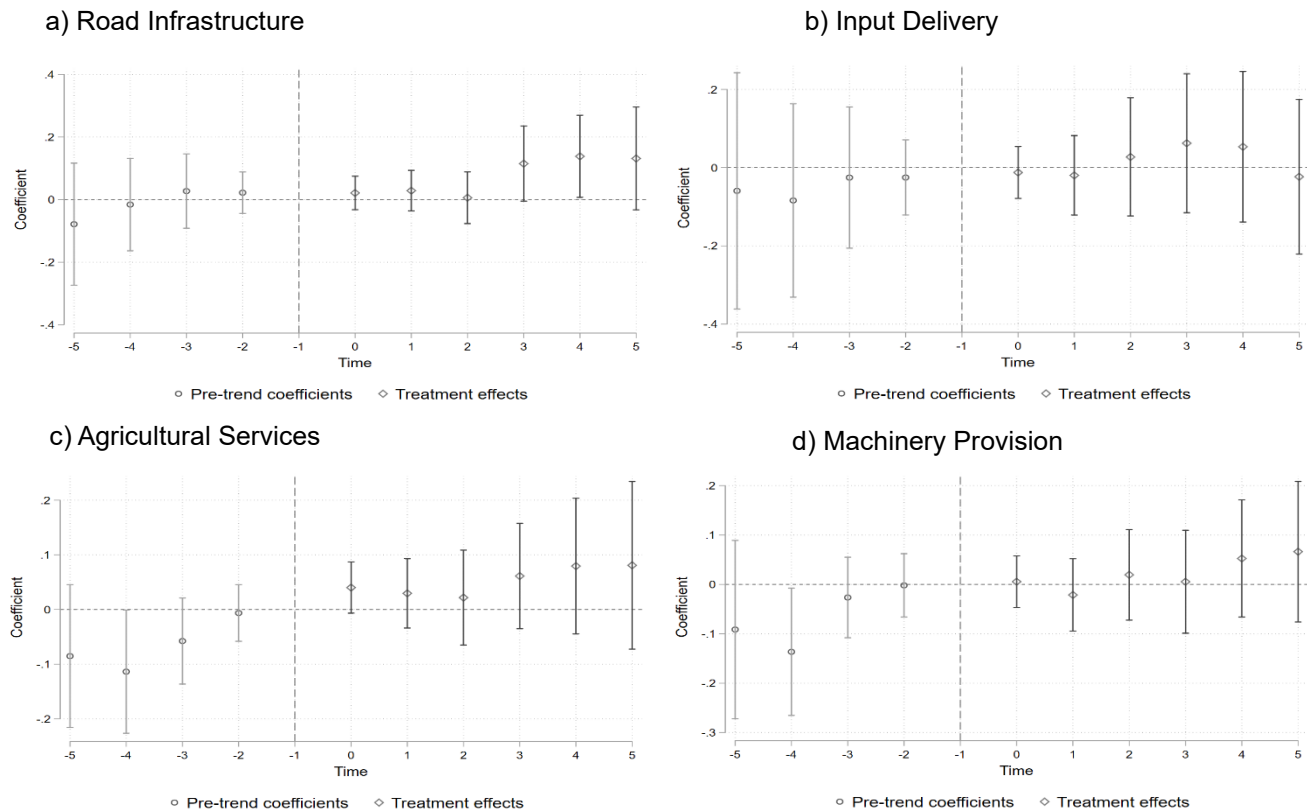
The results on agricultural services (including extension services) are non-significant but unprecise, with a confidence interval that includes substantial positive effects, hence our results are mostly inconclusive. The lack of impact may stem from low service quality or intensity, inadequate or outdated technical recommendations, or persistent barriers that constrain adoption. Also, the broad and heterogeneous nature of contracts classified under the category, combined with the difficulty of accurately identifying true extension contracts from textual descriptions, likely introduce some measurement noise explaining positive coefficients with large confidence intervals. These findings call for further studies exploring potential heterogeneities in the effects of extension services on agricultural productivity and the mechanisms driving these effects.

Figure 6 presents the event study estimates of the dynamic relationship between each type of rural public intervention and agricultural productivity, as specified in equation 7. The absence of differential pre-treatment trends across treated and control municipalities supports the validity of the identification strategy. The results show that the effect of rural road investments materialize gradually, with the productivity gains that emerge three years after the first infrastructure contract is completed and persist for at least one more year. This lagged effect suggests that enhanced connectivity and improved access to markets and services take time to be internalized by producers but eventually yield durable productivity improvements. On average, as shown in Table C3, agricultural productivity rises by 9% in municipalities that begin receiving projects for the construction and improvement of rural road infrastructure between 2015-2023. In contrast, interventions focused on input transfers do not exhibit any statistically significant impacts in the post-treatment period. Service provision shows some movement in the expected direction yet still non-significant.

Our results align with prior evidence, which finds positive effects of investments in public goods, in contrast to the limited impacts of input-based interventions (Mogues & Benin, 2014; Anríquez et al., 2016; Gulati & Narayanan, 2003). These results underscore the importance of prioritizing interventions that tackle structural constraints collectively, which, by altering the structural constraints faced by rural producers, are more likely to generate sustained improvements in productivity. While the provision of inputs may offer temporary relief from immediate production limitations, its structural and long-term impact might be very limited if one believes that farmers are already likely to invest in such inputs or machinery when profitable. In this context, rather than allocating public resources primarily toward input distribution, policy efforts should focus on strengthening the rural financial system and institutional frameworks, ensuring that producers can independently acquire the resources they need when they need them. In contrast, infrastructure investments lay the foundation for more sustainable productivity growth by addressing systemic

barriers that individual farmers cannot resolve alone and by generating spillover benefits across the broader rural economy.

Figure 6. Dynamic effects of public contracts on productivity across categories



Note: The figure presents event study estimates based on Callaway and Sant'Anna (2021), measuring the impact of a municipality having at least one completed public contract in each SECOP category on agricultural productivity during 2015-2023. All models include municipality and year fixed effects. The omitted period corresponds to one year prior to the first contract completion. Vertical lines denote 95% confidence intervals with standard errors clustered at the municipal level.

To assess the effects of each type of investment conditional on the presence of other interventions, a joint specification is estimated in which the cumulative investment values for all categories are included simultaneously within the same regression. The results, presented in Table C4, confirm the positive and significant impact of rural road infrastructure, with a magnitude that remains very similar when the four SECOP types of projects are pooled in the same regression. This finding suggests that the productivity gains associated with road infrastructure are not merely driven by correlations with other types of public investment.

Finally, column (6) suggests that the ceasefire had a negative effect on TFP in municipalities with prior FARC presence, an effect possibly driven by the expansion of cultivated area into lower-yielding lands. Supportive of this hypothesis, the results of Table C5 show that the post-conflict treatment is associated with an increase in crop value and increase in area cultivated, that is significant and in greater proportions (thus driving the reduction in yield). This may reflect a dynamic of land-use driven by the prospect of the relative security that might have induced the incorporation of marginal or less productive lands into cultivation. Figure B9 presents the dynamic

effects of the ceasefire on productivity. Pre-treatment estimates support parallel trends, while post-2016 coefficients suggest a persistent, though not always significant decline.

7.2 Household-level results

Table 9 presents the results of the effect of the two determinants evaluated at the household level: the ceasefire with the FARC and access to agricultural credit.

Table 9. Average impact of agricultural determinants on household-level TFP

Dependent variable: Ln (Agricultural production value)	Post conflict indicator	Credit access (2SLS)
D_{mt}	0.389* (0.214)	0.406 (0.850)
Cultivated area (Ln)	0.092*** (0.023)	0.124*** (0.016)
Family labor index (Ln)	0.184** (0.082)	0.089 -0.083
Capital stock of animals (Ln)	0.239*** (0.028)	0.181*** (0.025)
Machinery rental value (Ln)	-0.009 (0.073)	-0.028 (0.03)
Cost of purchased inputs (Ln)	0.192*** (0.033)	0.214*** (0.029)
Cost of hired labor (Ln)	0.070** (0.029)	0.118*** (0.017)
Average Monthly Temperature (°C)	0.744 (2.03)	3.068 (1.979)
Average Cumulative Monthly Precip. (mm)	0.092*** (0.018)	0.039 (0.033)
Average Monthly Temperature (sq)	0.011 (0.027)	-0.026 (0.027)
Average Cumulative Monthly Precip. (sq)	-0.0002*** (3.91e-05)	-0.0001* (0.00006)
Temperature Anomaly	-1.173 (1.126)	-1.182 (0.942)
Precipitation Anomaly	-0.671** (0.255)	-0.232 (0.366)
Observations	1,093	8,957
Number of households	717	3,377

Note: Specifications include household and year fixed effects. To address zeros in input factors, we follow Battese (1996) by replacing zeros with one and including dummies for households reporting zero values for each input. Credit estimates correspond to the second stage of the IV analysis, measuring the effect of credit on productivity. Estimates for the post-conflict analysis use standard errors clustered at the community-FARC presence level, while the credit analysis clusters standard errors at the municipal level. Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The estimated coefficients indicate that after the ceasefire, agricultural productivity among households located in areas with prior FARC presence increased by 38% more than their counterfactuals. Figure B10 shows the evolution of production value and land use among households in the sample. While in the years before the ceasefire households in non-FARC areas had higher production values, after the agreement both groups experienced growth relative to 2013, with a significantly larger increase in FARC-affected municipalities, surpassing the average production value of non-FARC households by 2016. This growth was also accompanied by a

reduction in cultivated area, suggesting that the ceasefire enabled households to make better use of available land in a context of greater stability and potentially fewer constraints on production.

This result, which at first glance may appear counterintuitive when contrasted with the findings at the municipal level, can be explained by how the interpretation of the results vary with the scale of analysis. Following the end of the conflict, some households may have optimized the use of their plots, by improving techniques, focusing on more productive land, or abandoning marginal areas, which translated into increased productivity at the household level. In contrast, at the municipal level, the expansion of cultivated area reflects not only greater activity by existing producers but also the incorporation of new land from new farmers. These newcomers, possibly encouraged by the ceasefire to return or settle in the municipalities, might exhibit lower productivity levels, thus driving down national productivity through a composition effect not captured in household level panel data analysis. The combination of the two studies warns us that the negative effect observed at the municipality level does not necessarily imply a decline in productivity among given already established households. An alternative explanation is the rise in coca cultivation in some municipalities after the ceasefire, which resulted from the reconfiguration of armed groups in municipalities with previous presence of FARC, and may have pushed other crops onto more marginal lands.

Regarding the effect of credit access on household productivity in the ELCA, we estimate a 2SLS model using as an instrument the interaction between travel time from the household to the municipal capital and the per-capita value of FINAGRO agricultural credit disbursed in the municipality. For this instrument to be valid, it must predict household credit access while remaining orthogonal to unobserved factors that directly affect household productivity. Table C6 presents the first-stage regression along with the F-statistic, which is above the conventional threshold of 10 (Stock, Wright, & Yogo, 2002). The results show that the instrument significantly predicts credit access: specifically, expanding agricultural credit supply reduces the negative effect of distance on households' access to credit.

Column (2) of Table 9 presents the second-stage estimates. Although the estimated coefficient points in the expected positive direction, we do not observe a statistically significant effect of credit access on agricultural productivity at the household level. Unlike the municipal-level estimates based on the EVA data, the household-level analysis is limited to 17 municipalities, which likely reduces statistical power and contributes to greater estimation noise as reflected by a coefficient magnitude of roughly ± 2 standard deviations (a concern that grows with the 2SLS approach when the instrument is not sufficiently strong). These limitations make it difficult to draw definitive conclusions from the household-level estimates.

8. Conclusions

This study shows that Colombian agricultural production growth in the past decade was driven predominantly by input expansion rather than by TFP gains, which recorded an average annual growth rate below 1%. Productivity improvements depended largely on climate conditions, with climate emerging as a double-edged factor. At the household level, extreme events significantly reduced productivity, underscoring the vulnerability of small producers with limited adaptive capacity. In contrast, at the municipal level, favorable weather conditions appeared as the main driver of TFP growth. This contrast highlights not only the importance of accounting for climate dynamics, especially as their magnitude intensifies over time, but also the need to invest in climate adaptation to sustain productivity growth.

Beyond climate, improvements in technical efficiency and technological adoption contributed only modestly to TFP growth, while scale effects had small or even negative contributions. Regional disparities persist: the Caribbean and Pacific regions outperformed the national average, whereas the Center-South Amazonia experienced declines. In most regions, technological progress had negligible or negative effects on productivity growth, pointing to persistent barriers to the adoption and effective use of advanced agricultural technologies. In South-Central Amazonia, the Central-Eastern Region, and the Eastern Plains, technical efficiency contributed little or negatively to productivity, reinforcing the presence of significant inefficiencies and indicating substantial untapped potential for improving agricultural performance.

The analysis of policy drivers highlights that interventions that support rural road infrastructure have positive effects on productivity that materialize gradually over years. In contrast, input transfers and agricultural services show limited or inconclusive effects, reflecting constraints in design, intensity, or complementarity with other enabling conditions. These findings emphasize that policies addressing structural constraints that farmers cannot overcome individually, rather than short-term input provision, are more likely to generate lasting improvements.

In addition, changes in access to agricultural credit correlate positively with changes in productivity at the municipal level. The end of the conflict generated effects that depend on the level of analysis. At the municipal level, areas with prior armed group presence experienced a decline in TFP after the conflict. In contrast, at the household level, producers in previously affected areas increased productivity. This contrast highlights that the scale of analysis matters: aggregate measures may reflect compositional effects driven by more farmers or land dedicated to agricultural production, while the household-level analysis captures variations among established producers.

The results of this study provide several policy implications for promoting sustainable agricultural productivity in Colombia. First, the findings highlight the importance of prioritizing public investments in public goods, particularly rural transportation infrastructure. Gaps in connectivity limit market access and reduce agricultural returns, while infrastructure improvements address structural barriers that individual farmers cannot overcome on their own. Strengthening rural transport networks should therefore be a central component of Colombia's rural development strategy, easing production frictions, lowering transaction costs, and promoting more efficient agricultural markets.

Second, the results are suggestive of the potential of scaling up rural financing programs by simplifying access requirements and addressing information asymmetries. Hence, it might be beneficial to enhance the institutional capacity of public rural finance institutions and to promote greater participation from the private sector to the extent that it maintains the preferential credits of FINAGRO, with low interest rates. More research is required though, to first confirm the causality of the positive relationship that we observe in this work.

Third, policies aimed at land use in post-conflict rural recovery should prioritize efficiency and sustainability. Land restitution, formalization, or productive reactivation programs must be guided by technical assessments of soil productivity and complemented with technical assistance and access to appropriate technologies. To prevent declines in productivity, these policies should discourage the expansion into marginal lands and instead incentivize the efficient, technology-driven, and sustainable use within the agricultural frontier.

Lastly, given that climate variability accounted for more than one-third of national TFP growth, a gradual structural transformation is required to dampen the consequences of weather variability on agricultural production. This could involve promoting sustainable and climate-smart agricultural practices, improving access to timely climate information, and leveraging agroecological approaches that offer multiple pathways to reduce this dependency.

References

- Acemoglu, D., Robinson, J. A., & Santos, R. J. (2013). The monopoly of violence: Evidence from Colombia. *Journal of the European Economic Association*, 11(1), 5–44. <https://doi.org/10.1111/j.1542-4774.2012.01099.x>
- Agronet. (2021, September 29). *Hay cerca de 31 millones de hectáreas de frontera agrícola sin aprovechar en todo el territorio*. Ministerio de Agricultura y Desarrollo Rural. <https://www.agronet.gov.co/Noticias/Paginas/Hay-cerca-de-31-millones-de-hectáreas-de-frontera-agrícola-sin-aprovechar-en-todo-el-territorio.aspx>
- Ali, E., & Awume, A. N. (2025). The nexus between credit rationing and the adoption of climate-smart agricultural practices: Implications for agricultural household revenue in Togo. *Development and Sustainability in Economics and Finance*, 6, 100052. <https://doi.org/10.1016/j.dsef.2025.100052>
- Amaglobeli, D., Benson, T., & Mogues, T. (2024). Agricultural producer subsidies: Navigating challenges and policy considerations (IMF Notes 2024/002). International Monetary Fund. <https://www.imf.org/en/Publications/IMF-Notes/Issues/2024/08/26/Agricultural-Producer-Subsidies-Navigating-Challenges-and-Policy-Considerations-553529>
- Anríquez, G., Foster, W., Ortega, J., Falconi, C., & De Salvo, C. P. (2016). Public expenditures and the performance of Latin American and Caribbean agriculture (IDB Working Paper No. IDB-WP-722). Inter-American Development Bank. <https://doi.org/10.18235/0012284>
- Arias, M. A., Ibáñez, A. M., & Zambrano, A. (2019). Agricultural production amid conflict: Separating the effects of conflict into shocks and uncertainty. *World Development*, 119, 165–184. <https://doi.org/10.1016/j.worlddev.2017.11.011>
- Akudugu, M. A. (2016). Agricultural productivity, credit and farm size nexus in Africa: A case study of Ghana. *Agricultural Finance Review*, 76(2), 288–308. <https://doi.org/10.1108/AFR-12-2015-0058>
- Banerjee, A. V., & Duflo, E. (2010). Giving credit where it is due. *Journal of Economic Perspectives*, 24(3), 61–80.
- Barrios, S., Bertinelli, L., & Strobl, E. (2010). Trends in rainfall and economic growth in Africa: A neglected cause of the African growth tragedy. *The Review of Economics and Statistics*, 92(2), 350–366. <http://www.jstor.org/stable/27867541>
- Battese, G. E. (1997). A note on the estimation of Cobb–Douglas production functions when some explanatory variables have zero values. *Journal of Agricultural Economics*, 48(1–3), 250–252. <https://doi.org/10.1111/j.1477-9552.1997.tb01149.x>

- Bernal, C., Prem, M., Vargas, J. F., & Ortiz, M. (2024). Peaceful entry: Entrepreneurship dynamics during Colombia's peace agreement. *Journal of Development Economics*, 166, 103119. <https://doi.org/10.1016/j.jdeveco.2023.103119>
- Bohórquez-Peñuela, C., Gáfaró-González, M. M., Guzmán-Finol, K. K., & Pérez, A. (2025). Climate risk and access to credit: Evidence from Colombian potato growers (Borradores de Economía No. 1307). Banco de la República. <https://doi.org/10.32468/be.1307>
- Bojacà, J. A. T. (2024, January). Exportaciones colombianas del sector agropecuario y agroindustrial: una aproximación regional (Documento 560). Dirección de Estudios Económicos, Departamento Nacional de Planeación. <https://www.dnp.gov.co/estudios-y-publicaciones/estudios-economicos/Paginas/archivos-de-economia.aspx>
- Bravo-Ortega, C., & Lederman, D. (2004). Agricultural productivity and its determinants: Revisiting international experiences. *Estudios de Economía*, 31(2), 133–163.
- Bravo-Ureta, B. E., Jara-Rojas, R., Moreira López, V. H., & Riveros Villegas, P. (2021). Data challenges in the measurement of agricultural productivity: Lessons from Chile. *International Journal of Agriculture and Natural Resources*, 48(3), 126–148. <https://doi.org/10.7764/ijanr.v48i3.2318>
- Bravo-Ureta, B. E., Njuki, E., Palacios, A. C., & Salazar, L. (2022). Agricultural productivity in El Salvador: A preliminary analysis (IDB Working Paper No. IDB-WP-01319). Inter-American Development Bank. <https://doi.org/10.18235/0004020>
- Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200–230. <https://doi.org/10.1016/j.jeconom.2020.12.001>
- Castro Rodríguez, R., Morera Torres, S., Velásquez Zabaleta, M., & Viveros Barrera, J. (2024). El impacto del Programa Colombia Siembra sobre la producción primaria del arroz: ¿Quién se benefició más? Universidad de los Andes. <https://hdl.handle.net/1992/73984>
- Centro Nacional de Memoria Histórica. (s.f.). *Cátedra Basta Ya: Orígenes, dinámicas y crecimiento del conflicto armado (Módulo 2)*. <https://centrodememoriahistorica.gov.co/descargas/CatedraBY/modulo-2.pdf>
- Cristancho Murcia, N. D. (2022, agosto 8). *Efectos del proceso de paz en la producción agrícola* [Undergraduate thesis, Universidad del Rosario]. Universidad del Rosario. https://doi.org/10.48713/10336_37823
- De Chaisemartin, C., & D'Haultfœuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9), 2964–2996. <https://doi.org/10.1257/aer.20181169>
- De Salvo, C. P., Salazar, L., González, M., Schling, M., Muñoz, G., Rondinone, G., & Le Pommellec, M. (2025). *Desarrollo sostenible de la agricultura en América Latina y el Caribe: desafíos y oportunidades*. <https://doi.org/10.18235/0013382>

- Díaz Díaz, C., & López Bayona, A. (2021). *Concentración de tierras en Colombia: Una radiografía rural*. Penguin Random House Grupo Editorial.
<https://www.oxfamcolombia.org/concentracion-de-tierras-en-colombia-una-radiografia-rural/>
- Echavarría, J. J., Villamizar-Villegas, M., & McAllister, D. (2017, September). *Impacto del crédito sobre los productores de café en Colombia* (IDB Discussion Paper No. IDB-DP-544). Inter-American Development Bank.
- Ehiakpor, D. S., Danso-Abbeam, G., & Mubashiru, Y. (2021). Adoption of interrelated sustainable agricultural practices among smallholder farmers in Ghana. *Land Use Policy*, 101, 105142. <https://doi.org/10.1016/j.landusepol.2020.105142>
- Engel, S., & Ibáñez, A. M. (2007). Displacement due to violence in Colombia: A household-level analysis. *Economic Development and Cultural Change*, 55(2), 335–365.
<https://doi.org/10.1086/508712>
- Fernandes-Tavares, T., Yagüe Blanco, J. L., & Pascual, C. (2024). Dispossessed lands and land-use change in the Colombian armed conflict: Exploring a link through a regional case study. *Journal of Rural Studies*, 108, 103303. <https://doi.org/10.1016/j.jrurstud.2024.103303>
- Fournier, J. (2016). The positive effect of public investment on potential growth (OECD Economics Department Working Papers No. 1347). OECD Publishing.
<https://doi.org/10.1787/15e400d4-en>
- Fulginiti, L. E., & Perrin, R. K. (1998). Agricultural productivity in developing countries. *Agricultural Economics*, 19(1–2), 45–51. [https://doi.org/10.1016/S0169-5150\(98\)00045-0](https://doi.org/10.1016/S0169-5150(98)00045-0)
- González, M. A., & Lopez, R. A. (2007). Political violence and farm household efficiency in Colombia. *Economic Development and Cultural Change*, 55(2), 367–392.
<https://doi.org/10.1086/508715>
- Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254–277. <https://doi.org/10.1016/j.jeconom.2021.03.014>
- Guirking, C., & Boucher, S. R. (2008). Credit constraints and productivity in Peruvian agriculture. *Agricultural Economics*, 39(3), 295–308. <https://doi.org/10.1111/j.1574-0862.2008.00334.x>
- Gulati, A., & Narayanan, S. (2003). *The subsidy syndrome in Indian agriculture*. IFPRI.
<https://hdl.handle.net/10568/157772>
- Haryanto, T., Wardana, W. W., Jamil, I. R., Brintanti, A. R. D., & Ibrahim, K. H. (2023). Impact of credit access on farm performance: Does source of credit matter? *Heliyon*, 9(9), e19720.
<https://doi.org/10.1016/j.heliyon.2023.e19720>
- Ibáñez Londoño, A., & Moya Rodríguez, A. (2006). ¿Cómo el desplazamiento forzado deteriora el bienestar de los hogares desplazados?: Análisis y determinantes del bienestar en los municipios de recepción. Universidad de los Andes, Facultad de Economía, CEDE.
<https://hdl.handle.net/1992/8002>

- Jiménez, M. I., Abbott, P., & Foster, K. (2019). Measurement and analysis of agricultural productivity in Colombia. *Ecos de Economía*, 22(47), 4–37. <https://doi.org/10.17230/ecos.2018.47.1>
- Jondrow, J., Lovell, C. A. K., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 19(2–3), 233–238. [https://doi.org/10.1016/0304-4076\(82\)90004-5](https://doi.org/10.1016/0304-4076(82)90004-5)
- Jorgenson, D. W., & Griliches, Z. (1967). The explanation of productivity change. *The Review of Economic Studies*, 34(3), 249–283. <https://doi.org/10.2307/2296675>
- Lachaud, M. A. (2025). Agricultural productivity convergence in Latin America: The role of research and development, knowledge spillovers, and education spending. *Journal of Agricultural Economics*, 76(3), 602–623. <https://doi.org/10.1111/1477-9552.12643>
- Lachaud, M. A., Bravo-Ureta, B. E., & Ludeña, C. E. (2017). Agricultural productivity in Latin America and the Caribbean in the presence of unobserved heterogeneity and climatic effects. *Climatic Change*, 143, 445–460. <https://doi.org/10.1007/s10584-017-2013-1>
- Lozano-Espitia, I., & Restrepo-Salazar, J. C. (2015). El papel de la infraestructura rural en el desarrollo agrícola en Colombia (Borradores de Economía No. 904). Banco de la República. https://www.banrep.gov.co/sites/default/files/publicaciones/archivos/be_904.pdf
- Ludeña, C. E. (2010, mayo). Agricultural productivity growth, efficiency change and technical progress in Latin America and the Caribbean (IDB Working Paper No. 61). Inter-American Development Bank. <https://doi.org/10.2139/ssrn.1817296>
- Makate, C., Makate, M., Mutenje, M., Mango, N., & Siziba, S. (2019). Synergistic impacts of agricultural credit and extension on adoption of climate-smart agricultural technologies in southern Africa. *Environmental Development*, 32, 100458. <https://doi.org/10.1016/j.envdev.2019.100458>
- McAllister-Harker, D., Echavarría, J. J., & Villamizar-Villegas, M. (2018). Evolución del crédito agropecuario en Colombia. En M. Villamizar-Villegas & D. McAllister-Harker (Eds.), *Superando barreras: El impacto del crédito en el sector agrario en Colombia* (pp. 1–39). Banco de la República. <https://repositorio.banrep.gov.co/handle/20.500.12134/9595>
- Medrano Acosta, D. A. (2018, septiembre 17). *Agricultura en la Orinoquia, un potencial desafiante*. Universidad de los Andes, Centro de Estudios de la Orinoquia. <https://hdl.handle.net/1992/31324>
- Mejía Tejada, D., Díaz Baca, M. F., Enciso Valencia, K. J., & others. (2024). The impact of agricultural credit on the cattle inventory and deforestation in Colombia: A spatial analysis. *npj Climate Action*, 3(1), 34. <https://doi.org/10.1038/s44168-024-00107-3>
- Ministerio de Agricultura y Desarrollo Rural. (2018). *Estrategia de política pública para la gestión integral de riesgos agropecuarios en Colombia: Revisión integral*. <https://www.minagricultura.gov.co/Documents/LIBRO%20ESTRATEGIA%20VERSION%20FINAL.pdf>

Ministerio de Agricultura y Desarrollo Rural. (2025, 17 de febrero). *El sector Agricultura, protagonista en 2024 de la reactivación económica del país*. <https://www.minagricultura.gov.co/noticias/Paginas/El-sector-Agricultura,-protagonista-en-2024-de-la-reactivaci%C3%B3n-econ%C3%B3mica-del-pa%C3%ADs.aspx>

Misión para la Transformación del Campo. (2015). *Diagnóstico económico del campo colombiano (Informe de la Misión para la Transformación del Campo)*. Dirección de Desarrollo Rural Sostenible del Departamento Nacional de Planeación. https://colaboracion.dnp.gov.co/CDT/Agriculturapecuarioforestal_y_pesca/DiagnosticoEconomico-del-Campo-Colombiano.pdf

Mogues, T., Fan, S., & Benin, S. (2015). Public investments in and for agriculture. *European Journal of Development Research*, 27(3), 337–352. <https://doi.org/10.1057/ejdr.2015.40>

Nillesen, E. (2016). Empty cups? Assessing the impact of civil war violence on coffee farming in Burundi. *African Journal of Agricultural and Resource Economics*, 11(1), 69–83. <https://doi.org/10.22004/ag.econ.233851>

Niño, G., Baylis, K., & Crost, B. (2023). Conflict and small-scale investment: Evidence from Colombian peace agreement. *Journal of the Agricultural and Applied Economics Association*, 2(1), 67–83. <https://doi.org/10.1002/jaa2.46>

Njuki, E., Bravo-Ureta, B. E., & O'Donnell, C. J. (2018). A new look at the decomposition of agricultural productivity growth incorporating weather effects. *PLoS ONE*, 13(2), e0192432. <https://doi.org/10.1371/journal.pone.0192432>

O'Donnell, C. J. (2016). Using information about technologies, markets and firm behaviour to decompose a proper productivity index. *Journal of Econometrics*, 190(2), 328–340. <https://doi.org/10.1016/j.jeconom.2015.06.009>

O'Donnell, C. J. (2022). Estimating the effects of weather and climate change on agricultural productivity. *Q Open*, 2(2), qoac018. <https://doi.org/10.1093/qopen/qoac018>

Odozi, J. C., & Uwaifo Oyelere, R. (2021). Does violent conflict affect labor supply of farm households? The Nigerian experience (IZA Discussion Paper No. 14579). IZA Institute of Labor Economics. <https://ssrn.com/abstract=3896791>

OECD. (2022). *Rural policy review of Colombia 2022*. OECD Rural Studies. OECD Publishing. <https://doi.org/10.1787/c26abeb4-en>

OECD. (2023). *Agricultural policy monitoring and evaluation 2023: Adapting agriculture to climate change*. OECD Publishing. <https://doi.org/10.1787/b14de474-en>

Oficina de las Naciones Unidas contra la Droga y el Delito - Sistema Integrado de Monitoreo de Cultivos Ilícitos, UNODC – SIMCI. (2025). Monitoreo de territorios con presencia de cultivos de coca 2023.

Parra-Peña, R. I., & Puyana, R. (2021). Análisis de la productividad del sector agropecuario en Colombia y su impacto en temas como: encadenamientos productivos, sostenibilidad e

internacionalización, en el marco del programa Colombia más (Informes de Investigación No. 19147). Fedesarrollo. <https://fedesarrollo.org.co/sector-agropecuario/a4264121-28c0-40fe-8672-0a6ccbbbed13f>

Pardo, J. C., & Orbegozo, M. C. (2024, febrero 23). *Informe Perspectiva Sectorial – Agropecuario: Perspectivas de crecimiento y precios del sector agropecuario para 2024*. Corficolombiana, Investigaciones Económicas. [https://investigaciones.corfi.com/documents/38211/0/Perspectiva sectorial Panorama sector agropecuario Feb 2024.pdf/5a8a0bc3-246a-4385-135a-a87d3fe1c099](https://investigaciones.corfi.com/documents/38211/0/Perspectiva+sectorial+Panorama+sector+agropecuario+Feb+2024.pdf/5a8a0bc3-246a-4385-135a-a87d3fe1c099)

Prem, M., Rivera, A. F., Romero, D. A., & Vargas Duque, J. F. (2018). Killing social leaders for territorial control: The unintended consequences of peace (Serie Documentos de Trabajo N.º 016385). Universidad del Rosario. https://doi.org/10.48713/10336_18133

Prem, M., Rivera, A. F., Romero, D. A., & Vargas, J. F. (2022). Selective civilian targeting: The unintended consequences of partial peace. *Quarterly Journal of Political Science*, 17(3), 317–354. <https://doi.org/10.1561/100.00020088>

Prem, M., Saavedra, S., & Vargas, J. F. (2020). End-of-conflict deforestation: Evidence from Colombia's peace agreement. *World Development*, 129, 104852. <https://doi.org/10.1016/j.worlddev.2019.104852>

Prem, M., Vargas, J. F., & Namen, O. (2023). The human capital peace dividend. *Journal of Human Resources*, 58(3), 962–1002. <https://doi.org/10.3368/jhr.59.1.0320-10805R2>

Programa de las Naciones Unidas para el Desarrollo [PNUD], & Red de Observatorios Regionales del Mercado de Trabajo [ORMET]. (2014). *Prospectiva laboral en la región del Eje Cafetero: Caso cadena productiva del café* (pp. 7–105). Programa de las Naciones Unidas para el Desarrollo. https://www.cinterfor.org/sites/default/files/file_publicacion/Eje%20Cafetero%20Prospectiva.pdf

Puyana, R., García, H., Mejía, L. F., Porto, I., Bernal, M., & Zambrano, C. (2025). Propuesta para el desarrollo de la Orinoquía colombiana. Fedesarrollo.

RAP Eje Cafetero. (2021). *Plan Estratégico Regional (PER) 2021–2033*. RAP Eje Cafetero. https://ejecafeterorap.gov.co/wp-content/uploads/2021/10/PER-2_compressed.pdf

Rockmore, M. (2020). Conflict-risk and agricultural portfolios: Evidence from Northern Uganda. *The Journal of Development Studies*, 56(10), 1856–1876. <https://doi.org/10.1080/00220388.2019.1703953>

Salazar, L., Tadeo Ruesta, D. V., Alvarez, L., Bernal Hernandez, S., & Martel, P. (2025). *Agricultural productivity in Latin America and the Caribbean (1961-2021): Subregional and national analysis*. <https://doi.org/10.18235/0013695>

Seven, U., & Tumen, S. (2020, febrero 10). Agricultural credits and agricultural productivity: Cross-country evidence (IZA Discussion Paper No. 12930). IZA Institute of Labor Economics. <https://ssrn.com/abstract=3534478>

Stock, J. H., Wright, J. H., & Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, 20(4), 518–529. <http://www.jstor.org/stable/1392421>

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2), 175–199. <https://doi.org/10.1016/j.jeconom.2020.09.006>

Unidad Nacional para la Gestión del Riesgo de Desastres. (2016). *Fenómeno El Niño: Análisis comparativo 1997-1998 // 2014-2016*. Unidad Nacional para la Gestión del Riesgo de Desastres. https://repositorio.gestiondelriesgo.gov.co/bitstream/20.500.11762/20564/3/Fenomeno_nino-2016.pdf

UPRA. (2024). *Frontera Agrícola Nacional*. https://upra.gov.co/es-co/Documents/01_Frontera_Agricola.pdf

Wang, Q., Gui, L., Meng, Q., Wang, H., & Hu, J. (2025). Rural credit and new technology adoption among family farms: Evidence from two demonstration areas in China. *Humanities and Social Sciences Communications*, 12, Article 1109. <https://doi.org/10.1057/s41599-025-05491-7>

World Bank. (2021). *Climate Risk Profile: Colombia*. https://climateknowledgeportal.worldbank.org/sites/default/files/country-profiles/16698-WB_Colombia_Country_Profile-WEB.pdf

World Bank. (2023). *Employment in agriculture (% of total employment)* [Data set]. World Bank. <https://data.worldbank.org/indicator/SL.AGR.EMPL.ZS>

Woutersen, T., Hauck, K., & Khandker, S. R. (2024). Estimating the effects of credit constraints on productivity of Peruvian agriculture. *Econometrics*, 12(4), 27. <https://doi.org/10.3390/econometrics12040027>

Appendix A

Appendix A1. Variable creation using the ELCA survey

Land

There are several challenges arising from the structure of the surveys that needed to be addressed. One of the main issues is the difference in the temporality between the agricultural and land modules. While the agricultural module refers to production in the last 12 months, the land module asks about the current situation of the household at the time of the interview. Due to this difference, we assumed that the production reported in the last 12 months corresponded to the land area that the household reported having at the time of the interview. As a result of this temporal discrepancy, some households report production but not the area planted. To address this inconsistency and avoid excluding these households from the analysis, we calculated the planted area as the average of the area reported in previous rounds.

The planted area is calculated as the sum of the area dedicated to permanent crops, temporary crops, and livestock. In order to distinguish between different land uses, we adjust based on the contribution of each land type in terms of average production value per hectare, in the total sample for each land type. The factors used are 1.4 for permanent crops and 0.23 for livestock, with temporary crops as the reference (factor = 1).

Production value

The survey allows for the identification of production for each crop as well as the production of livestock products raised or sold by each household in the 12 months prior to the interview in each round. The 2010 survey collects information on the kilograms produced, broken down into those used for household consumption and those sold, as well as the income from the sales of each crop and livestock product. This allows for the construction of the implicit price for each crop and livestock product⁵. Based on these prices, a unified variable of production value per household is created, integrating both agricultural and livestock production into a single metric. This facilitates weighting the relative importance of each type of product within the household, reflecting its contribution to the total value of agricultural activity.

Family labor

To incorporate family labor while considering differences in contribution by gender and age, we follow Helfand and Rada (2015), using a factor of 1 for men, 0.8 for women, and 0.6 for children between the ages of 5 and 14, allowing us to express the labor in male adult equivalents.

Hired labor

Hired labor is defined as the total expenditure, in constant 2010 prices, on temporary paid labor employed in agricultural activities over the past 12 months. This information was only collected in the 2013 and 2016 rounds. For the 2010 round, labor costs were estimated using a backward projection based on the observed rate of change between 2013 and 2016.

Purchased inputs

⁵ For 18 crops for which prices were not collected in the 2010 survey, we used prices from the *Sistema de Informacion de Precios* (SIPSA) generated by DANE.

This variable includes the value of expenses for inputs such as seeds, fertilizers, pesticides/fungicides/herbicides, as well as for breeding stock, feed, vaccines, veterinary medicines, and vitamins. These costs were collected separately in the 2013 and 2016 rounds, allowing for greater precision in identifying expenses related to agricultural and livestock activities. However, in the 2010 round, the costs were aggregated, requesting joint information on agricultural inputs and costs related to livestock breeding or production. This difference in the way the questions were asked led to the reported values in 2010 being relatively lower compared to those in 2013 and 2016, where producers could be more specific when breaking down their expenses.

To address this inconsistency, we adjusted the data based on the differences observed between the survey rounds. Specifically, we used the ratio between the average costs reported in 2016 and 2013 to project an expected value for 2010, assuming a constant rate of change. We then compared this projected value with the actual average observed in 2010 to calculate an adjustment factor. This factor is applied only to the 2010 data, providing a more consistent measure of purchased inputs. The value is expressed in constant 2010 prices.

Capital stock of animals

Since detailed information on key aspects such as age, breed, or specific characteristics of the animals, which could directly influence their productivity as capital within the production process, is not available, the animal capital variable is constructed in a more aggregated way. To do this, the inventory of cattle, goats, pigs, and poultry recorded in the household asset module for each round is used. This inventory is multiplied by an implicit price derived from the values reported in the 2010 round. This approach allows for an approximate estimate of the value of animal capital, although individual productivity differences of the animals are not accounted for due to the lack of more specific information.

Machinery rental value

For the 2013 and 2016 surveys, the variable is constructed based on the machinery rental expenditure for the 12 months prior to the interview date in each round. However, the 2010 survey does not include this information. To estimate the capital cost for 2010, we perform a regression using the machinery rental costs from the 2013 ELCA, which are based on the number of machines by type. The estimated coefficients for each machine type are then applied to the number of machines of each type recorded in the 2010 ELCA, allowing us to derive the corresponding capital cost for that year.

Appendix A2. Data filtering and processing of public contract records from SECOP

The selection of contracts within the four categories under study (road infrastructure, inputs delivery, agricultural services, machinery delivery) relied on a filtering procedure designed to retain contracts related to the agricultural sector. The process was implemented in the following steps:

1. Initial classification (UNSPSC codes):

Contracts were first restricted to those falling under specific UNSPSC groups, segments, and families that are directly relevant to agriculture and rural investment (see Table C1).

2. Merging SECOP I and SECOP II contracts.

3. Data cleaning.

From this subset, duplicate contracts were removed, as well as contracts that were not finalized

or presented missing information after the web scraping process. Finally, only contracts within the study period (2015-2023) were retained.

4. Inclusion filter.

Contracts were selected if their description contained at least one keyword from a pre-defined list of agricultural terms (examples provided in Table A2.1). This step ensured that the majority of contracts with an explicit agricultural focus were retained.

5. Exclusion filter.

From the sample obtained in Step 3, contracts were removed if their description also contained keywords associated with activities unrelated to agriculture (examples provided in Table A2.1). This step substantially reduced the likelihood of including false positives, contracts that had passed the inclusion filter but were not truly agricultural, although some non-agricultural contracts may still remain.

Table A2.1. Examples of keywords used for inclusion and exclusion of contracts

Filter type	Examples of keywords (original wording in Spanish)
Inclusion	cosecha, siembra, semilla, cultivo, agro, pecuario, plaguicida, fertilizante, sembradora, productor, bovino, cafe, abono, forraje, rural, predio
Exclusion	mascotas, acueducto, alcantarillado, incendios, jardin, feria, hospital, policia, libreria, colegio, universidad, parque, urbano, sena

6. Resulting datasets.

After applying all filters, the final datasets retained contracts belonging to the four categories under study. To illustrate the type of contracts captured, Table A2.2 presents examples of contracts included in each category.

Table A2.2. Contract descriptions retained after filtering, by category (original wording in Spanish)

Category	Examples of selected contracts
Inputs delivery	<ol style="list-style-type: none"> 1. compra fertilizante necesario apoyo a pequeños y medianos productores agropecuarios del municipio Caicedo. 2. compraventa insumos materiales agrícolas proyectos productivos afectados ola invernal municipio Morales Cauca. 3. suministro abono granulado fertilizantes agrícolas fortalecimiento huertas caseras madres cabeza de familia resguardo indígena.
Agricultural services	<ol style="list-style-type: none"> 1. apoyar asistencia técnica extensión agropecuaria municipio Belmira. 2. prestación servicios asistencia técnica agropecuaria ambiental capacitación sector agropecuario. 3. prestar servicios profesionales como ingeniero agricola secretaria desarrollo rural.
Machinery provision	<ol style="list-style-type: none"> 1. adquisicion rotocultivador dirigido fortalecer asistencia tecnica directa rural produccion agricola municipio quetame Cundinamarca. 2. adquisición maquinaria e implementos agrícolas. 3. suministro molino trilla arroz industrial impulsar agroindustria arroceras.

Road infrastructure	1. mantenimiento vías terciarias vereda San José León municipio Mutatá. 2. construcción placa huella sector Hoyo vereda Macías municipio Cuitiva Boyacá. 3. rehabilitación vía acceso a vereda Agua Bendita resguardo Avirama municipio Páez Cauca.
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Appendix A3. Specification tests

In order to test the suitability of the Stochastic Frontier Analysis (SFA), as well as to assess the model specifications and the hypotheses regarding the parameters of the stochastic production frontier, a series of log-likelihood ratio tests were conducted at both the municipal and household levels. This test compares the restricted and unrestricted models using their log-likelihood values, which measure how well each model explains the data, through the likelihood ratio statistic (LR):

$$LR = -2 \times (\ln L_R - \ln L_U)$$

Where L_R is the maximum log-likelihood of the restricted model and L_U is that of the unrestricted model.

OLS production function vs frontier specification: To test for technical inefficiency, we perform a likelihood ratio test comparing a standard OLS production function (restricted model, $\gamma = 0$) with a stochastic frontier specification (unrestricted model, $\gamma > 0$). Here, γ is the variance ratio capturing the share of total output variation attributable to technical inefficiency ($\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$)

Results in Table A3 show that the likelihood ratio (LR) exceeds the critical value, confirming the presence of technical inefficiency.

Translog vs Cobb-Douglas: To select the most appropriate specification of the production function, we conducted a log-likelihood ratio test of the stochastic frontier model, comparing the Cobb-Douglas (CD) and translog (TL) functional forms. Table A3 shows that the null hypothesis $H_0 = \beta_{ij} = 0$ which tests whether the second-order interaction terms in the translog function are jointly equal to zero, is rejected, indicating that the translog production function provides a better statistical fit than the more restrictive Cobb-Douglas form. Nevertheless, we choose to adopt the Cobb-Douglas specification. Although the translog form allows for more complex relationships between inputs and output and provides a better fit to our model, the decomposition of the TFP requires compliance with a set of properties derived from index number theory, which are only satisfied under the Cobb-Douglas functional form (O'Donnell, 2016; 2018).

Truncated-normal distribution vs Half-normal distribution: The test is conducted to compare two assumptions regarding the distribution of the inefficiency term. The first model assumes a half-normal distribution, where $u \sim N^+(0, \sigma_u^2)$; that is, a normal distribution truncated at zero with a mean of zero. This specification implies that most observations are clustered near full efficiency. The second model allows for a truncated-normal distribution, $u \sim N^+(\mu, \sigma_u^2)$, which relaxes the previous restriction by allowing the mean of inefficiency to differ from zero, providing more flexibility in the shape of the inefficiency distribution. Since the test statistic exceeds the corresponding critical value, the null hypothesis of a half-normal inefficiency distribution is rejected in favor of the more flexible truncated-normal specification.

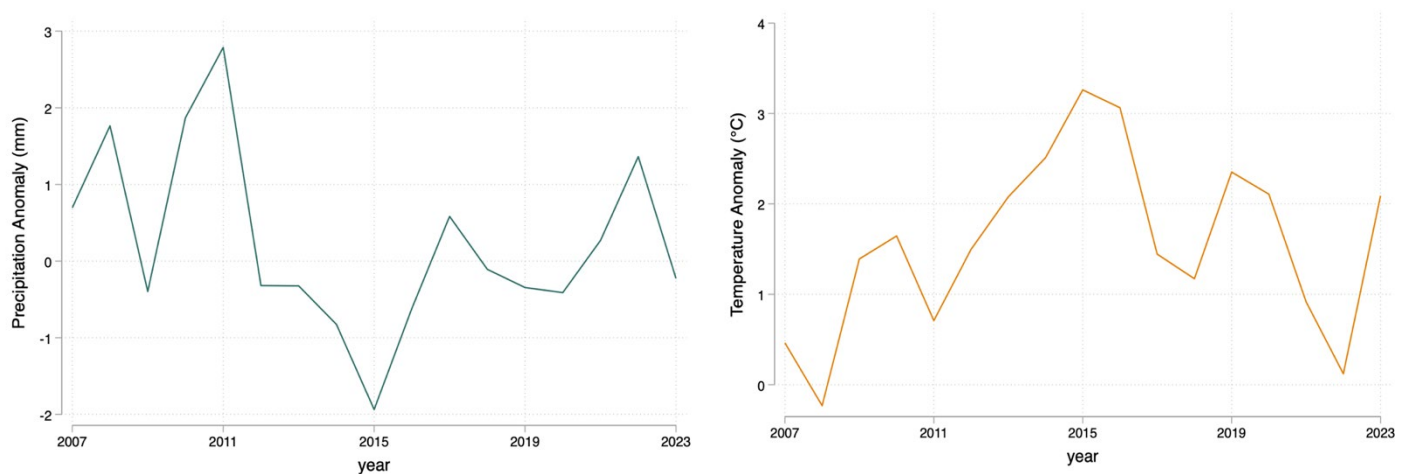
Table A3. Likelihood-ratio test results at the household and municipal levels

	Null Hypothesis	Test Statistic (λ)	Critical Value	Decision	Choice
Household level	$H_0: \gamma = 0$	572.14	7.81	Reject H_0	Stochastic frontier model
	$H_0: \beta_{ij} = 0$	184	19.67	Reject H_0	Translog
	$H_0: \mu = 0$	177.08	3.84	Reject H_0	Truncated normal
Municipal level	$H_0: \gamma = 0$	11,266	7.81	Reject H_0	Stochastic frontier model
	$H_0: \beta_{ij} = 0$	52.59	19.67	Reject H_0	Translog
	$H_0: \mu = 0$	267.71	3.84	Reject H_0	Truncated normal

Note: Critical value at 5%. The TL vs CD test is conducted using a truncated-normal distribution. γ is the variance ratio, which captures the share of total output variation from the frontier level that is attributable to technical efficiency ($\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$)

Appendix B. Supplementary figures

Figure B1. Evolution of precipitation and temperature anomaly, 2007-2023



Note: The anomaly is calculated as the deviation of each annual temperature observation from the long-term mean (1950-2000), divided by the historical standard deviation. The figure shows the annual average anomaly across all municipalities for the period 2007-2023.

Figure B2. Number of loans disbursed by FINAGRO by producer size

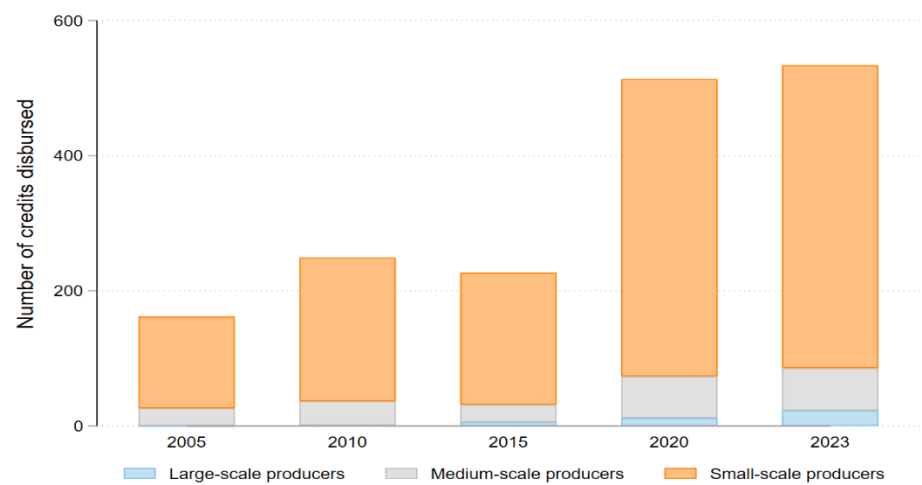
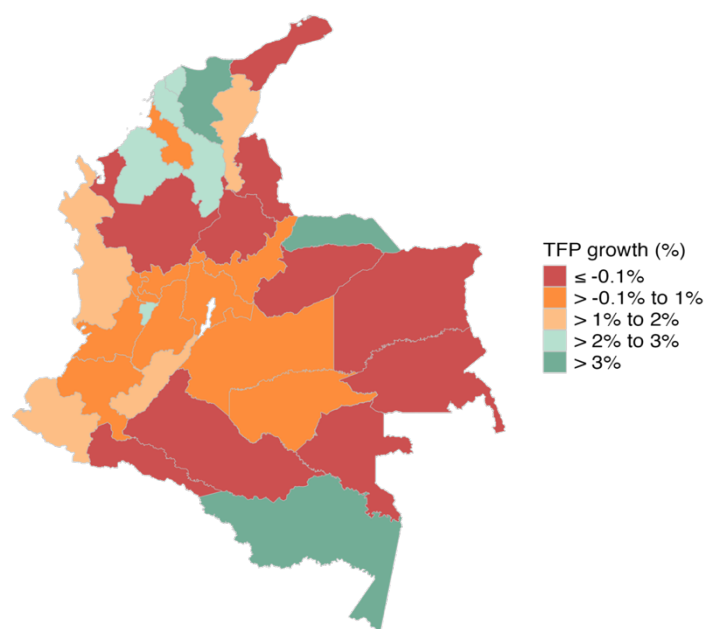


Figure B3. Annual department-level TFP growth rates (2015-2023)



Note: Departmental indexes are constructed by taking the geometric mean of municipal values, which are then used to compute compound annual growth rates between 2015 and 2023.

Figure B4. Trends in technical efficiency at household level (mean, 1st and 3rd quartiles)

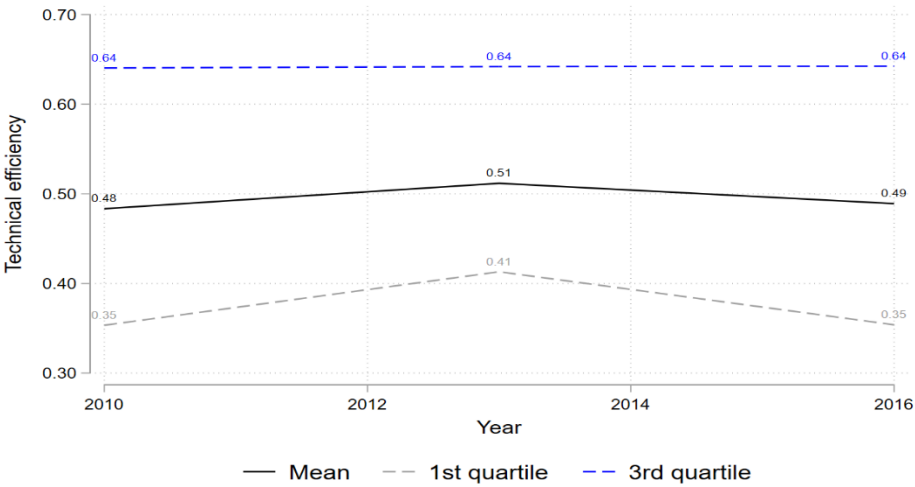
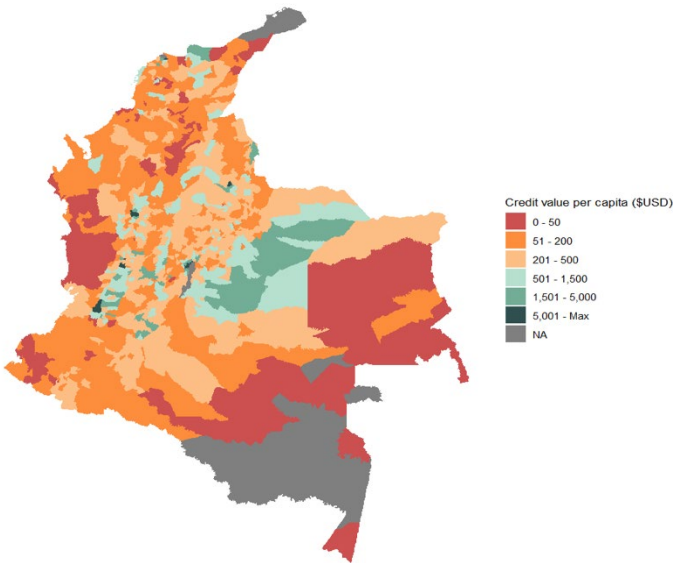
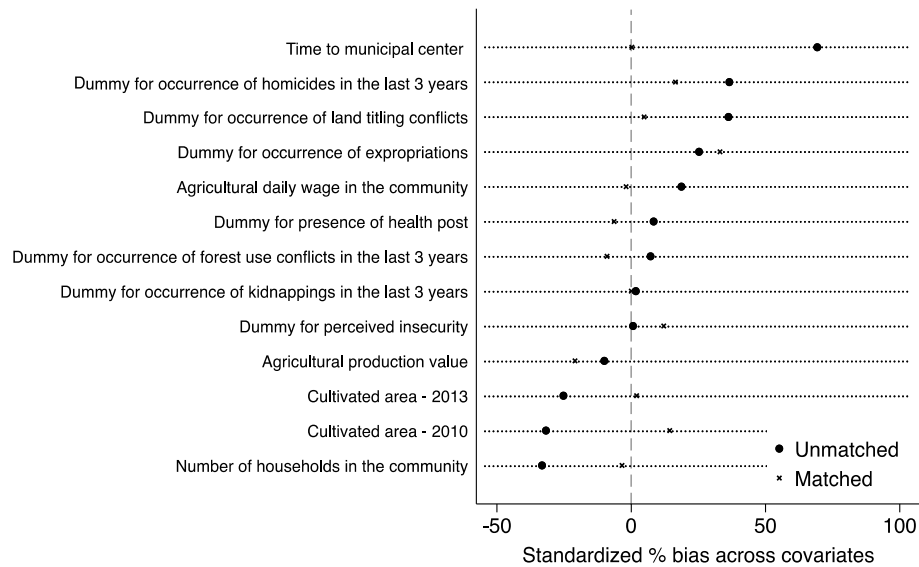


Figure B5. Municipal distribution of per capita FINAGRO credit



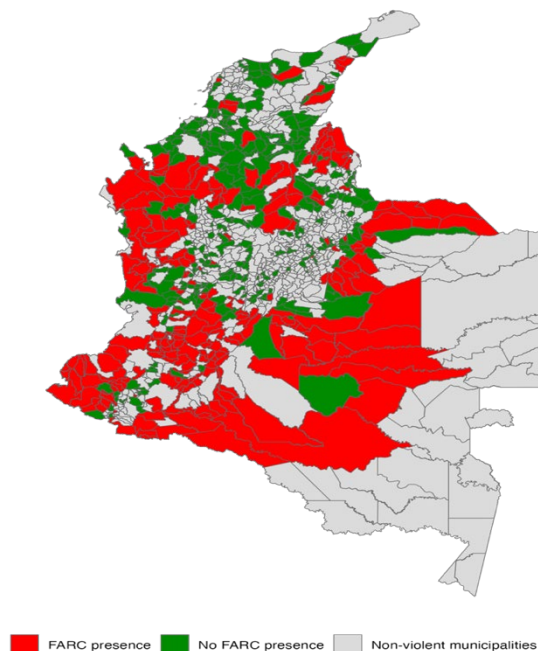
Note: Credit value per capita in 2010 constant dollars.

Figure B6. Covariate balance before and after matching



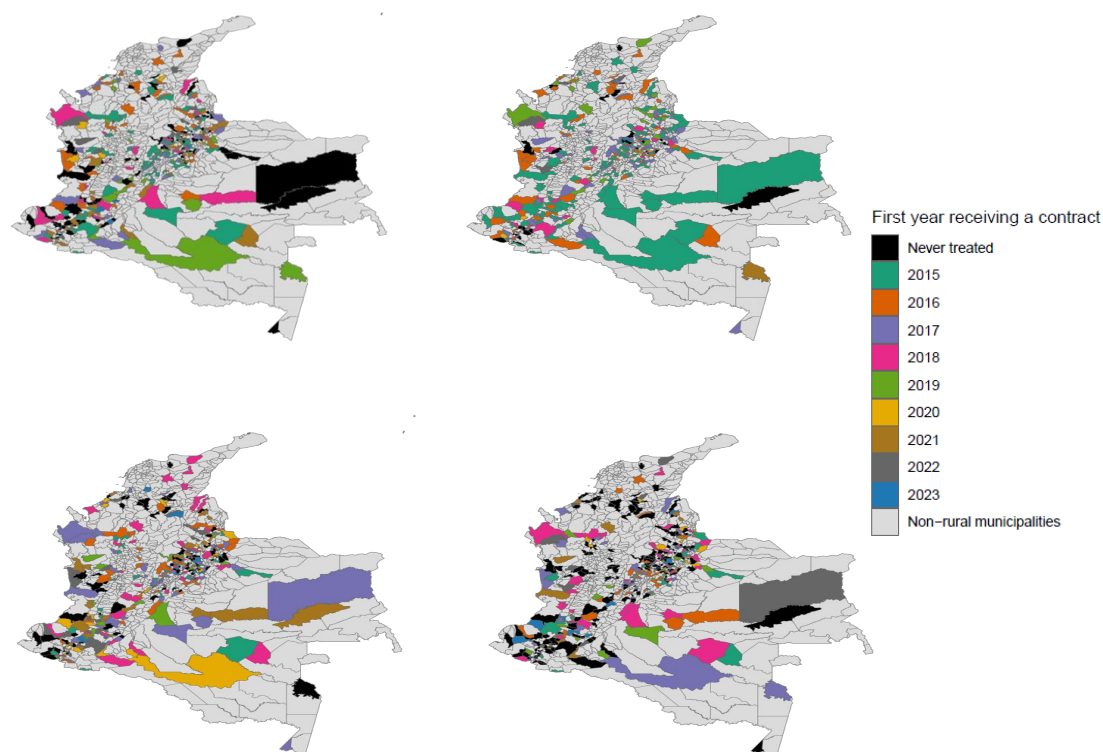
Note: The figure shows standardized % bias in observable characteristics between communities with FARC presence and communities without FARC presence, reported both before matching and after applying nearest-neighbor matching.

Figure B7. FARC presence by municipality, 2010-2014



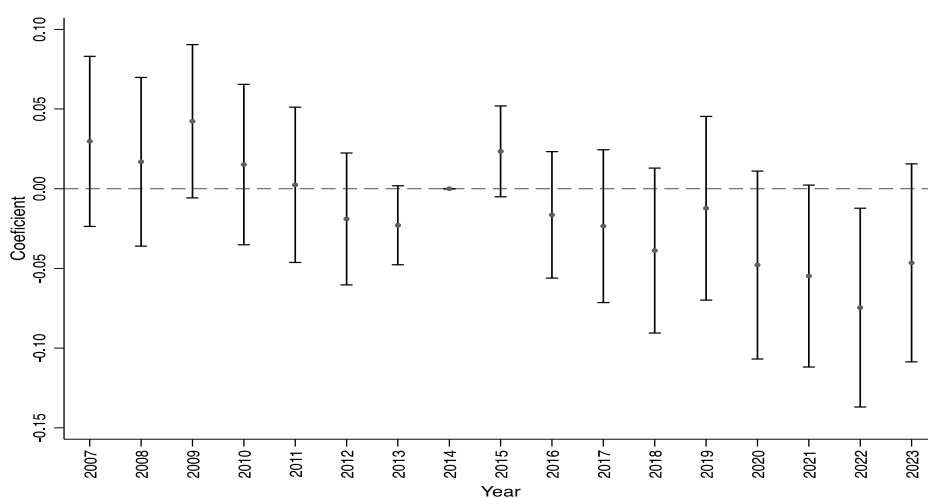
Note: Non-violent municipalities are defined as those that did not report any violent actions by an armed group between 2010 and 2014, according to ViPPA.

Figure B8. Year of completion of the first contract by municipality across public investment categories



Note: The map is restricted to rural municipalities with contracts exceeding 2 dollars per farm. The first year a municipality receives a contract is defined by its completion date. Rural municipalities are defined as those with a rurality index greater than 70%.

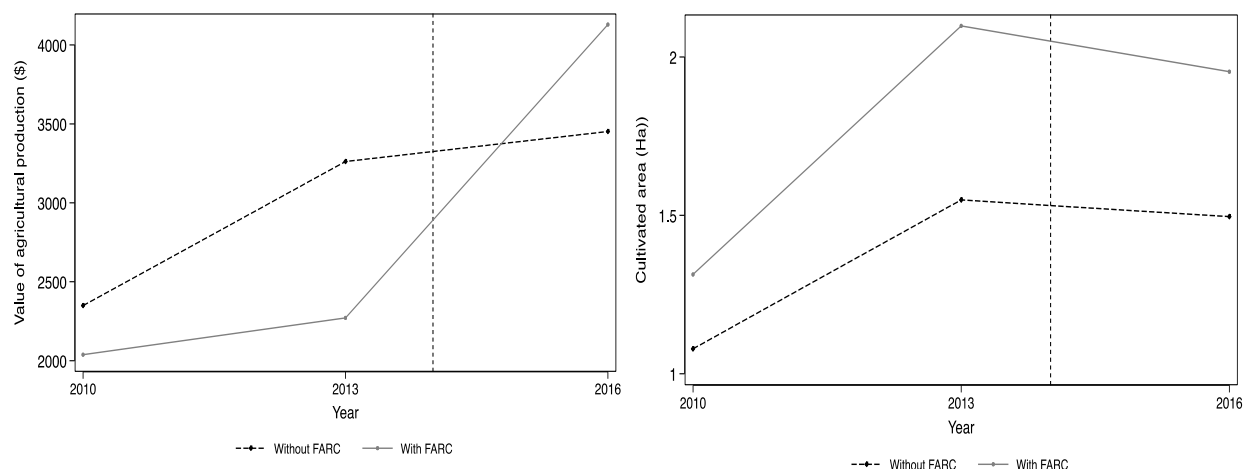
Figure B9. Dynamic effects of the end of the conflict on agricultural productivity



Note: The figure presents the dynamic estimation of the impact of the ceasefire with the FARC. Since the ceasefire took place in December 2014, the post-treatment period is defined as 2015.

Vertical lines represent 95% confidence intervals with standard errors clustered at the municipal level.

Figure B10. Agricultural production value and cultivated area in FARC vs. Non-FARC municipalities, 2010-2016



Appendix C. Supplementary tables

Table C1. Classification of public investment contracts by UNSPSC categories

Public Investment Category	Group	Segment	Family
Road infrastructure	G. Land and Buildings and Structures and Thoroughfares	95. Land and Buildings and Structures and Thoroughfares	9511. Thoroughfares
Inputs delivery	A. Live Plant and Animal Material	10. Live Plant and Animal Material and Accessories and Supplies	1010. Live animals; 1015. Seeds, bulbs, seedlings, and cuttings; 1017. Fertilizers, plant nutrients, and herbicides; and other subcategories related to agricultural inputs
Agricultural services	F. Services	Segments 70-94 (mainly professional and technical services)	Families 7010-7017; Additional families from segments 72, 73, 76, 77, 78, 80, 81, 82, 83, 84, 85, 86, 90, 91, 92, 93, 94
Machinery provision	C. Mining and Well Drilling Machinery and Accessories	Segments 20-27	All families

Table C2. Number of municipalities awarded their first contract under each category, by year

Type of public investment	Never treated	2015	2016	2017	2018	2019	2020	2021	2022	2023	Total
Road infrastructure	73	90	54	39	29	27	11	29	22	6	380
Input delivery	26	153	60	62	30	23	10	6	7	3	380
Agricultural services	78	34	49	56	48	19	22	27	33	14	380
Machinery provision	175	24	31	35	39	17	15	15	13	16	380

Table C3. Event-study estimates of the impact of public contracts on productivity

Dependent variable: Ln (Agricultural production value)	Road infrastructure	Input delivery	Agricultural services	Machinery provision
Pre-event average	-0.012 (0.082)	-0.144 (0.103)	-0.059 (0.062)	0.004 (0.070)
Post-event average	0.094* (0.052)	0.023 (0.068)	0.065 (0.053)	0.066 (0.049)
t-8	0.091 (0.327)	-0.619** (0.255)	0.141 (0.232)	0.194 (0.270)
t-7	0.074 (0.151)	-0.245 (0.340)	-0.148 (0.122)	0.126 (0.156)
t-6	-0.207* (0.111)	0.048 (0.221)	-0.146 (0.092)	-0.035 (0.095)
t-5	-0.078 (0.099)	-0.059 (0.154)	-0.085 (0.067)	-0.091 (0.092)
t-4	-0.016 (0.075)	-0.084 (0.126)	-0.114** (0.058)	-0.136** (0.066)
t-3	0.027 (0.060)	-0.025 (0.092)	-0.058 (0.040)	-0.026 (0.042)
t-2	0.022 (0.034)	-0.025 (0.049)	-0.006 (0.026)	-0.002 (0.033)
t0	0.021 (0.027)	-0.012 (0.034)	0.040* (0.024)	0.006 (0.027)
t+1	0.029 (0.033)	-0.020 (0.052)	0.030 (0.032)	-0.021 (0.037)
t+2	0.006 (0.042)	0.027 (0.077)	0.022 (0.044)	0.019 (0.047)
t+3	0.115* (0.061)	0.062 (0.091)	0.061 (0.049)	0.005 (0.053)
t+4	0.138** (0.067)	0.053 (0.098)	0.079 (0.063)	0.053 (0.060)
t+5	0.131 (0.084)	-0.023 (0.101)	0.081 (0.078)	0.068 (0.073)

t+6	0.092 (0.105)	-0.020 (0.111)	0.130 (0.096)	0.148 (0.097)
t+7	0.220* (0.123)	0.113 (0.162)	0.076 (0.135)	0.248* (0.134)
Number of municipalities	380	380	380	380

Note: Event study estimates based on Callaway and Sant'Anna (2021), measuring the impact of a municipality having at least one completed public contract in each SECOP category on agricultural productivity during 2015-2023. All models include municipality and year fixed effects. Standard errors clustered at the municipal level (in parentheses) *** p<0.01, ** p<0.05, * p<0.1

Table C4. Joint estimation of the effect of accumulated contract value on productivity by public investment category

Dependent variable: Ln (Agricultural production value)	
Road Infrastructure (US\$1000/farm)	0.008*** (0.002)
Input Delivery (US\$1000/farm)	-0.008 (0.013)
Agricultural Services (US\$1000/farm)	0.003 (0.002)
Machinery Provision (US\$1000/farm)	0.001 (0.009)
Ln (Harvested Area in ha)	0.997*** (0.029)
Ln (Rural Population)	-0.037 (0.040)
Ln (Seeds in Kg)	0.022 (0.014)
Ln (Fertilizer in Kg)	0.005 (0.006)
Ln (Machinery in Kg)	-0.004 (0.008)
Average Monthly Temperature (°C)	0.185 (0.170)
Average Cumulative Monthly Precipitation (mm)	-0.001 (0.001)
Average Monthly Temperature (sq)	0.003** (0.002)
Average Cumulative Monthly Precipitation (sq)	0.000 (0.000)
Temperature Anomaly	-0.108

	(0.077)
Precipitation Anomaly	0.013
	(0.019)
Observations	3,420
Number of municipalities	380

Notes: Model includes municipality and year fixed effects. Road infrastructure, input delivery, agricultural services, and machinery provision are measured as the cumulative value of public contracts per UPA in thousands of USD. Standard errors clustered at the municipal level (in parentheses) *** p<0.01, ** p<0.05, * p<0.1

Table C5. Effect of the ceasefire with the FARC on crop value, cultivated area and rural population, 2007-2023

Dependent variable: Ln (Agricultural production value)	Ln (Crop value)	Ln (Cultivated area)	Ln (Rural population)
FARC*POST	0.072 (0.045)	0.113*** (0.038)	0.005 (0.020)
Average Monthly Temperature (°C)	-0.391 (0.249)	-0.309 (0.232)	0.134 (0.083)
Average Cumulative Monthly Precipitation (mm)	0.0002 (0.001)	0.0006 (0.001)	-0.0002 (0.001)
Average Monthly Temperature (sq)	0.001 (0.002)	0.004** (0.002)	0.001 (0.001)
Average Cumulative Monthly Precipitation (sq)	-0.0000 (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)
Temperature Anomaly	0.081 (0.108)	0.044 (0.099)	-0.085** (0.041)
Precipitation Anomaly	-0.009 (0.021)	-0.017 (0.017)	-0.006 (0.008)
Observations	8,483	8,483	8,483
Number of municipalities	499	499	499

Note: All models include municipality and year fixed effects. Standard errors clustered at the municipal level (in parentheses) *** p<0.01, ** p<0.05, * p<0.1

Table C6. First-stage regression of credit access on the instrument

Dependent variable: Credit access (dummy)	
IHS (Per capita value of rural credit) * Minutes to the municipal seat	0.002*** (0.0004)
IHS (Per capita value of rural credit)	-0.062** (0.027)
Minutes to the municipal seat	-0.01***

	(0.002)
Cultivated area (Ln)	0.006
	(0.004)
Family labor index (Ln)	0.064***
	(0.022)
Capital stock of animals (Ln)	0.007
	(0.006)
Machinery rental value (Ln)	0.003
	(0.008)
Cost of purchased inputs (Ln)	0.020***
	(0.003)
Cost of hired labor (Ln)	0.010
	(0.007)
Average monthly temperature	1.280**
	(0.592)
Average cumulative monthly precipitation	-0.017***
	(0.006)
Average monthly temperature (sq)	-0.003
	(0.007)
Average cumulative monthly precipitation (sq)	0.00003***
	(0.00001)
Temperature anomaly	-0.332
	(0.227)
Precipitation anomaly	0.228***
	(0.086)
Observations	8,957
Number of households	3,377
F-statistic	15.19

Note: Model includes municipality and year fixed effects. Credit value in 2010 constant dollars, transformed using the inverse hyperbolic sine (IHS). Standard errors clustered at the municipal level (in parentheses) *** p<0.01, ** p<0.05, * p<0.1

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