THREE ESSAYS ON RURAL DEVELOPMENT

BY

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DISSERTATION

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Abstract

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This dissertation combines research on three topics related to rural development in low-income countries. It is motivated by my experience as a farmer and extension agent in Colombia and the conviction that efforts made to address these challenges can significantly improve the lives of rural communities. The first chapter, evaluates the impact of partial conflict resolution on legal and illegal economic activity. The second chapter, based on the joint work with Mary Paula Arends-Kuenning and Anina Hewey, tests the potential of the teacher-student-parent channel of information exchange built around vocational training programs for the diffusion of agricultural technology. The third chapter, based on joint work with Sandy Dall´Erba, estimates the effect of climate variability on future coffee productivity in Colombia.

The first chapter links the occurrence of positive or negative outcomes after a conflict resolution process to the configuration of armed group presence that existed in a locality before the peace talks started. Specifically, I look at two possible configurations: (i) local bilateral conflicts where the legitimate state is engaged in a contest with a single armed group in the process of demobilization and (ii) local multilateral conflicts where the legitimate state opposes two armed groups, one which is demobilizing and one that continues its activity unabated. Identification is based on a difference-in-differences design that leverages the heterogeneity in the configuration of armed group presence and estimates the effect of the configuration on economic activity, intensity of violence, and coca leaf cultivation. The results show unequivocally positive outcomes after the demobilization of the armed group in local bilateral conflicts evidenced by a decrease in number of violent incidents, and increase in economic activity, and no evidence of an increase in coca cultivation. In contrast, I find evidence of negative outcomes in local multilateral conflicts where coca cultivation increased and no significant increase in economic activity is observed. I argue that these opposing results relate to the shift (or absence thereof) of the local monopoly of

violence. In the former case, the legitimate state regains the monopoly of violence and is able to control illegal activity more effectively. In the latter case, the state still fights for control of the monopoly of violence with the remnant armed group, which in turn is able to consolidate the illegal activity around itself after the competitor armed group is removed from the scene.

The second chapter consists of a randomized control trial (RCT) to assess the potential of using the teacher-student-parent channel of information exchange for the diffusion of agricultural technologies to underserved rural communities. We posit this channel as a complement to the increasing literature on social learning and the farmer-promoter models that looks at increasing farmers' exposure to new technologies on the extensive margin (by reaching more farmers through the extended networks of the promoters) and the intensive margin (by increasing the frequency of the interactions between farmers and promoters). The RCT was conducted among high school students - and their parents – to whom the Fabretto Foundation was gradually offering the vocational training program known as Tutorial Learning System (SATec). By comparing the results of knowledge based tests and survey data we were able to show that the knowledge of agricultural and accounting techniques improved among students and parents. More importantly, we find evidence that those techniques were being adopted by the parents who were also more likely to access credit markets to finance these new endeavors.

The last chapter builds a bridge between the crop physiology literature and the econometric estimation of the effects of climate change on agriculture. We build a simplified agronomic model that links changes in temperature and precipitation to the productivity of coffee. The insights from this model are used to estimate a dynamic panel model that accounts for the perennial nature of coffee production. After showing that this model outperforms conventional econometric models, we use it to predict future coffee productivity in Colombia using up-to-date forecasts of future weather for 2041-2060. The results show that national coffee productivity won't be affected on average, but that careful attention must be paid to the heterogeneity of the predictions at the local level. In particular, we show that low-altitude municipalities will likely experience a decrease in productivity, whereas high altitude municipalities will increase productivity.

AKNOWLEDGEMENTS

I am grateful to many people who contributed to this dissertation; their input was both useful in content and kind in delivery. First, I want to thank my advisor, Benjamin Crost, for excellent mentorship. Explicitly, he impressed on me the importance of asking useful questions and pressed me to deliver contributions on them. Implicitly, he set an example of academic integrity that I will carry onto my life. Second, I want to thank the other members of my committee, Alex Winter-Nelson, Mary Paula Arends-Kuenning, and Ana María Ibañez for their generous advice, which greatly improved this dissertation. I also want to thank my other co-authors, Sandy Dall'Erba and Anina Hewey, from whom I learned so much in the process of writing these papers.

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My family and friends also played an important role in this process, my happiness is only complete through sharing this accomplishment with them.

A mi madre, María Eugenia Sierra Velásquez y mi padre, Luis Fernando Ceballos Loaiza

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CHAPTER 1

INCOMPLETE PEACE: UNINTENDED CONSEQUENCES OF PARTIAL CONFLICT RESOLUTION IN MULTILATERAL CONFLICTS

Abstract: This chapter provides evidence on the impact of conflict resolution processes (CRPs) in settings of multilateral conflict. Previous studies on CRPs have focused on bilateral conflicts between a state and a single armed group, finding positive impacts on economic activity after the demobilization of the armed group, a phenomenon known as the peace dividend. This chapter studies the case where the state is warring multiple armed groups and a peace agreement is reached with only one of them. I find that the impact of a CRP in this setting is heterogeneous: areas where the sole armed group demobilized, experience an increase in economic activity; while areas where the demobilizing group was outlived by another armed group experience no change in economic activity and a surge in illegal economic activity in the form of coca production.

1.1 Introduction

Multilateral conflicts are widespread and particularly persistent. According to the Uppsala Conflict Data Program, approximately one in three currently active conflicts over control of the government involve the legitimate State and at least two armed groups and have, on average, lasted for 52 years (Gleditsch et al. 2002; Pettersson and Öberg 2020). In those conflicts, it is often difficult to negotiate peace with all parties at the same time. Governments therefore try to negotiate peace sequentially, in the hope that demobilizing one armed group will have positive political and economic impacts (Bell 2006).

The existing evidence on economic impacts of conflict resolution processes (CRPs) is limited to bilateral conflicts between a strong state and a single armed group. In Northern Ireland, Besley and Mueller (2012) find that the peace agreement between the English government and the Irish Republican Army lead to an increase in housing prices between 1.3% and 3.5%. Similarly, Colino (2012) find that employment in the Basque Country surged by 4% after a ceasefire was agreed between the Spanish government and the separatist armed group ETA.

While these studies suggest that a peace dividend exists after the end of bilateral conflicts, it is not clear that the same is true after the partial end of a multilateral conflict.[1] For instance, while the demobilization of a single armed group in a bilateral context returns the monopoly of violence to the state, the same is not the case for a partial peace agreement in a multilateral conflict where the state remains in conflict with another armed group. This distinction is non-trivial: the uncontested use of violence is the foundation of the state and a necessary condition to govern effectively (Acemoglu, Robinson, and Santos *2013*). A CRP that fails to return the monopoly of violence to the State might not reap the full peace dividend.

Furthermore, CRPs in bilateral and multilateral conflicts may differ in their effect on illegal markets, such as drug production and distribution, in which armed groups are often heavily involved. In many contexts, demobilizing the sole armed group in a bilateral conflict would remove the dominant actor from the market, giving the government a chance to regain control. However, demobilizing an armed group in a multilateral conflict potentially consolidates the illegal market in the hand of the remaining armed group(s). Therefore, the demobilization of one armed group might have unintended consequences on the local economy as the market structure reorganizes. To the knowledge of the author, there is no empirical evidence to support or reject these hypotheses, obfuscating the understanding of the impact of CRPs in multilateral conflicts.

This chapter estimates the effect of partial conflict resolution by studying the CRP between the Colombian government and the Revolutionary Armed Forces of Colombia (FARC). This CRP began in August 2012 and ended in October 2016 with a final peace agreement that included the demobilization of most FARC combatants. Similar efforts to sign a peace agreement with the National Liberation Army (ELN), the country's second-largest guerrilla group, were unsuccessful. Importantly, the territorial presence of FARC and ELN partly overlapped prior to the CRP. Thus, areas with only FARC presence saw the demobilization of the sole armed group, while areas with joint presence of FARC and ELN went from a multilateral conflict with two groups to a bilateral conflict with only the ELN. Furthermore, both armed groups were involved in illegal markets – in this case the cocaine business – often competing for market share in areas where both groups were present. The Colombian case thus presents a unique opportunity to study the effects of partial CRPs in multilateral conflicts on economic activity and illegal markets.

[1] More generally, it is also not clear that the effect of conflict resolution will be the same in other countries. Northern Ireland and Spain are developed economies with a high level of state capacity. Other states, like Colombia, have much lower levels of territorial control, which could have important implications for the economic effects of peace agreements.

I estimate the effect of the CRP with a difference-in-difference approach that compares changes in violence, economic activity, and coca production across municipalities with different configurations of armed group presence before the CRP: (i) sole FARC municipalities; (ii) joint FARC-ELN municipalities; and (iii) sole ELN municipalities. Sole FARC municipalities represent the case of "complete conflict resolution," after which no armed group is locally present and full control reverts to the government. Joint FARC-ELN municipalities experience "partial conflict resolution," as the demobilizing FARC is outlived by the ELN. In these municipalities, the CRP replaces a multilateral conflict with a bilateral one. Sole ELN municipalities form the control group, as they do not experience a change in armed group presence. We overcome the challenge of measuring economic activity in war-stricken areas by using high-quality remotely-sensed night lights imagery which has been previously used for measuring the impact of war on economic activity (Li et al. 2015; Shortland, Christopoulou, and Makatsoris 2013).

I begin by showing that both types of municipalities with FARC presence experienced a decrease in number of violent incidents, confirming that the FARC abided by the peace agreement. However, the effect of the CRP on economic activity and coca production differed substantially across municipalities with different armed group configurations. Municipalities where FARC was the sole armed group prior to the CRP experienced an increase in rural economic activity and no change in coca cultivation, consistent with the evidence for a peace dividend after the end of bilateral conflicts (Besley and Mueller 2012; Colino 2012). In contrast, municipalities where the demobilizing FARC was outlived by the ELN, experienced no improvement in economic activity and an increase in coca cultivation.

Based on this evidence, this study proposes a mechanism that relates the local configuration of armed group presence to the outcomes of the conflict resolution process. In this mechanism, the occurrence of positive or negative outcomes depends on the shifts of the monopoly of violence and the illegal market structure brought by the demobilization of the armed group. In local bilateral conflicts, the State regained the monopoly of violence and was better able to control illegal activity. In contrast, in local multilateral conflicts, the monopoly of violence remained elusive as the State continued warring the remaining group, which in turn consolidated the illegal businesses after the competing armed group was forced to abandon the market.

This study also contributes to the growing literature on remote sensing and economic outcomes. Due to the difficulty of capturing data on economic activity in war-stricken areas, we rely on satellite imagery of night-time lights to construct a variable that measures of economic activity. Previous works have found that remote sensing is a useful tool for measuring economic conditions in war-stricken areas (Shortland, Christopoulou, and Makatsoris 2013; Li et al. 2015) and has been applied in the Colombian context (Ch, Martin, and Vargas 2020).

This study provides another setting in which satellite imagery is used for economic empirical analysis, that of using night lights data to measure recovery of economic activity after a CRP. Moreover, as the presence of the state is still weak in frontier areas of armed group presence, satellite imagery can be used in the study of economic conditions and the design of timely policies.

Finally, this study has important implications for the peace agreement in Colombia. Empirical evidence of the benefits reaped by the country can strengthen its implementation by showing the current skeptical Government the positive short-term impact of peace, and by giving the citizens a renewed sense of hope in the outcome of it. Furthermore, it can incentivize the Government to pursue peace agreements with the remaining rebel groups that, like the one signed with FARC, might seem politically costly before the implementation but whose final benefits are found to outmatch the costs. The evidence of the cost of inadequately filling the void left by the demobilized groups should also encourage the design of public policies as to avoid negative impacts in peace agreements of that kind.

The outline of the chapter is as follows: Section 1.2 of this chapter describes the background of the civil conflict in Colombia as well as the CRP between the Colombian Government and FARC. Section 1.3 describes the data set and presents the descriptive statistics. Section 1.4 presents the results for the impact of the CRP on the intensity of violence (Subsection 1.4.1), the effect of the change in intensity of violence on economic activity (Subsection 1.4.2), the relationship between rural activity and coca cultivation (Subsection 1.4.3), an exploration of heterogeneous effects by the stability of armed group presence, and initial levels of coca cultivation and mining activity (Subsection 1.4.4), and a set of ancillary estimations performed as robustness checks to test the validity of the results presented in the previous three subsections (Subsection 4.5). Section 5 offers conclusions and a discussion on policy implications of the study and states the limitations of this study.

1.2 Background

1.2.1 Guerrilla conflict, violence, and drug trafficking in Colombia

FARC and ELN share similar origins rooted in the turbulent political period known as "La Violencia", when partisans of the Liberal and Conservative parties waged a civil war that resulted in 200,000 deaths (Saumeth Cadavid *2010*). "La Violencia" ended with the creation of the National Front, a political agreement between both parties to alternate power and share control of the Government (Behar *1985*). Other political movements, of which FARC and ELN are prominent examples, were effectively excluded from representation resulting in the birth of groups of resistance (LeoGrande and Sharpe *2000*). FARC grew out of the peasant self-defense groups originated in predominantly liberal areas as protection against conservative violence, but eventually transitioned to a Communist agenda (Saumeth Cadavid *2010*). ELN traces its origin to student-organized militias inspired by the Cuban revolution, later joined by revolutionary catholic priests who instructed the Marxist-Christian Theology of Liberation into the group (Baca *2018*).

For the most part of the 60s and 70s, guerrilla conflict was a low intensity affair, with the notable exception of the US-backed LASSO plan that resulted in the bombardment of the Marquetalia Region in 1964 (Behar *1985*). This period is characterized by a stalemate in which the guerrillas never seriously challenged the Colombian forces for the control of the State, but neither could the armed forces subdue the guerrilla groups, as they were firmly entrenched in areas of historic presence where they had established a strong base (LeoGrande and Sharpe *2000*). Some of these areas were the remnants of the liberal guerrillas' strongholds of the "La Violencia" period, which embodied the fights of the peasantry against the social injustices brought by the large-landowner or "latifundista" economic system (Galli *1981*).

The incursion of drug trafficking, and in particular the expansion of the cocaine market in the early 1980s, led to a shift in the dynamics of the guerrilla war. The areas under guerrilla occupation, already neglected by the Colombian State, provided a fertile ground where coca leaf could be produced under the protection and taxation of the guerrillas (Mejía and Rico *2017*). This new influx of revenue resulted in an intensification of the conflict, as guerrillas expanded their ranks, increased their firepower, and extended their area of operation (Pécaut *2008*). By 1999, FARC had approximately 15,000 combatants divided in some 60 fronts operating in 40% of the territory (LeoGrande and Sharpe *2000*). At the same time, ELN reached their peak with some 3,500 combatants split into 30 fronts (Saumeth Cadavid *2010*).

The relation between the Colombian conflict, and illicit drugs has been well documented in the literature (Mejía and Rico *2017*). First, coca cultivation and trafficking provided an alternative source of revenue once the funds provided by the Soviet Union dwindled (Topel *2009*). Second, it fostered the colonization of large tracts of land by peasants wanting to improve their economic situation (Pécaut *2008*). This wave of colonizers provided guerrillas with a political base as well as recruits to man their increasing number of fronts (Trigoso *2017*). After a particular turbulent period at the end of the 1990s and beginning of the 2000s, Colombia's military strategy was strengthened by the signature of the Plan Colombia, which included funding and training of the Colombian military forces in anti-insurgent operations. This agreement played a major role in reversing the tide of guerrilla success, particularly of FARC, eventually leading to the signing of a peace agreement between this guerrilla and the Colombian Government in 2016 (Franz *2016*).

1.2.2 Conflict resolution process and the 2016 peace agreement

In late 2012, President Santos announced that secret explanatory talks had taken place between his Government and FARC, and that both parts were willing to initiate formal talks towards the termination of the conflict. President Santos made it clear that mistakes committed during previous peace talks would not be repeated, namely that the Colombian State would not demilitarize areas of the territory to host the peace talks (Beittel *2014*). Both parties agreed on a framework consisting of six principal themes to be addressed during the negotiations: (1) rural development and land policy; (2) political participation of FARC; (3) ending the armed conflict including reinsertion into civilian life of rebel forces; (4) illicit crops and illegal drug trafficking; (5) victims' reparations, and (6) the implementation of the final negotiated agreement, including its ratification and verification. Talks were to be held in Norway initially and then in Cuba. A condensed timeline of the actual development of the CPR is shown in Figure 1.1:

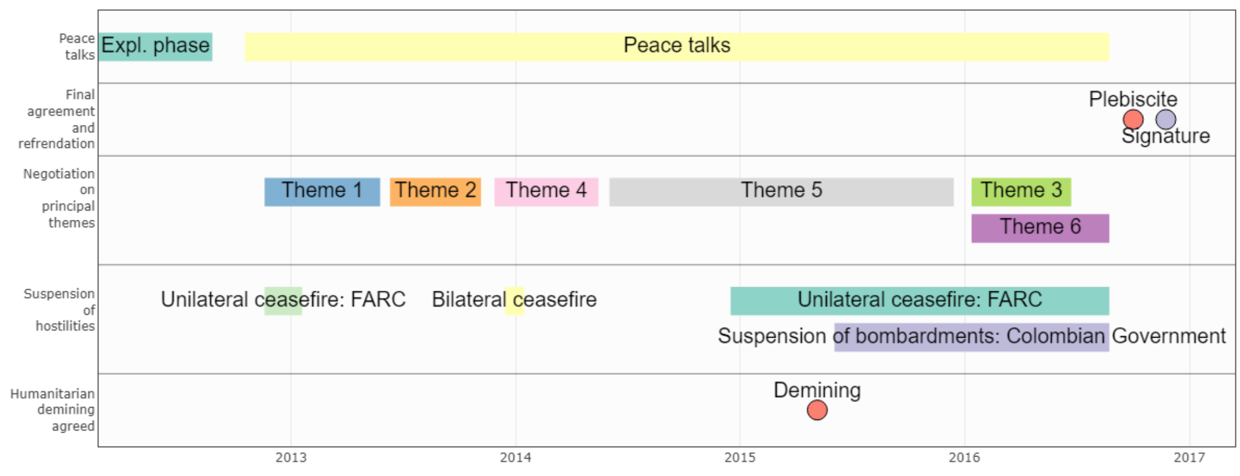

Figure 1.1. Timeline of the peace talks between the Colombian government and the Revolutionary Armed Forces of Colombia (FARC)

Agreement on theme one was geared specifically to address inequality and lack of opportunities for the rural population. In particular, it created a fund for the redistribution of land (Land for Peace Fund) as well as the institutional tools for the formalization of land ownership. Provisions for investment in infrastructure, technical assistance services and loans, among other measures to alleviate rural poverty were also included (Oficina del Alto Comisionado para la Paz *2016*).

The agreement on theme four included the creation of a National Program for the substitution of Illicit Crops (PNIS). The prioritization of formalization of land ownership in areas of high illicit crop cultivation density and demining was a top priority for rural communities. In addition to this, the agreement provided mechanisms for the substitution of illicit crops, such as loans and technical assistance. Furthermore, it included a commitment by FARC to cease any drug-related activities (Beittel *2014*).

The agreement on theme five stated the strategy for the reparation of victims. It was envisioned as a mechanism to strengthen the long-standing Governmental Comprehensive Program for Reparation of Victims (CRPV). A total of 1,2 billiard pesos (400 million dollars) are expected to be invested in communities affected by the conflict over the 2016-2026 period. The money is to be funneled through the CRPV favoring communal reparation in hand with the Regional Development Programs (PDET), incentives to returning to their lands, land restitution and psycho-social attention to communities (Oficina del Alto Comisionado para la Paz *2016*).

This chapter is an evaluation of the events that happened between the start of the peace talks (pre-treatment) and the signature of the Final Agreement for the Termination of Conflict and the Construction of Stable and Durable Peace. As such, it evaluates the changes in intensity of conflict product of the de-escalation of conflict through uni- and bilateral ceasefires, cessation of bombardments, and demining efforts. It also captures the change in public opinion about the end of conflict and the expectation of improvement of economic conditions related to the compromises in reparation of victims, investments in rural development, and weakening of illicit markets.

1.3 Data and descriptive statistics

The empirical strategy used to prove causality faces two challenges: first, the identification of armed group presence at the municipal-level is a challenge given the belligerent nature of guerrilla warfare (Cubides *2009*). Second, the observation of the dependent variable economic activity is difficult given that areas where rebel groups operate closely match areas where State presence is weak, official data is scarce, and economic transactions are usually informal (Gáfaro, Ibáñez, and Justino *2014*). Traveling to these areas is also a risky endeavor and armed groups are known to attack outsiders, especially if they are gathering information (Krøvel *2017*; Garcés Prettel and Arroyave Cabrera *2017*). This section addresses these challenges, and in the process describes the data.

The identification of armed group presence was done using the Electoral Risk Maps prepared in 2011 by the Electoral Observation Mission of Colombia (López, 2011). The 2011 maps were published in anticipation of the 2011local elections. They identify municipalities where rebel group presence can influence the outcomes of the election based on their presence and continued activity. Three groups are included: FARC, ELN, and criminal gangs. Due to their operative differences and involvement in urban delinquency, we exclude criminal gangs from the baseline analysis; however, we include an estimation that also accounts for criminal gang presence in the Appendix. Figure 1.2(A) presents the geographic distribution by treatment.

I complement this data with the 2016 electoral risk map (Misión de Observación Electoral, 2016), which was elaborated in anticipation of the 2016 plebiscite on the peace agreement by a multi-disciplinary panel of experts streaming from a wide range of institutions including leading universities, think-tanks focusing on conflict, national and international Governmental Organizations. We perform a robustness check using the distribution of armed group presence reported by this study.

The second challenge is addressed by using night lights imagery, which has proven adequate for the study of human activity in conflict areas (Shortland, Christopoulou, and Makatsoris *2013*; Li et al. *2015*). We exploit a happy coincidence: The National Aeronautics and Space Administration (NASA) released two global maps of night lights at a 500 x 500 m. resolution - the highest one available yet - for the years 2012 and 2016 called Black Marble HD (Román et al. *2018*). We use these images to extract values of night lights at the municipal level and employ them in all estimations involving economic activity. Figure 1.2(B) presents the geographic distribution of changes in economic activity. The pattern of increase in economic activity appears to match those areas of FARC-presence, especially in the West and Southeast regions, where the most belligerent blocks where active (Peña *2013*).

The use of Black Marble HD, although limiting in the fact that only offers imagery for 2012 and 2016, is crucial for addressing two limitations of night lights data for the study of human activity in general, and in conflict settings in particular. First, top-coding of night lights value is possible specially in densely populated areas (Hsu et al. *2015*). Even though this study mostly comprises scarcely populated areas (the mean population per municipality is between 12100 and 22200 people). Black Marble HD imagery is generated from the Visible Infrared Imaging Radiometer Suite (VIIRS), which represents and improvement from the Defense Meteorological Program (DMSP) Operational Line-Scan System (OLS), leading to fewer over-glow effects and spatially more explicit lights within densely populated areas (Li et al. *2020*). The second concern is that nigh light imagery obtained from different satellites or at different periods of time can be shifted by a couple of pixels. The construction of Black Marble HD images addresses this issue as it is a set of composite images that corrects for these spatial and temporal errors (Román et al. *2018*). The suitability of these images for the measurement of economic activity in war-stricken areas has been validated by its use in the Syrian conflict (Román et al. *2018*).

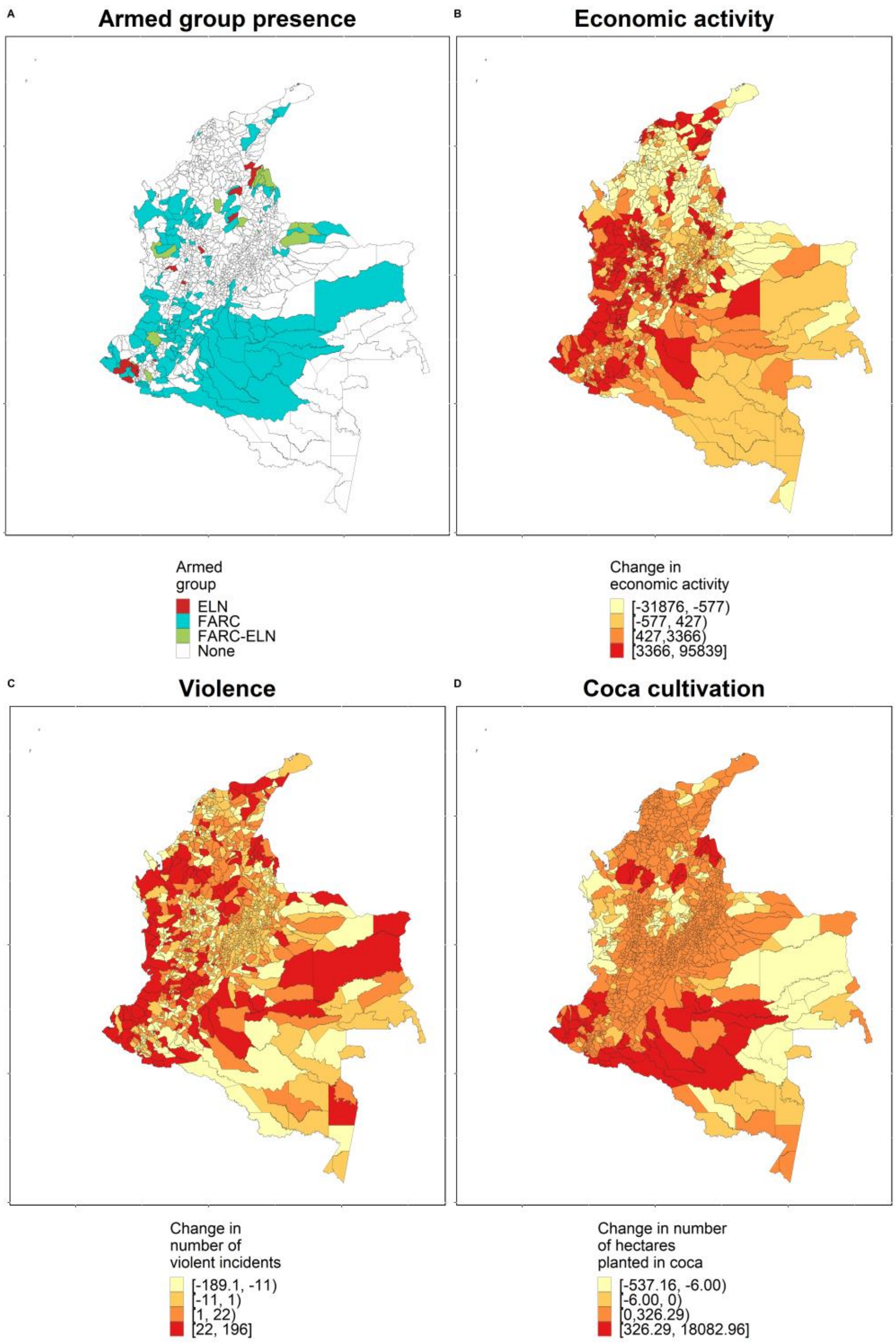

Figure 1.2. Geographic distribution of (A) treatment and control municipalities, (B) Changes in economic activity measured by night lights between 2012 and 2016, (C) Changes in number of violent incidents between 2012 and 2016, and (D) Changes in number of hectares planted in coca leaf between 2012 and 2016.

Data on violent incidents were obtained from the Aggregate Register of Victims, a database compiled by the Unit for the Attention and Integral Reparation of Victims of Colombia. This database comprises micro-data for approximately 1 million incidents of violence from 1984 until the present. Each incident is detailed with the year, code of the municipality in which it happened, type of violence, gender of the victim(s), whether they belong to an ethnic group, age group, and total number of victims. Changes in number of violent incidents are presented in Figure 1.2(C) and follow a similar pattern where the largest decreases match areas of FARC presence. Illegal crops data were obtained from the System for the Observation of Drugs of Colombia (SIDCO) annual monitoring of territories affected by illegal crops (Observatorio de Drogas de Colombia *2017*). SIDCO compiles yearly information on coca cultivation using satellite imagery that, although susceptible to a degree of measurement error, provides consistent measurements over time and are not affected by changes brought by the CRP. Changes in number of hectares cultivated in coca leaf are presented in Figure 1.2(D), however no distinct geographic pattern can be discerned.

Municipal level data on demographic characteristics, Government revenues and expenditures, and public services coverage were obtained from the Municipal Panel compiled by the University of los Andes, Colombia (Acevedo and Bornacelly *2014*). Data on the continuity of presence of rebel groups were obtained from the Conflict Analysis Resource Center (CERAC) (CERAC *2019*). Summary statistics are presented in Table 1.1, and show that baseline characteristics are well balanced between treatment groups:

Table 1.1. Baseline summary statistics.

Variable:	**ELN**	**FARC**	**FARC-ELN**	**P-value**
Economic activity	8.21	14.9	23.3	0.418
Violent incidents	80.8	91.1	107	0.227
Coca cultivation (has)	3.21	3.2	5.03	0.475
Mining revenues (1000000000 COP	2.91	0.727	3.44	0.478
Urban population (1000 people)	19.5	95.6	54.3	0.876
Rural population (1000 people)	14.9	16.1	21.2	0.183
Local Government income (1000000000 COP)	0.021	0.117	0.083	0.824
Local Government expenditure (1000000000 COP)	0.02	0.111	0.071	0.844
Water service (%)	59.5	55	53.6	0.621
Garbage service (%)	43.6	48.2	47.3	0.754
Sewer service (%)	47.9	44.9	43.2	0.693
	14	155	14	

Source: Author's calculations

Notes: The unit of analysis is the municipality year. P-values corresponding to the F-test in which H_0: all population means are equal, are reported in the last column.

Figure 1.3 presents the time trends of the three outcomes of interest. The dashed vertical line represents the start of the peace talks between the Colombian Government and FARC. The figure validates the assumption of equal trends which is necessary for the validity of the difference-in-difference estimations that are carried in this chapter. It also points at an increase in in economic activity and coca cultivation and a decrease in intensity of violence across all configurations of treatment.

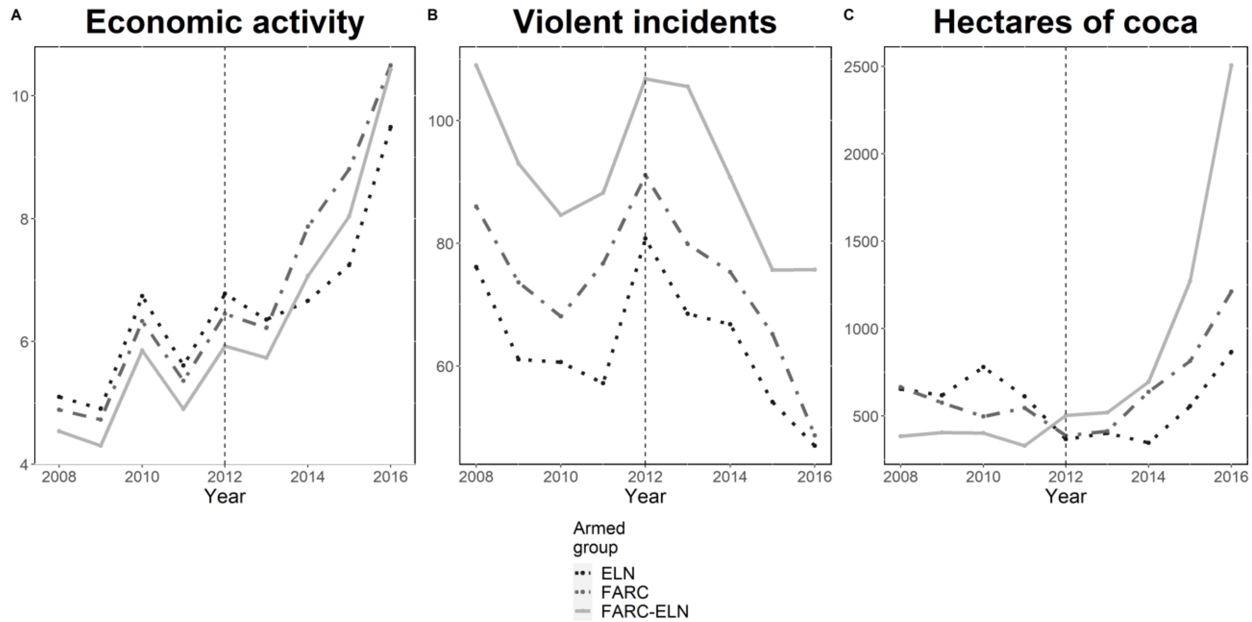

Figure 1.3. Time trends of (A) economic activity measured by night lights, (B) number of violent incidents, and (C) number of hectares planted in coca leaf, disaggregated by treatment group. Note: Economic activity data for 2008 to 2011, and for 2013 were obtained from the DMSP-OLS imagery; Economic activity data for 2012 and 2016 were obtained from NASA's Black Marble HD product.

1.4. Results

1.4.1 The CRP and violence

The initial estimation tests whether the CRP with FARC influenced the intensity of violence using a difference in difference approach that relates the configuration of armed group presence with the number of violent incidents at the municipal level before and after the start of the peace talks in 2012 (equation (1.1)). The sample is restricted to municipalities that had reports of presence of at least one armed group. This restriction accounts for the fact that armed group presence is not random, and therefore by only using municipalities that have reports of one armed group We am constructing comparable groups with similar history and characteristics; this claim is supported by the balance tests presented in table 1. Moreover, the timeframe of this study implies that the impact of the CRP is evaluated in the short-term, which leads me to assume that there is no significant reconfiguration of armed group presence at this time, a claim supported by the "negotiation in the midst of conflict" approach of this CRP. Treatment encompasses all the peace-building efforts undertaken by FARC and the Government, including uni- and bilateral ceasefires, cessation of bombardments, demining activities, among others.

$$Violence_{it} = \beta_0 + \beta_1 POST_t + \beta_2 (FARC_i \times POST_t) + \beta_3 (FARC\_ELN_i \times POST_t) + \alpha_i + \varepsilon_{it} \quad (1.1)$$

In this equation, $FARC_{it}$ and $(FARC\_ELN)_i$ denote municipalities of sole FARC and joint FARC-ELN presence reported at the baseline (2011), respectively. Sole ELN municipalities are the omitted category, so the β_2 and β_3 coefficients capture the slope of sole FARC or joint FARC-ELN municipalities with respect to sole ELN municipalities. $POST_t$ is a binary variable that takes value of 0 for years before 2012 and 1, otherwise. Municipality fixed effects, α_i, are also included. Standard errors are clustered at the municipal level.

Table 1.2. The Colombian CRP and the change in number of violent incidents after the start of the peace talks in 2012.

	(1)	(2)	(3)
Post 2012	-13.90 ***	-44.91 ***	-53.90 ***
	(4.11)	(4.50)	(6.94)
Post 2012 X FARC	-6.31	-6.09	-4.29
	(4.36)	(4.50)	(4.48)
Post 2012 X FARC/ELN	0.18	-9.32 *	-2.05
	(6.11)	(5.55)	(5.91)
Observations	2013	2013	2013
Department by time fixed effects	NO	YES	YES
Region by time fixed effects	NO	NO	YES

Source: Author's calculations

Notes: The unit of observation is the municipality-year. The sample is restricted to municipalities that had reports of presence of at least one armed group. All specifications include municipality and department-by-year fixed effects. Standard errors clustered at the municipal level are presented in parenthesis. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 1.2 reports the results of the estimation of equation (1). It shows that violence decreased across all municipalities studied in the period after 2012, yet no discernible pattern can be seen for FARC-present municipalities. A possible explanation of this result is that the decrease in violence was not uniform after 2012 and varied across years. Therefore, we complement the results from equation (1.1) by exploring how the changes in number of violent incidents evolve over time for each configuration of armed group presence by estimating the following equation:

$$Violence_{it} = \beta_0 + \sum_{k \in \{FARC, FARC\_ELN\}} \sum_{j=2008, j \neq 2012}^{2018} \theta_j^K \left(GROUP_i^k \times \mathbb{1}(TIME_t = j)\right) + \alpha_i + \lambda_t + \mu_d t + \varepsilon_{it} \quad (1.2)$$

There are two omitted categories: sole ELN municipalities and the pre-treatment year, 2012. Therefore, the slope coefficients θ_j^{ELN}, θ_j^{FARC} and $\theta_j^{FARC-ELN}$ capture the change in number of violent incidents for municipalities with sole FARC presence and joint FARC-ELN presence, with respect to 2012 minus the change in number of violent incidents in sole ELN municipalities with respect to 2012. Figure 1.4 presents the result of this estimation:

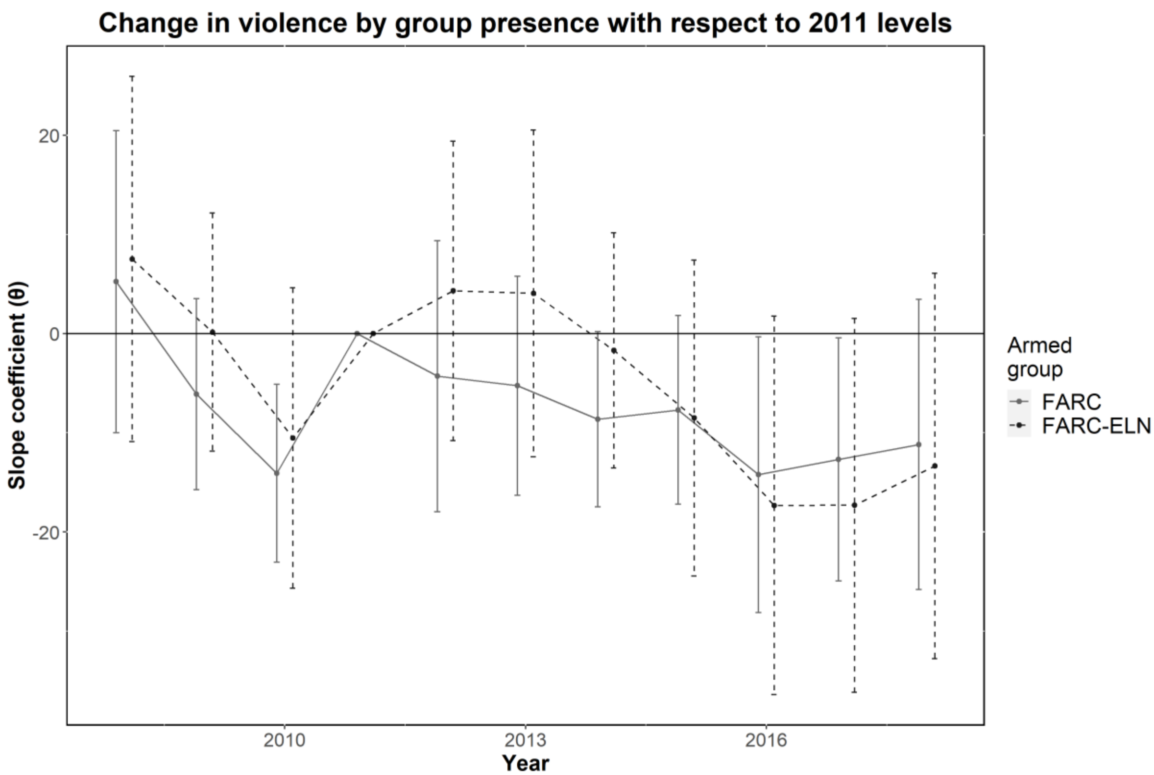

Figure 1.4. Configuration of armed group presence and conflict. The figure traces the slope of the relationship between the year and the number of violent incidents for each configuration of armed group presence. 2012 and sole ELN municipalities are the omitted categories so all slope coefficients, Θ, capture the change in number of violent incidents in FARC or FARC_ELN municipalities with respect to 2012 versus the change in number of violent incidents in ELN municipalities with respect to 2012.

The year-by-year analysis paints a clearer picture of the change in violence across armed group presence configurations. Before 2011 the slope coefficients associated to sole FARC and FARC/ELN municipalities follow a similar trend; however, after 2011 those trends appear to diverge. Figure 1.4 shows a decrease of the slope coefficient in FARC municipalities after 2011 up to the point where the 2016 and 2017 values are significantly different from the reference year. In contrast, the slope coefficient associated to FARC/ELN municipalities increased briefly in 2012 and 2013 before decreasing. However, this decrease is not statistically significant.

1.4.2 Change in intensity of violence and economic activity

Similar decreases in violence have been reported by Colino (*2012*) in the case of the 1998 ceasefire between the Spanish Government and ETA, and by Besley and Mueller (*2012*) in the case of the 1994 ceasefire between the Irish Government and the IRA. These decreases have been linked to reduced uncertainty and the ensuing improvement in economic activity. This Subsection test the robustness of these results in the context of partial conflict resolution process by performing an analogous estimation as the one proposed in equation (1.1) with my metric of economic activity as dependent variable.

Table 1.3. The Colombian CRP and the change in economic activity after the start of the peace talks in 2012.

	(1)	(2)	(3)
POST	1.86	20.78 ***	-6.53 *
	(1.90)	(4.63)	(3.65)
POST X FARC	5.34 **	9.32 **	9.41 ***
	(2.38)	(4.63)	(3.46)
POST X FARC/ELN	2.36	9.56	6.14
	(3.99)	(6.19)	(4.07)
Observations	366	366	366
Department by time fixed effects	NO	YES	YES
Region by time fixed effects	NO	NO	YES

Source: Author's calculations

Notes: The unit of observation is the municipality-year. The sample is restricted to municipalities that had reports of presence of at least one armed group. All specifications include municipality and department-by-year fixed effects. Standard errors clustered at the municipal level are presented in parenthesis. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

The results are presented in Table 1.3. Two things are worth noting: first, municipalities of sole FARC presence experienced an increase in economic activity in line with the findings of the literature on the peace dividend. Second, there is no matching increase in municipalities where FARC and ELN were jointly present. The latter result is markedly different from the findings in sole FARC municipalities and those from the Basque and Northern Irish conflicts raising questions about the consistency of the mechanism that links the peace dividend to a reduction in uncertainty as violence decreases.

First, we argue that this mechanism is indeed consistent across the subset of bilateral conflicts. In fact, the positive and significant increase in economic activity in sole FARC municipalities (where the Government was involved in a bilateral contest with FARC) supports it. It is in the context of multilateral conflicts where the mechanism falters. We argue that this is because when FARC demobilized it was outlived by at least one other armed group: ELN. Therefore, the Colombian State had to continue to contest the use of violence in those territories to the detriment of the efficiency of the Government (Acemoglu, Robinson, and Santos *2013*).

One limitation of this analysis is that it relies on the two available Black Marble HD images provided by NASA (2012 and 2016) impeding the estimation of a model analogous to that of equation (1.2). However, we believe the baseline analysis presented in Table 1.3 is valid as it captures the conditions before (pre-treatment) and after (post-treatment) the peace talks and frame the bulk of the changes in public order conditions that resulted from the conflict resolution process. Furthermore, the DMSP-OLS readings of night lights show that the trends were similar between groups in the year prior to 2012.

1.4.3 Economic activity and coca cultivation

I consider the possibility that the previous result, which suggests the existence of a peace dividend in areas where the sole armed group demobilized, can be contested as originating from an increase in illegal activities. In particular, the possibility that it is associated with an increase in coca cultivation in areas of sole FARC presence as the control that the guerrilla had over the market loosened. Previous studies have found that areas of FARC presence (either sole or joint) increased coca cultivation compared to other coca-cultivating areas (for example, Lopez et al. (*2019*)). This subsection tests this hypothesis by conducting a set of estimations exploring the changes in coca cultivation using the same methods proposed in the previous two subsections. The results of the analogous estimation of equation (1.1) with number of hectares planted in coca as dependent variable are presented in table 1.4:

Table 1.4. The Colombian CRP and the change in number of hectares planted in coca leaf after the start of the peace talks in 2012.

	(1)	(3)	(4)
Post 2012	0.64	-10.78 ***	4.03
	(0.48)	(3.26)	(2.78)
Post 2012 X FARC	1.29	3.94	2.05
	(0.90)	(3.26)	(1.45)
Post 2012 X FARC/ELN	9.79 *	11.23 **	10.25 *
	(5.49)	(5.44)	(5.33)
Observations	2013	2013	2013
Department by time fixed effects	NO	YES	YES
Region by time fixed effects	NO	NO	YES

Source: Author's calculations

Notes: The unit of observation is the municipality-year. The sample is restricted to municipalities that had reports of presence of at least one armed group. All specifications include municipality fixed effects. Standard errors clustered at the municipal level are presented in parenthesis. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

The results presented in Table 1.4 reject the hypothesis that the increase in economic activity can be traced to areas where the sole armed group (FARC) was demobilizing. The coefficient associated with this municipalities is negative and insignificant, showing that the change in coca cultivation in sole FARC municipalities is not statistically different from the change observed in sole ELN municipalities. This finding shows that positive outcomes experience by sole FARC municipalities corresponds to an improvement in the legal economic activity of these areas and constitutes evidence of a measurable peace dividend. Due to the data limitations of this chapter, we cannot further disentangle the source of this peace dividend.

Interestingly, the coefficient associated with areas of joint armed group presence is positive and statistically significant, showing that coca cultivation increased in areas where the demobilization of FARC left ELN as the sole armed group. Although it cannot be proven empirically due to the limitation of the data, we believe this result can be explained by the old maxim of illegal enterprises: "war is bad for business". Once FARC abandoned the market - as was required by the peace agreement - ELN was able to manage the coca business much more efficiently without the added cost of exertion of violence and intimidation of the competition. It also opens new questions about the political undertones of peace seeking endeavors. For instance, Fergusson, et al. (2016) argue that governments adjust the intensity of their counterinsurgency efforts - avoiding completely eliminating the threat of armed groups - so that they can leverage this violent threat for political and electoral gains. If that is the case, peace-building efforts at the national level might encounter a tacit push-back from local governments who have a vested interest in keeping the conflict alive.

Next, we perform an analogous estimation to the one presented in equation (1.2) following the yearly changes in coca cultivation by armed group configuration. The results are presented in Figure 1.5:

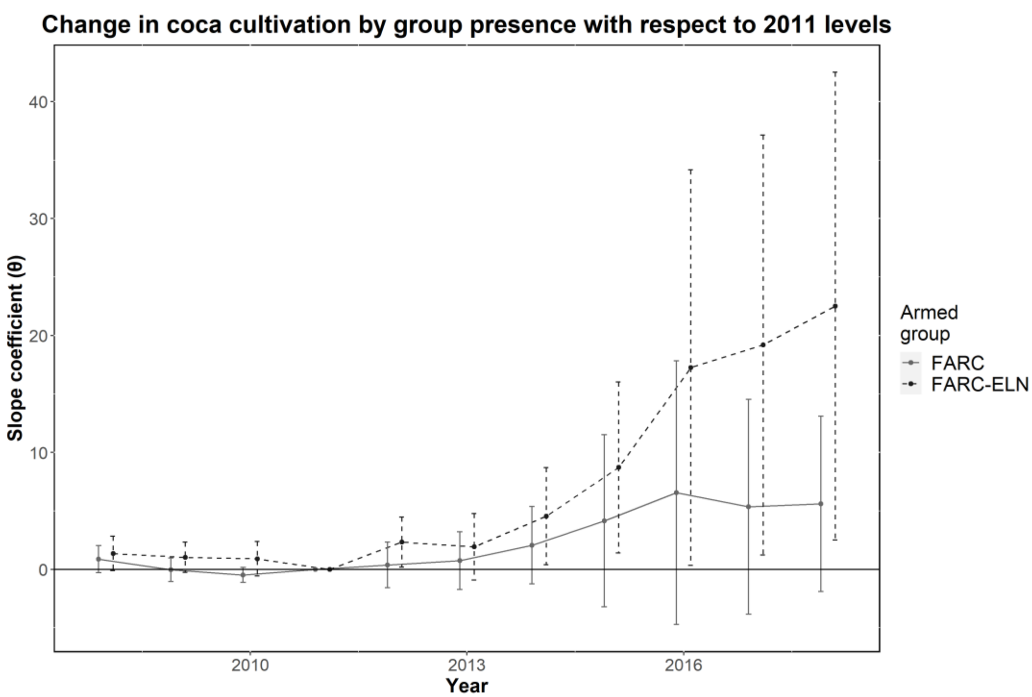

Figure 1.5. Configuration of armed group and coca cultivation. The figure traces the slope of the relationship between the year and intensity of coca cultivation for each configuration of armed group presence. 2012 and sole ELN municipalities are the omitted categories so all slope coefficients, Θ, capture the change in number of violent incidents in FARC or FARC_ELN municipalities with respect to 2012 versus the change in number of violent incidents in ELN municipalities with respect to 2012.

It confirms the findings of the baseline estimation: the change in coca leaf cultivation can be traced to a positive and statistically significant increase in cultivation in joint FARC-ELN municipalities, which was statistically different from the baseline values after 2014. No similar increase is observed in sole FARC municipalities.

1.4.4 Heterogeneous effects

First, we unpack the results of the previous subsections by estimating a triple difference model exploring the stability of presence of the armed group in the municipality. Two further configurations are considered: whether the armed group was continuously present over the 12 year prior to the start of the peace talks or not. The results of this estimation are reported in Table 1.5. In terms of economic activity our results show that Economic activity increased across all FARC present municipalities, it was more pronounced in sole FARC municipalities with longstanding armed group presence. Finally, the results in column (3) show that the increase in coca cultivation can be traced to areas of longstanding FARC/ELN presence.

Table 1.5. Heterogeneous effects by stability of armed group presence.

	Economic Activity	Violence	Coca cultivation
Post 2012	-8.13 *	-46.48 ***	-10.17 ***
	(4.64)	(4.34)	(2.24)
FARC X Post 2012	7.70 *	-4.52	3.33
	(4.64)	(4.34)	(2.24)
FARC/ELN X Post 2012	12.97 *	-4.23	1.93
	(7.57)	(5.35)	(2.17)
Post 2012 X Presence 2000-2012	3.28	-22.45 ***	-4.17
	(3.49)	(4.65)	(2.59)
FARC X Post 2012 X Presence 2000-2012	6.86 *	-15.53 ***	4.52
	(3.79)	(4.02)	(4.09)
FARC/ELN X Post 2012 X Presence 2000-2012	-7.82	-16.29 ***	22.17 **
	(5.76)	(6.03)	(9.23)
Observations	366	2013	2013

Source: Author's calculations

Notes: The unit of observation is the municipality-year. The sample is restricted to municipalities that had reports of Presence 2000-2012 of at least one armed group. All specifications include municipality and department-by-year fixed effects. Standard errors clustered at the municipal level are presented in parenthesis. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Second, we explore another source of heterogeneity by performing another triple difference estimation that accounts for initial levels of coca cultivation and mining activity. Both activities have been identified as funding sources to armed groups (Rettberg and Ortiz-Riomalo, 2016).

Table 1.6. Heterogeneous effects by baseline levels of coca cultivation and mining activity.

	Economic activity		Violence		Coca cultivation	
	(1)	(2)	(3)	(4)	(5)	(6)
Post 2012	-3.26 ***	-2.72 ***	6.34	-27.39 **	-27.83 ***	-10.87 ***
	(0.84)	(0.90)	(7.83)	(11.29)	(2.10)	(3.85)
FARC X Post 2012	1.17	1.41	-6.98	-10.61	-0.54	4.03
	(0.84)	(0.90)	(8.76)	(11.29)	(0.66)	(3.85)
FARC/ELN X Post 2012	1.67 *	1.50	-20.87	-25.33 *	-3.14	14.03 **
	(1.00)	(1.02)	(13.21)	(14.18)	(2.14)	(6.89)
Post 2012 X Baseline coca cultivation	0.04		-3.04 ***		-0.12 ***	
(ha)	(0.04)		(0.69)		(0.04)	
FARC X Post 2012 X Baseline coca	0.02		0.01		1.86 ***	
cultivation (ha)	(0.05)		(0.68)		(0.18)	
FARC/ELN X Post 2012 X Baseline	-0.15 **		2.40 **		2.93 ***	
coca cultivation (ha)	(0.07)		(1.12)		(0.96)	
Post 2012 X Baseline mining revenues		0.34 **		-2.19		0.56
(COP 1000000000)		(0.17)		(2.71)		(0.55)
FARC X Post 2012 X Baseline mining		0.11		-0.79		0.23
revenues (COP 1000000000)		(0.49)		(3.26)		(0.80)
FARC/ELN X Post 2012 X Baseline		-0.38 *		3.58		-2.02 **
mining revenues (COP 1000000000)		(0.20)		(3.89)		(0.91)
Observations	366	366	2013	2013	2013	2013

Source: Author's calculations

Notes: The unit of observation is the municipality-year. The sample is restricted to municipalities that had reports of presence of at least one armed group. All specifications include municipality and department-by-year fixed effects. Standard errors clustered at the municipal level are presented in parenthesis. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

The results in Table 1.6 show that higher initial levels of coca cultivation are linked to higher levels of coca production in the period studied in sole FARC and FARC/ELN municipalities, as well as less economic activity and more violence in FARC/ELN municipalities .These characteristics throw a light onto the dynamics of armed group involvement in illicit markets: the association with areas of proven coca productivity suggests that armed groups invested heavily in the control of these strategic areas and were unwilling to part from them and risk jeopardizing one of their main sources of revenue. After demobilization, ELN seized the market share left by FARC and increasing production in those areas where coca crops were already highly productive.

Similarly, higher initial levels of mining activity are linked to less economic activity and less coca cultivation in FARC/ELN municipalities. No analogous effect was observed in sole FARC municipalities. The smaller increase in economic activity is in line with previous findings that economic activity is suppressed in areas of partial conflict resolution and is exacerbated by large illegal activities. Interestingly, the negative coefficient on the triple interaction term exploring the heterogeneous effects of initial levels of mining activity municipalities in FARC/ELN municipalities is negative. This implies that coca cultivation decreased in these areas once FARC demobilized potentially suggesting that there is a substitution effect between coca cultivation and mining.

1.4.5 Robustness checks

I conduct a set of ancillary estimations to validate the robustness of the estimations presented in the previous subsections. First, we consider the possibility that the difference-in-difference estimation is capturing a different underlying trend than the one claimed in this chapter. For instance, it is possible that, instead of a change in public order conditions in FARC municipalities compared to all other conflict municipalities (of which ELN municipalities is the representative group), there is a change solely in ELN municipalities, which, when compared to FARC municipalities, might suggest an improvement in the public order conditions of the latter, when in fact there is none.

To test this hypothesis, we conduct a placebo test in which We assign fake treatment status to a set of municipalities where there have been public order issues in the past, but which have not had FARC presence. We select the groups where the right-wing paramilitary groups were present, and perform the same estimations proposed in equation (1.1) evaluating the changes in intensity of violence, economic activity, and coca cultivation. Under the assumption that public order conditions did not change in either ELN or paramilitary municipalities, the expectation is for the coefficient on the (fake) treatment to be insignificant. This expectation is validated through the results presented in table 1.7:

Table 1.7. Placebo with fake assignment into treatment

	Dependent variable:		
	Number of violent incidents	Economic activity	Coca cultivation
	(1)	(2)	(3)
POST	4.14	6.14	-60.06
	(199.43)	(4.35)	(337.18)
POST x Fake treatment	-80.81	-4.67	507.28
	(190.73)	(3.89)	(319.2)
Observations	378	378	378

Source: Author's calculations

Notes: The unit of observation is the municipality-year. All specifications include municipality and department-by-year fixed effects. Standard errors clustered at the municipal level are presented in parenthesis. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Second, we consider the possibility that the changes in public order conditions in FARC municipalities, although significantly different from those in ELN municipalities, are unrelated to the CRP. For instance, the possibility that a large enough number of FARC municipalities had able Governments in that period that, on top of improving the outcomes studied in this chapter, improved other security indicators. To test this hypothesis, we perform an analogous estimation to the one presented in equation (1.1) yet using a security indicator that should not be affected by a CRP with FARC: house robbery. If security and public order conditions improved across the board, regardless of whether FARC engaged in them or not, a decrease in house robbery is expected as well. A negative and significant coefficient on house robbery would support the hypothesis that the change in public order conditions in FARC municipalities is unrelated to the CRP with the guerrilla. The results present in table 1.8 reject this hypothesis:

Table 1.8. Robustness check. The Colombian CRP and house robbery.

	Dependent variable:
	Number house robberies
	(1)
POST	$-9.52x10^{-3}$
	(3.34)
POST x FARC	6.80
	(881.38)
POST x FARC_ELN	5.33
	(813.54)
Observations	488

Source: Author's calculations

Notes: The unit of observation is the municipality-year. The sample is restricted to municipalities that had reports of presence of at least one armed group. The specification includes municipality and department-by-year fixed effects. Standard errors clustered at the municipal level are presented in parenthesis. *** p < 0.01; ** p < 0.05; * p < 0.1.

Third, we consider the possibility that there is a geographic component driving the results. In all but the southern region (Andes-Amazon-Orinoquia) region, armed group presence is interspersed. Because of this cluster, we ask ourselves if maybe the effects We am finding are driven by a geographically-related (and conflict-unrelated) situation happening in this cluster, for instance, the expansion of the agricultural border in the Amazon. To test this, we exclude the municipalities in this cluster and re-estimate the baseline models. The results are presented in Table 1.9.

Table 1.9. Robustness check. Excluding municipalities in the Andes-Amazon-Orinoquia region.

	Economics activity	Violence	Coca cultivation
POST	-9.79 **	-26.91 ***	-3.94
	(4.63)	(4.50)	(3.26)
POST X FARC	9.32 **	-6.09	3.94
	(4.63)	(4.50)	(3.26)
POST X FARC/ELN	9.56	-9.32 *	11.23 **
	(6.19)	(5.55)	(5.44)
Observations	288	1627	1628
Department by time fixed effects	YES	YES	YES
Region by time fixed effects	YES	YES	YES

Source: Author's calculations

Notes: The unit of observation is the municipality-year. The sample is restricted to municipalities that had reports of presence of at least one armed group. All specifications include municipality and department-by-year fixed effects. Standard errors clustered at the municipal level are presented in parenthesis. *** p < 0.01; ** p < 0.05; * p < 0.1.

The fact that the results are robust to this exclusion means that the effect is not driven by any geographically-related effect in the southern region.

Finally, we estimate the baseline regressions using the geographic distribution of armed group presence reported by the 2016 electoral risk map. The results presented in Table 1.10 show that the results are robust to the use of either electoral risk map, strengthening the claim that even minor changes in armed group distribution do not influence the significance of the results.

Table 1.10. Robustness check. Baseline estimations using the 2016 electoral risk map.

	Economic activity	Violence	Coca cultivation
	(1)	(2)	(3)
POST	-1.68	2.91	0.17
	(1.20)	(2.11)	(1.19)
POST X FARC	6.60 *	-18.30 **	1.31
	(4.02)	(7.53)	(2.09)
POST X FARC/ELN	1.11	-17.06 ***	6.63 *
	(2.40)	(5.98)	(2.77)
Observations	366	358	366
Department by time fixed effects	YES	YES	YES
Region by time fixed effects	YES	YES	YES

Source: Author's calculations

Notes: The unit of observation is the municipality-year. The sample is restricted to municipalities that had reports of presence of at least one armed group. All specifications include municipality and department-by-time fixed effects. Standard errors clustered at the municipal level are presented in parenthesis. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

1.5 Conclusions

Governments in developing countries have reasons to believe that peace agreements can bring a much-needed economic boost to war-stricken areas. The literature on the peace dividend unequivocally points to improved economic conditions after temporary or permanent peace agreements (Colino *2012*; Besley and Mueller *2012*), linking the decrease in violence to a reduced perception of uncertainty that prompts more economic activity. This believe has incentivized several Governments, including the Colombian Government, to seek peace agreements with however many armed groups are willing to undertake conflict resolution processes.

Recent evidence of negative outcomes in multilateral conflicts where Governments negotiated peace with a subset of warring factions, raised questions about the seemingly straightforward path to reaping the benefits of peace in this context. In particular, recent studies on the Colombian conflict found that deforestation rates (Prem, Saavedra, and Vargas *2020*) and murder of social leaders (De-Arteaga and Boecking *2019 and Prem et al, 2018*) surged after the signature of the peace agreement. Although there is compelling evidence that these negative outcomes relate to the failure of the Government to fill the void left by the demobilizing group, it is still a challenge to reconcile the seemingly contradictory evidence provided by these two streams of literature.

This chapter builds a bridge between these two camps by exploring the difference between bilateral and multilateral conflicts. We leverage the unique setting of the Colombian conflict - in which the State was simultaneously involved in bilateral and multilateral contests with two guerrillas: The Revolutionary Armed Forces of Colombia (FARC) and the national Liberation Army (ELN) - to evaluate the differential impact of the demobilization of one armed group (FARC) on the economic activity and coca leaf cultivation at the municipal level. The evidence supports the existence of a peace dividend in areas where the State engaged in a bilateral conflict with FARC in line with the findings of Colino (*2012*) and Besley and Mueller (*2012*), and negative outcomes when it was engaged in a multilateral contest in which ELN outlived FARC. This suggests that partial conflict resolution processes can have unintended consequences if the situation with the remaining armed groups is not addressed carefully. Particularly, governments engaged in multilateral conflicts might not reap a peace dividend and must be ready to fill in the void left by the demobilizing armed group to avoid potential negative outcomes.

1.6 Chapter 1 References

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CHAPTER 2

TECHNOLOGY DIFFUSION WITHIN FAMILIES: EXPERIMENTAL EVIDENCE FROM NICARAGUA

With Mary-Paula Arends-Kuenning and Anina Hewey

Abstract: Farmer adoption of new agricultural technologies requires reliable and persuasive information as well as clarity regarding the technology's suitability to local conditions. Often, these standards are not met in developing countries due to the scarcity of local research facilities and a sparse and over-burdened network of extension agents. Different forms of social learning have been explored to act as complements to conventional extension services. This chapter explores a new possibility: vocational training to high school students. We conduct a randomized control trial in nine communities in rural Nicaragua and evaluate changes in the knowledge of agricultural technologies, access to credit markets, and technology adoption for parents and students. Our results show improvements in knowledge-based outcomes for students and parents, and increased access to credit markets and adoption of agricultural technologies by parents. Given the increase in schooling across developing countries, our results suggest that programs designed around within-family information diffusion can complement more conventional forms of agricultural extension.

2.1 Introduction

Farmers' adoption of new agricultural technologies is a risky endeavor that requires reliable and persuasive information, clarity about the technology's suitability to local conditions, and careful instruction to be successful (BenYishay and Mobarak *2019*). Often, these standards are not met in developing countries due to the scarcity of local research facilities where these technologies can be tested and the scarcity of agricultural extension services that transfer those technologies to farmers. Moreover, the imperfections of credit markets, insurance markets, land rights, output markets, and limited literacy are also significant deterrents of technology adoption in poor rural communities (Jack *2013*; Mittal and Kumar *2000*). This results in chronically low adoption rates of technologies that could significantly improve the quality of life of farmers across the developing world (Birkhaeuser, Evenson, and Feder *1991*).

A stream of literature has focused on ways to cost-efficiently improve technology adoption by leveraging different channels of social learning, which have been shown to match (Krishnan and Patnam 2014) and even outperform (Vasilaky and Leonard 2018) traditional extension services. The first attempts focused on "passive" forms of social learning in which farmers are assumed to costlessly observe the technology being applied by their social network and make the decision to adopt based on the updated expected profitability of the technology (Munshi 2004; Bandiera and Rasul 2006). More recent research explored hybrid arrangements in which trained extension agents (EAs) create a network of farmers who are expected to learn from them and transmit this knowledge to the farmers in their own network (Niu and Ragasa 2018; BenYishay and Mobarak 2019; Shikuku 2019).

The training of farmers close to the targeted population as promoters increases access to technology on the extensive and intensive margins, at the potential cost of accuracy in the information as it is passed through the links (Niu and Ragasa 2018). On the extensive margin, it allows the sparsely populated network of EAs to expand and reach previously unserved farmers through the trained promoters. On the intensive margin, it increases the exposure of farmers to the technology, because the promoter is a member of the community with more frequent interactions with the community (Kondylis, Mueller, and Zhu 2014). However, these extension models are not free of complications; for instance, inadequate selection of promoters can hinder adoption if the target population does not have confidence in them (Hunecke et al. 2017; BenYishay and Mobarak 2019). Furthermore, it implies costly efforts from farmers (promoters and others) as they have to interrupt agricultural activities to be trained, which can limit the effectiveness of these extension models.

Our study explores whether We can overcome these limitations by leveraging a different channel of information diffusion: high school students undergoing vocational training. In essence, this model borrows from the public health literature, whose findings suggest that this channel is an effective way to transmit information from public health agents to parents (Magalhães et al. 2009). In line with the farmer-promoter models, this model maximizes exposure on the extensive and intensive margins, yet reduces the costs of training because farmers do not have to interrupt their activities to be trained. As such, the question is not whether the high school vocational training model can replace either conventional extension models or the recently developed social learning models, but whether it can complement either one of those strategies to bolster adoption.

In order to test the validity of this hypothesis, we conduct a randomized control trial (RCT) in the setting of the Tutorial Learning System (SAT) (Stifel 1982) implemented by the Fabretto Foundation in Northern Nicaragua. This program offers vocational training to high school students in poor rural communities on topics related to agricultural production. Aside from increasing the human capital of students, it also encourages them to remain in their communities, either through their insertion in the local labor market or through ventures of their own. We follow the first cohort of the SAT program in the Nueva Segovia department in the treatment group and a suitable control group that were chosen randomly from a pool of schools suggested to Fabretto by the Ministry of Education of Nicaragua.

For each group we monitor changes in key outcomes of both parents and students that fall into three broad categories: knowledge of the material covered, adoption of technologies that relate to that material, and income and access to credit markets. These outcomes capture the comprehensive nature of the SAT intervention, through which students are trained in relevant agricultural and accounting practices and encouraged to share their knowledge with their families. If the message was reliably transmitted to the household decision-maker, the expectation is that the adoption of those technologies covered will increase. Foreseeing that the adoption of technology might be constrained by availability of capital, Fabretto also offered a loan program to SAT participants and opened up market opportunities to the affiliated farmers through their commercial branch. This holistic approach is an innovation of its own, and therefore worth studying.

Our results show that the aforementioned intervention pipeline has had positive effects on knowledge-based outcomes, adoption of technology, and access to credit. Technical and accounting test scores increased for students and parents in the treatment group with respect to the control group; however, the results point to a larger increase in students' scores compared to parents, suggesting information loss as knowledge passes through this link. This result is in line with the findings of Niu and Ragasa (*2018*), in which information loss occurs as knowledge is transferred from promoters to farmers. Similarly, the SAT intervention increased parents' access to credit for treated students and parents, respectively compared to the control group. Finally, we observe that adoption of a new agricultural technology among parents (decision makers) was higher in the treatment group than in the control group, and that the new technologies adopted match those covered in the SAT module.

The contribution of the current chapter is framed in the social learning and technology diffusion literature (Niu and Ragasa *2018*; BenYishay and Mobarak *2019*; Shikuku *2019*). Instead of asking whether we can find more a more efficient extension model, we posit a complementary channel of technology diffusion and test whether it improves the same outcomes targeted by more conventional technology diffusion channels. Given the increase in schooling across developing countries, our positive results suggest promising returns to programs designed around within-family technology diffusion that can make adoption more effective and efficient. In the case of remote areas where school systems precede extension systems, the scheme proposed here can work as a primer for technology diffusion over which more refined extension services can be built. Furthermore, these results highlight the importance of comprehensive instruction programs that, in addition to delivering useful information, bolster technology adoption by alleviating illiteracy and economic constraints.

This chapter also provides meaningful insights for Nicaragua, the second poorest country in the western hemisphere[2] with a large vulnerable rural population (Carte et al. 2019). Providing education, either traditional or vocational, has been a challenge for the Nicaraguan Government (Lindenberg et al. 2016; Schiller et al. 2020), and the design and implementation of cost-effective technology diffusion models, such as the one presented here, can help alleviate poverty in underserved rural communities.

The outline of the chapter is as follows: Section 2.2 of this chapter describes the background concerning the SAT program and its implementation in rural Nicaragua. Section 2.3 describes the data set and empirical strategy. Section 2.4 presents the results for the transfer of knowledge from SATec tutors to students and from students to parents (Subsection 2.4.1), its impact on technology adoption decisions and access to credit markets (Subsection 2.4.2), and the heterogeneous treatment effects with respect to student gender and parents landholding (Subsection 2.4.3). Section 2.5 offers conclusions and a discussion on policy implications of the study and states the limitations of this study.

2.2 Background: Tutorial Learning System (SAT)

SAT was created in 1974 by the Foundation for the Application and Teaching of Science (FUNDAEC), for rural communities in Colombia (Stifel 1982). Later, it was implemented in Honduras, Guatemala (active until 2005), Ecuador, Brazil, and Nicaragua. A total of more than 300,000 students have benefited from it (Kwauk and Perlman Robinson 2016). SAT is an alternative rural education program that provides access to secondary, technical, and vocational education to rural youth, their families, and members of their communities. At the same time, it prepares them to start new entrepreneurial business ventures, continue their agricultural activities with improved climate adaptation measures and increased productivity, or pursue higher education.

Since 2007, Fabretto has implemented the Tutorial Learning System (SAT) in Nicaragua, serving more than 1,500 rural young people from over 50 communities and training 40 tutors in this methodology. A total of over 1,000 young people have completed their middle school education, and over 400 young people have completed five years of high school and obtained their diplomas. The young participants are usually selected through information and coordination meetings with community leaders and parents. For the current study, they

[2] https://data.worldbank.org/indicator/NY.GDP.PCAP.CD

were selected randomly. To enroll, students only are required to present documents verifying that they have completed primary education and written expressions of their interest in taking part in the program. Enrollment is open to men and women, regardless of their social, economic, ethnic, religious, or other status.

Several international organizations, including the Brookings Institution through its "Millions Learning" initiative, have recognized the SAT as an effective model that could be explored further because of its extended reach and adaptation to various countries, its proven impact, and its cost-effectiveness compared with other alternative secondary education programs (Marshall et al. *2014*). In 2012, the University of Pennsylvania evaluated the SAT in Nicaragua and found that it has a 100% graduation rate for students who reach the last year, and that 80% of SAT's graduates work, start their own business, or continue studying. It also found that 67% of students who took the college entrance exam were admitted. In addition, the study showed that the SAT stands out as a method to provide education about values, morals, self-esteem, respect, responsibility, and other influential positive character traits to students, teachers, families, and field staff (University of Pennsylvania Graduate School of Education *2012*). Additional studies have highlighted its potential to promote community unity, citizen participation, environmental awareness, public health, community safety, and gender equity (Murphy-Graham *2008*, *2012*; Honeyman *2010*).

2.2.1 Innovations to SAT in Nicaragua

In 2016, Fabretto began to introduce innovations to SAT, drawing from its experiences with the program in rural communities and aligned with global education trends and national public policy. With support from donors like the IDB and Tinker Foundation, Fabretto is executing an ambitious project that intends to increase SAT's sustainability and strengthen its focus on youth entrepreneurship and "learning by earning," while contributing to the development of resilience in rural families. The SAT methodology is currently implemented through two programs: (1) the traditional 5-year rural high school program, leading to a high school diploma certified by MINED, and (2) technical training courses certified by the National Technological Institute (INATEC).

In response to the need for a more flexible training modality, Fabretto adjusted the traditional SAT program to include the technical training courses, called "SATec." SATec provides 6- to 9-month technical courses in topics like sustainable farm management and agricultural skills, while preserving the personal development, service learning, and soft skills development aspects of SAT, as well as the learning-by-doing methodology. SATec courses are designed in response to community interests and potential market opportunities. For example, in the northern highlands, Fabretto offers SATec courses specifically designed to help youth develop the skills needed to strengthen coffee production on the family farm and the entrepreneurial and business knowledge to link to markets to sell high quality coffee. In addition to developing technical skills and practical, hands-on experience with production, youth are also exposed to the SAT methodology and curriculum to foster strong values, a spirit of service and entrepreneurship.

2.2.2 SATec in Nueva Segovia Department

Fabretto implemented "hybrid SATec" model as an innovation aligned with the national secondary education strategy, which focuses on universalizing basic secondary education and technical-vocational training for young people and adults. In order to achieve broader coverage in rural areas, where geographic dispersion is an issue, the Government of Nicaragua implements a Distance Rural Education program. Students in this program only attend classes for one day during the weekend (generally on Saturday), and work or receive vocational training during the week. Fabretto recognized the opportunity of working with young people who choose the Distance Rural Education program and offered them technical-vocational training. Five vocational modules were endorsed by INATEC: Comprehensive Agricultural Production Management (MIPA), Small Ruminant Production, Production Processes for Small Agricultural Units, Sustainable Rural Production systems, and Artisanal Food Production. We study the first cohort that received the MIPA module.

The department of Nueva Segovia was selected for the expansion of the program. For the period of implementation of the project - funded by IDB - nine communities were selected for treatment under a roll-out scheme. Three schools, located in the communities of El Jobo, Estancia and Macaralí, were randomly chosen to receive the MIPA module starting April of 2018, the remaining six communities were surveyed, but did not receive the program until November of 2018 or July 2019. This configuration of treatment allowed us to compared the three communities that received the SATec program to a suitable control group comprising the remaining six communities.

2.3 Data and empirical strategy

2.3.1 Data

This research is based on two main sources of data: a knowledge-based test, and an individual survey administered to students and parents of the selected schools. Three treatment and six control schools were randomly selected from a pool of suitable schools within the Department of Nueva Segovia provided by the Ministry of Education of Nicaragua (MinEd). Although the program was initially offered to the three treatment communities during this study, the remaining six communities received the program after the end of the evaluation. Within each school, a call for expression of interest was made to all enrolled high school students (last two years of schooling). 25 students and their parents were selected randomly from the pool of interested individuals to be part of the study, conditional on giving their consent to participate under the terms of the protocol #19560 of the University of Illinois' Institutional Review Board. A first round was conducted in March of 2019 prior to the start of the first SAT course in the treatment municipalities, and the follow up round was conducted in October of 2019 when the six-month SAT course was over.

The knowledge-based test was constructed based on the material used in the first module of SATec titled Comprehensive Agricultural Production Management (MIPA). The test is split into two sections: technical knowledge, and accounting knowledge. For the technical knowledge section, we selected four dimensions that comprise the key technology-related concepts that were taught during the MIPA module, in consultation with the Fabretto field team. Those four dimensions included questions about i) planting distance and density of corn, ii) preparation of organic fertilizers used in corn, iii) use of synthetic fertilizers in corn, and iv) forecasting corn yields. The accounting knowledge section included an accounting exercise using farm-related transactions analogous to the ones covered in the MIPA module. Each section was graded separately with maximum scores of 26 and 10, respectively.

The questionnaire for the individual surveys of students and parents included modules on household characteristics, assets and income, access to extension services and technology adoption, access to financial markets, and social networks. Particularly relevant for the variables used as dependent variables were the questions about i) access to financial products in the past 6 months (and the amounts), and ii) adoption of a new technology in the past 6 months and which technology was adopted. To produce a credible assessment, we included questions within these broad categories that would act as counterfactuals in the sense that they covered outcomes that were not targeted by SAT (see Appendix B.3). For instance, we asked about adoption of technologies in livestock, marketing, and natural resource management, which were not part of the SAT module. Similarly, we asked about access to savings products, also not a part of Fabretto's holistic program. Significantly larger effects on either of these outcomes would raise a red flag about the quality of the data and the results. Table 2.1 presents the baseline summary statistics.

Table 2.1. Baseline summary statistics.

	Students			Parents		
	Treatment	Control	P-value	Treatment	Control	P-value
Economic attributes						
Access to credit	0.027	0.025	0.94	0.286	0.308	0.843
Credit amount	68.493	20	0.499	47863.158	9937.5	0.253
Access to savings	0.082	0.025	0.165			
Savings amount	376.027	250	0.707			
Income				4788.819	3966.542	0.602
Farmland area				5.387	4.867	0.664
Technology diffusion						
Adoption of technology: Agriculture	0.151	0.225	0.35	0.094	0.08	0.835
Adoption of technology: Livestock	0.027	0.075	0.309	0.037	0.037	1
Adoption of technology: Marketing	0.041	0.05	0.833	0.074	0.111	0.606
Adoption of technology: Natural resources	0.219	0.2	0.812	0.164	0.037	0.046
Knowledge						
MIPA technical knowledge score	10.184	10.8	0.839	8.28	10.6	0.219
MIPA accounting score	2.872	2.429	0.499	2.643	2.571	0.896
Household characteristics and parent's attributes						
Household size	4.301	4.4	0.792			
Male-headed household	0.575	0.7	0.187			
Age of parent				40.548	41.533	0.626
Educational level of parent				1.581	1.767	0.65
Observations	40	73		30	62	

Source: Author´s calculations.

I perform a balance test between our treatment and control municipalities to validate the randomization strategy. The last column presents p-values from t-tests for differences in these means. Both groups are statistically identical at the mean, but for the exception of the adoption of natural resource management technologies in parents. We believe that this minor imbalance does not compromise the success of our randomization.

A source of concern with our sample is the attrition rate of nearly 50%. Prominent among the reasons for such a high rate was the wave of civil unrest that engulfed the country starting in 2018, which widely overlapped with our study. The fact that this was an exogenous shock, compounded with the fact that the attrition rates were similar in the treatment and control groups, leads us to believe that attrition bias is not an issue. To test this belief, we regress a binary variable that takes value of 0 if the individual wasn't interviewed in the follow-up and 1 otherwise, on the type of municipality (treatment or control) and the observed variables. Our results show that the type of group (treatment or control) has no relation with missed follow-up interviews. Similarly, the test of joint significance fails to reject the null hypothesis that all coefficients are equal to zero (p-value = 0.2267). Because the attrition showed no pattern by observable characteristics, we assume this is also true for unobservable characteristics.

In general, technology adoption is low in our sample, regardless of the area. The largest adoption rates are seen in natural resource management, with as much as 21.9% of students in the treatment group having adopted one such technology in the past 6 months. We believe this result is driven by the widespread recycling campaigns such as the "Nicaragua Toda Dulce" (Nicaragua All Sweet)[3]. Similar rates of adoption are seen for agricultural technologies in students (15.1% and 22.5% for treatment and control groups respectively), yet much lower rates for parents (9.4% and 8%). Unsurprisingly, access to credit is lower for students than parents, the latter having had access to loans in the past 6 months in about 30% of the cases. Finally, scores for MIPA technical and accounting knowledge are low and very similar across all groups averaging about 10/26 and 2.5/10, respectively.

2.3.2 Empirical strategy

Our baseline specification is a simple comparison of means between treated and control individuals:

$$y_{i,t=1} = \alpha + \beta T_i + \gamma y_{i,t=0} + \rho X_{i,t=0} + \varepsilon_{it=1}, \tag{2.1}$$

where $y_{i,t=1}$ is the outcome (access to credit, adoption of agricultural technology, agricultural knowledge score, or accounting knowledge score) for individual i at time t = 1. T_i is a binary variable that takes value of 1 if the individual was part of a community that was part of the SAT program, and 0 otherwise. We further control for baseline outcomes, $y_{i,t=0}$ and a set of individual and household-level characteristics, X_{it}, which include the age, sex, educational level, household size, and a dichotomous variable for whether the head of the household is male. The coefficient β captures the average treatment effect (ATE) of exposure to the first module of the SAT program. Standard errors are clustered at the school level to account for possible correlation of the error terms.

In addition, we estimate a difference-in-difference specification considering the possibility that, although our balance test suggests that the randomization was performed correctly, our samples differ in some characteristics that we are unable to observe. While these unobserved differences should not be correlated with the selection into treatment and control, they could still increase the variance of the error term, so that the difference-in-differences approach allows us to increase the precision of our estimates.

[3] https://www.el19digital.com/articulos/ver/titulo:104251-nicaragua-presenta-plan-de-trabajo-y-perspectivas-de-turismo-a-ong-nacionales-e-internacionales. *Also see industry-led initiatives by Claro Mobile* (https://www.elnuevodiario.com.ni/economia/empresas/490697-claro-ambiente-basura-reciclaje/*), and Raleigh International* (https://raleighnicaragua.ong/sobre-raleigh/sinplastico/campana/*)*

$$y_{it} = \alpha + \beta_1 T_i + \beta_2 t_t + \beta_3 T_i \cdot t_t + v_s + \varepsilon_{it}, \quad (2)$$

Where the coefficient of interest, β_3, captures the differential impact of the SAT on the outcomes of interest. The expectation is for the direction and significance of the coefficients of both estimations to match, further backing the claim that the randomization was successful and that our estimates are robust. Standard errors are clustered at the school-level.

2.4 Results

2.4.1 Knowledge transfer

As explained in section 2.3, we identify the causal effect of the SATec program on the outcome variables using data from a randomized control trial of 113 students and their respective (92) parents in nine randomly selected rural schools, which we observed at a baseline in March 2019 and an endline in October 2019. Figure 2.1 shows the changes in the test scores for students in both areas of knowledge. The left panel shows that changes in the accounting knowledge scores indicate a downward trend, which is more pronounced for control municipalities. The right panel plots the changes in scores for the agricultural knowledge test, with a different trend: both groups experienced increases in their scores, however the increase was more pronounced in the treatment group, for whom the average score increased by almost ten points compared to a more modest increase of three points in the control group.

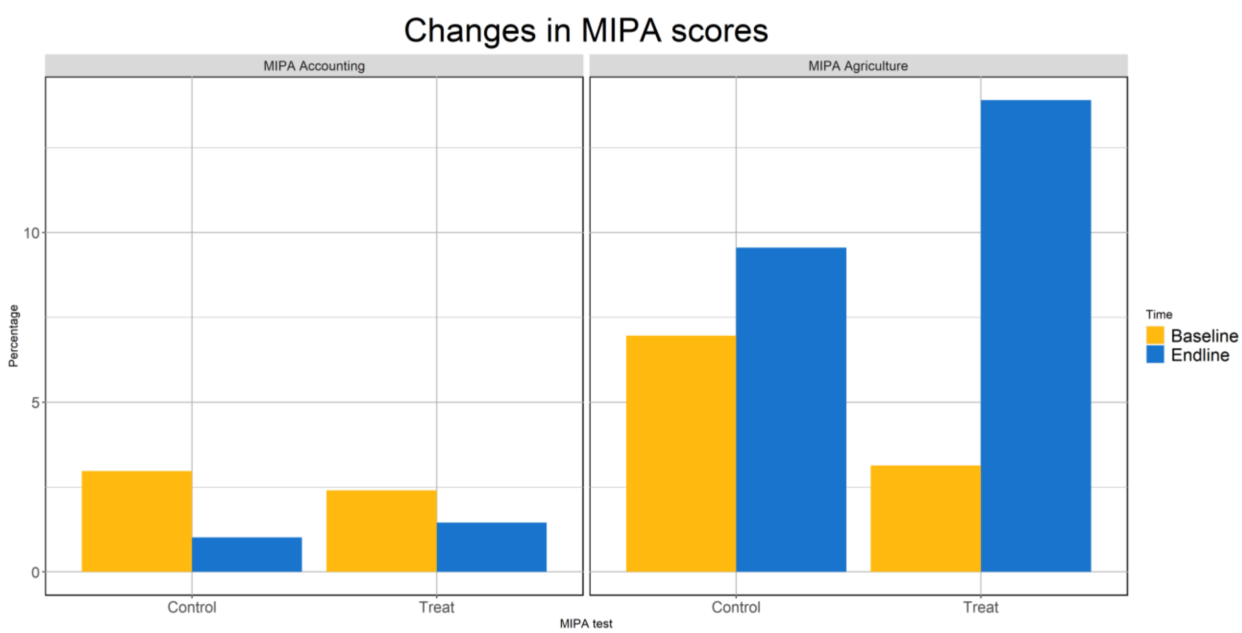

Figure 2.1. Changes in test scores for accounting knowledge (left) and agricultural knowledge (right): students

A similar situation is seen in Figure 2.2 for the case of parents: a decrease in the accounting scores, which is more acute for the control group and an increase in the scores of the agricultural knowledge test across both groups, but more pronounced in the treatment group.

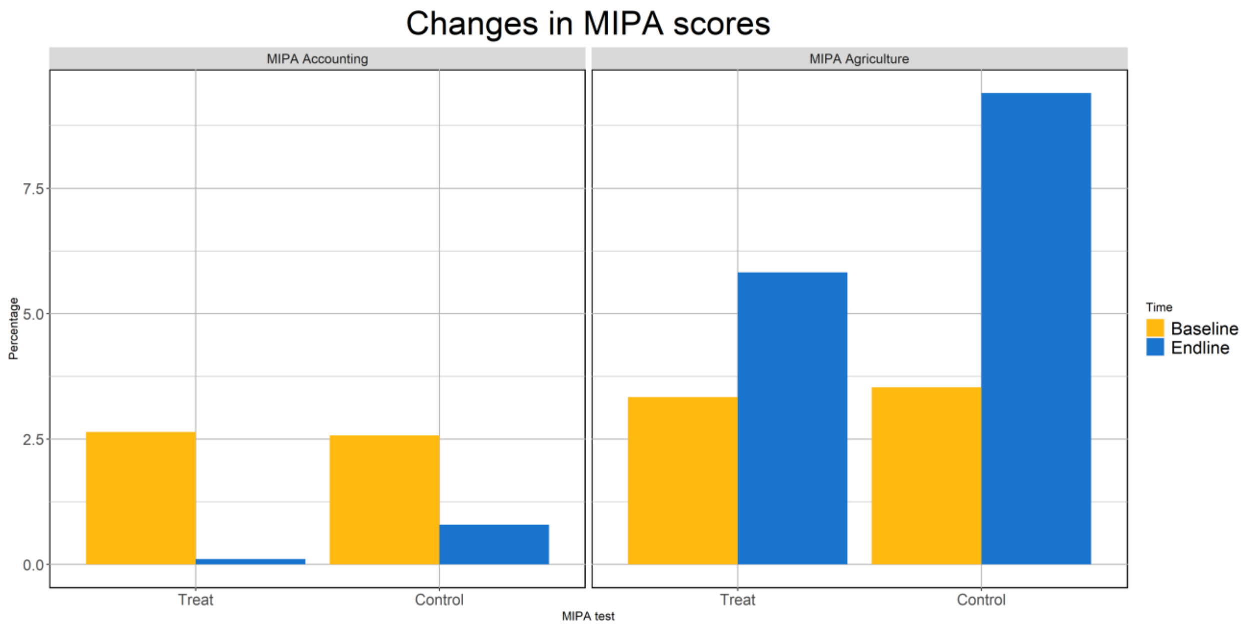

Figure 2.2. Changes in test scores for accounting knowledge (left) and agricultural knowledge (right): parents.

Although we cannot empirically identify the cause for the decrease in accounting scores, the consistency of this trend suggests an underlying mechanism with impact across both groups. A possible explanation can be the selective attention model (Schwartzstein *2014*; Niu and Ragasa *2018*) in which farmers choose to attend to limited dimensions of knowledge. we believe that in the second exposure of farmers to the agricultural and accounting knowledge test, they singled out the agricultural section as that with more potential for improvement, and considered the accounting section too complex and time draining to devote too much effort. Even so, the fact that the dip in scores is smaller in treatment municipalities suggests a positive impact of the SATec program that could have acted as a buffer against knowledge loss. The consistent increases in agricultural knowledge scores in treatment municipalities, contrasted to smaller gains or even decreases in control municipalities also point to a positive effect of the SATec program, suggesting the agricultural information flowed from tutors to students and from students to parents. This claim is backed by the empirical results of estimating equations (2.1) and (2.2) on the MIPA scores outcomes:

Table 2.2. Changes in MIPA scores for students and parents. Comparison of means and difference-in-difference estimates.

	Students		Parents	
	MIPA technical knowledge score	MIPA accounting knowledge score	MIPA technical knowledge score	MIPA accounting knowledge score
A. Comparison of means				
Treat	5.24 **	0.20	2.53 **	0.40 **
	(2.48)	(0.32)	(1.15)	(0.18)
Observations	226	226	184	184
B. Difference-in-differences				
Treat x time	7.19 ***	1.12 ***	3.84 **	0.77 **
	(2.32)	(0.38)	(1.94)	(0.38)
Treat	0.98	-0.16	-0.52	-0.56 *
	(2.45)	(0.29)	(2.45)	(0.32)
Time	-0.93	-0.40	2.72 ***	-0.38 *
	(2.52)	(0.44)	(1.01)	(0.20)
Observations	226	226	184	184

Source: Authors' calculations from surveys and tests. Notes: Each column and panel correspond to separate OLS regressions that control for individual- and household level attributes (gender, age, schooling, household size and male-headed household). Standard errors clustered at the school level in parenthesis; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 2.2 presents the comparison of means (panel A) and difference-in-differences (panel B) estimates using the agricultural and accounting scores as outcome variable. The results from either specification are similar with the difference-in-difference estimates displaying lower standard errors, and the additional significance of the ATE on the accounting knowledge score in students. we will use the difference-in-difference results for our discussion, as we believe that the modeling of unobserved characteristics through this specification reduces the variance of the error term and increases the precision of our estimates.

The empirical evidence presented in Table 2.2 points to the suitability of the tutor-student-parent channel for information transfer; however, the results also suggest that there is information loss between students and parents. In the case of agricultural knowledge, students in the treatment group outperformed their control counterparts by 7.19 points (95% confidence interval: [2.631041, 11.7589]), whereas parents of the treatment group had a 3.84-point difference compared to treatment parents (95% confidence interval: [0.008732742, 7.667964]). In the case of accounting knowledge, students in the treatment group outperformed their control counterparts by 1.12 points (95% confidence interval: [0.3642986, 1.867765]), whereas parents in the treatment group outperformed their control counterparts by 0.77 (95% confidence interval: [0.02381303, 1.520775]). The information loss is consistent with previous work on social learning and technology diffusion, which identified selective attention (Niu and Ragasa *2018*) and distrust (Hunecke et al. *2017*; BenYishay and Mobarak *2019*) as potential causes. However, we are careful about the interpretation of these results because we cannot reject that either pair of coefficients is statistically different.

2.4.2 Technology adoption and access to markets

I move on to analyze the effect that the information transfer discussed in the previous subsection had on technology adoption decisions and access to credit markets. Table 2.3 reports the results of employing the empirical strategy outlined in equations (2.1) and (2.2) on the binary outcomes adoption of agricultural technology in the previous six months and access to credit markets in the previous six months. No statistically significant difference was observed for students for either outcome, which can be attributable to the fact that students are not the decision maker in farm-related endeavors and that due to their young age are not suitable recipients of loans.

Table 2.3. Changes in adoption of agricultural technologies and access to credit markets for students and parents. Comparison of means and difference-in-difference estimates.

	Students		Parents	
	Access to credit	Adoption of technology: agriculture	Access to credit	Adoption of technology: agriculture
A. Comparison of means				
Treat	0.09	0.12	-0.01	0.02
	(0.06)	(0.09)	(0.13)	(0.13)
Observations	226	226	184	184
B. Difference-in-differences				
Treat x time	0.08	-0.01	0.26 **	0.19 **
	(0.06)	(0.10)	(0.13)	(0.09)
Treat	0.06	0.34 ***	-0.34 ***	-0.08
	(0.06)	(0.11)	(0.09)	(0.10)
Time	-0.07 *	0.03	-0.16 **	0.01
	(0.04)	(0.10)	(0.07)	(0.04)
Observations	226	226	184	184

Source: Authors' calculations from surveys and tests. Notes: Each column and panel correspond to separate OLS regressions that control for individual- and household level attributes (gender, age, schooling, household size and male-headed household). Standard errors clustered at the school level in parenthesis; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

A different story is true for parents: our difference-in-differences estimates show that the adoption of new agricultural technologies was higher in our treatment group compared to the control group after the implementation of the SATec program. According to our endline survey, these new technologies closely match the topics covered in the MIPA module including, but not restricted to contour planting, planting distance, live barriers, improved seed, seed selection, chemical and organic fertilizers, and pest control. Further evidence of the relationship between Fabretto's SATec program can be seen in panel A of Figure 3, where we plot the frequency of agricultural advice disaggregated by source for the control (left) and treatment (right) groups. It shows that a large share of the positive change in agricultural advice in the treatment group can be traced back to SATec tutors and students.

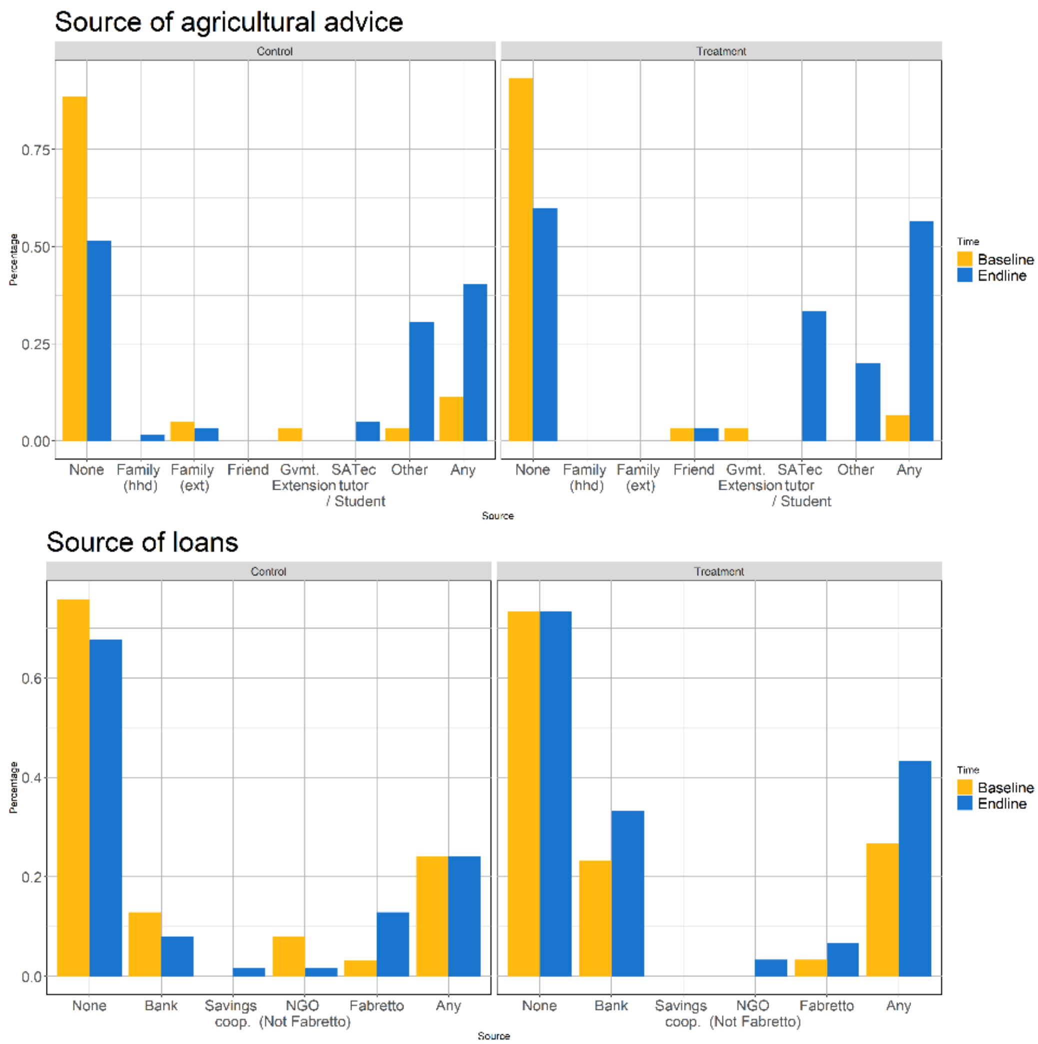

Figure 2.3. Main source of agricultural advice (top) and access to credit markets disaggregated by source (bottom).

Similarly, we observe a positive and statistically significant difference in access to credit markets among parents of the treatment group (Column 4 Table 3) compared to their control counterparts. However, contrary to the case of technology adoption, parents were using credit sources other than those offered by Fabretto, particularly favoring banks (Panel B, Figure 3). This is particularly relevant as Fabretto loans were not uniquely offered to communities undergoing SATec training. Also, the fact that farmers were willing to take loans from outside sources of credit attests to the confidence they derived from their new knowledge and ensuing ventures.

2.4.3 Heterogeneous treatment effects of gender and landholding

Finally, we conduct an analysis of the heterogeneity of the results presented in the previous two subsections focusing on two sources of heterogeneity: the gender of the student and the amount of land that parents have using a triple difference approach. Table 2.4 presents the results of this estimation, with panel A displaying the results of heterogeneity in student gender and heterogeneity in landholding in panel B:

Table 2.4. Heterogeneous effect of SATec by student gender and parent landholding.

	Dependent variable:			
	Access to credit	Adoption of technology: Agriculture	MIPA technical knowledge	MIPA accounting knowledge
A. Heterogeneity in students: gender				
Treat x time	0.07	0.00	9.85 ***	1.90 ***
	(0.08)	(0.14)	(3.23)	(0.49)
Treat x time x female (female = 1)	-0.00	-0.05	-5.36	-1.57 **
	(0.14)	(0.21)	(4.76)	(0.73)
Observations	226	226	226	226
B. Heterogeneity in Parents: landholding				
Treat x time	0.67 ***	0.14	9.98 **	1.01
	(0.22)	(0.21)	(4.37)	(0.81)
Treat x time x low area (<median area = 1)	-0.58 **	0.08	-7.93	-0.35
	(0.26)	(0.23)	(4.84)	(0.88)
Observations	184	184	184	184

Source: Authors' calculations from surveys and tests. Notes: Each column and panel correspond to separate OLS regressions that control for individual- and household level attributes (gender, age, schooling, household size and male-headed household). Standard errors clustered at the school level in parenthesis; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Panel A shows no statistically significant difference in ATE between male and female students in terms of access to credit, adoption of agricultural technology, and agricultural knowledge scores. However, there is a statistically significant difference in accounting knowledge scores. Unfortunately, we do not conduct any qualitative analysis that could help us understand this result better. However, this result could be an indication that the message is not reaching males and females equally and that tutors and Fabretto staff should pay attention to gender discrepancy. Furthermore, it could be evidence of disparity in the selective attention between genders and an interesting question for future research.

Due to the constraint of the sample size, we limit our analysis to a split of our sample between above median and below median size of the farm. Panel B shows a statistically significant difference in the ATE of the SATec program in access to credit markets, with below median farmers being less likely to receive loans over the previous six months. This result would be in line with the expectation that poorer farmers - who have fewer assets to use as collateral - are less likely to receive loans from credit institutions. As the program is expanded in Nicaragua and other countries, the credit constraints of the poorer household should be considered, as lack of access to credit programs among the poorest individuals in the program can curtail adoption of technology and ultimately dampen the success of the program.

2.5 Conclusions

This chapter presents an experimental evaluation of the effect of a vocational training program - Tutorial Learning System (SATec) - on agricultural technology diffusion and adoption in vulnerable rural communities in Northern Nicaragua. We approach the question of its impact through the comprehensive nature of the program, which supersedes the traditional vocational training program objective of improving human capital to offer a more comprehensive scheme that encourages information transfer to farmers and alleviates credit and literacy constraints. Similar SAT programs have been implemented in numerous developing countries including Colombia, Honduras, Guatemala, Ecuador, and Brazil; however, none of these programs have embraced the comprehensive nature of SATec. As such, this study provides novel experimental evidence on the impact of the SATec program in rural communities and its potential to close the technological gap of poor farmers across the developing world.

The results of our analysis indicate two key findings. First, we show that the tutor-student-parent channel is an effective means of information transfer. SATec students improved their knowledge in the accounting and agricultural topics that were taught during the Comprehensive Agricultural Production Management (MIPA) module. Their parents also improved their scores, albeit to a lesser extent. Second, we show that the increased exposure to new technologies through the tutor-student-parent channel led to an increase in adoption of technology and access to credit markets. To the knowledge of the authors, this is the first study to provide empirical evidence of within-family technology diffusion and measurable increases in technology adoption. In line with other forms of social learning, the within-family channel increases exposure to new technologies on the extensive and intensive margins, without entailing the costs of displacement and interruption of activities that are common in the farmer-promoter system.

These findings have significant policy implications for extension programs targeting unserved and underserved rural communities. In the case of the former - and particularly in Latin America, schooling systems often created by the Catholic Church precede many of the other institutions of Government, including extension networks (Gill *2008*). Organizations fostering technology adoption can leverage this channel, which builds on the educational system, and is therefore less taxing in terms of capital and time. In the case of the latter, the channel We posit can act as a complement of established extension systems and reinforce the message delivered by more conventional channels of technology diffusion.

Our study is subject to a number of limitations. First, our study was impacted by the civil unrest that swept through Nicaragua between 2018 and 2020, and the 2020 COVID-19 pandemic. The former was identified as one of the leading causes for the high attrition rate, and smaller than planned sample size. Nevertheless, we show that the significant results we provide here are robust, given their consistency across specifications; however, we might have missed identifying other significant effects due to our diminished predictive power. Regarding the COVID-19 pandemic, it impeded the execution of an additional round of surveys which was designed to test the cumulative effect of exposure to SATec. Therefore, the hypothesis of increasing returns to instruction remains untested and is left for future research. Finally, we lack qualitative data that could enrich the interpretation of the results presented in this chapter.

2.6 Chapter 2 References

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CHAPTER 3

THE EFFECT OF CLIMATE VARIABILITY ON COLOMBIAN COFFEE PRODUCTIVITY: A DYNAMIC PANEL MODEL APPROACH

With Sandy Dallérba

Abstract: Coffee is one of the trademarks of Colombia. Currently, up to a half million Colombian families depend directly on coffee production for their livelihoods. As such, there has been increasing concerns about how coffee productivity will react to changing climate conditions and how coffee growers could adapt their production practices. This chapter is one of the first to estimate the production function of Colombian coffee at the municipal level and to make projections about its future productivity. Using a panel dataset measured across municipalities over 2007-2013, we find that productivity depends on altitude as well as on March temperature and precipitation. We estimate projections based on the 2.6, 4.5, and 6.0 Representative Concentration Pathways derived from Global Circulation Models we find that productivity over 2041-2060is expected to increase by 7.6% on average. However, we find that this forecast varies greatly according to altitude. Indeed, municipalities above median elevation will increase their productivity by 16%, while those below the median will experience an 8.1% decrease in productivity. Our result implies that place-tailored strategies for coffee production in Colombia are required to adapt to changing climate conditions in the future.

3.1 Introduction

Coffee is one of the major crops produced in Colombia, as it is the world's third largest producer of coffee after Brazil and Vietnam. Currently, up to 550,000 families depend directly on coffee production for their livelihoods (Federacion Nacional de Cafeteros de Colombia, 2017). Many more depend on it indirectly. Due to changing climate conditions, there have been increasing concerns about the future quantity and quality of the coffee yield in the decades to come. While a wealth of literature relies on a crop production function framework and panel data to forecast future yields of crops such as corn (Burke and Emerick, 2016), soybeans (Fodor et al.,

2017) and rice (Shrestha et al., 2016), much less work has focused on coffee. The few exceptions include the work of Gay et al. (2006) and Sachs et al. (2015), who conclude that coffee is very sensitive to unpredictable weather. These studies estimated a 2°C increase in temperature and losses in productivity of up to 34% for Mexico and 20% for Brazil, respectively, by 2020. When it comes to Colombia, the findings of Sachs et al. (2015) forecast a 4-24% increase in yields in the scenario where temperatures increase not more than 2°C. However, these results provide us with limited guidance, as the Sachs et al. (2015) study is not peer-reviewed (yet), and Gay et al.'s findings (2006) are based on a specific region within Mexico. Since there are more than 500 municipalities producing coffee in Colombia, one cannot assume that each of them will be affected in the same way. As a result, this chapter builds on the existing literature in order to offer the first estimates and forecasts of the impact of climate variability at the municipal level.

Crop production estimation efforts that rely on longitudinal data, such as the one conducted by Gay et al. (2006), explicitly estimate the effect of varying weather conditions on coffee productivity. However, they face a number of challenges: first, the availability of labor and capital input data is often limited (Barrientos and Castrillón, 2007; Jiménez et al., 2018), and model specification is therefore constrained by the remaining variables. The result is that ensuing models are highly discretionary in their choice of variables and functional form; therefore, they could suffer from an omitted variable bias if the relevant variables are not explicitly modeled (Wooldridge, 2002). Furthermore, the lack of comparable data on coffee production across a large set of locations limits the external validity of the conclusions (Fellmann, 2012).

Yet, the limited availability of socioeconomic data has not been addressed by Maximum Entropy literature (MaxEnt), such as that of Scroth et al. (2009), Bunn et al. (2015) and Magrach and Ghazoul (2015). They model how changing climate conditions affect the location of coffee production by relying on presence-only data. For them, the absence of recorded production in one area indicates it is unsuitable for the cultivation of the crop under study (for an in-depth explanation of MaxEnt algorithms, see Elith et al., 2011). Furthermore, by only considering the relationship between the exogenous weather conditions and productivity, the MaxEnt approach can be applied to a large number of areas. For instance, Bunn et al. (2015) and Magrach and Ghazoul (2015) have each estimated a MaxEnt model on coffee at the global scale and have concluded that the largest future losses will happen in areas located at elevations below 1,000 meters above sea level (henceforth, m.a.s.l), particularly within Brazil and Southeast Asia. Läderach et al. (2017) have estimated similar models at the regional level in Nicaragua, where the suitability for coffee cultivation is expected to decrease in 90% of the current growing areas, by at least 25% in the areas located between 500 and 800 m.a.s.l. A potential shortcoming of MaxEnt models is that, contrary to econometric estimations of crop production functions, they do not explicitly model changes in productivity.

Additionally, the accuracy of their predictions is highly dependent on the quality and availability of past presence-only data; hence, they do not account for the option of cultivating land that has not been yet cultivated for coffee (Elith et al., 2011).

The strengths and shortcomings of both approaches imply a trade-off. For instance, using the MaxEnt method leads to more accurate predictions when socioeconomic data is scarce or unavailable, but the estimated marginal effects of the weather variables on either yield or productivity cannot be readily interpreted (Elith et al., 2011). Inversely, calculating marginal effects in the frame of a crop production function is a common process, but the model selection might be discretionary—as in Gay et al. (2006), which can lead to biased and unreliable estimates. Sachs et al. (2015) propose a way to bridge the gap between the two approaches. Using panel data and fixed effects models allows both time-variant and time-invariant unobserved characteristics to be implicitly modeled, thereby improving the accuracy of the estimates (Wooldridge, 2002). Based on this approach, Sachs et al. (2015) estimate highly heterogeneous future coffee yields with a decrease of up to 70% in Guatemala and Kenya and 60% increases in Nigeria and Gabon from the 2004-2009 levels.

Compared to the previous literature, this chapter offers further refinements of the estimated impact of climate variability on coffee productivity in Colombia. The first contribution lies in the dataset used: a panel of municipal-level data based on yield and planted area data published by the Colombian Ministry of Agriculture for the years of 2007 to 2013. We believe this is a crucial endeavor, as nationwide estimates might be misleading for policy-making decisions at the local level. In particular, the forecasts by Sachs et al. (2015) point to an increase in productivity of at least 4% at the national level. However, the works of Bunn et al. (2015), Magrach and Ghazoul (2015), and Läderach et al. (2017) suggest that areas suitable for coffee production is very likely to change under future climate conditions. By offering productivity estimates at the local level, we hope to complement their findings and guide policy-making decisions that fit the conditions of each municipality.

Another contribution of this chapter is that it tackles the issue of model selection. Econometric analysis is susceptible to misspecification if the variables and functional form are not properly selected given the available data (Wooldridge, 2002). Even though previous works on this topic have drawn from the agronomic literature to guide the model selection process, we believe that greater efforts should be made to combine the biological processes taking place during the production of a crop and the way the impact of climate variability is estimated econometrically. For that purpose, we dedicate a subsection to the design and interpretation of a simplified agronomic model that draws from the ecological models proposed by Rodríguez et al. (2011), Rodríguez et al. (2013) and Rahn et al. (2018). We derive the expectation of the functional form and the direction of the marginal effects of our weather variables on coffee productivity from the latter contributions.

This chapter is outlined as follows. Section 3.2 presents the data and the methods. Subsection 3.2.1 is devoted to the description of the data. Subsection 3.2.2 is devoted to adapting a coffee physiology model to the Colombian case in order to derive testable hypotheses for the econometric analysis. Finally, Subsection 3.2.3 builds the econometric model around these testable hypotheses, drawing from the previous literature on coffee physiology models and coffee production functions. Section 3.3 presents and discusses the results, including the forecasts across different global climate models and representative concentration paths. Finally, section 3.4 summarizes our main findings and offers some concluding remarks.

3.2 Data and methods

3.2.1 Data

Our data set is comprised of 521 coffee-producing municipalities that continuously registered at least one hectare of Arabica coffee (*Coffea arabica*) production from 2007 to 2013. Some municipalities registered planted hectares but no production, which means these hectares are likely newly planted and have not started producing. Municipalities that had records of coffee cultivation for a subset of the years studied were excluded. The yield data as well as planted area were obtained from the Municipal Agricultural evaluations performed by the Colombian Ministry of Agriculture.

Developing countries such as Colombia have a very limited network of weather stations. For instance, the National Center for Coffee Research in Colombia manages a network of 56 weather stations in 36 distinct municipalities that comprise only 6% of Colombia's coffee production areas. The limited extent of the network leaves us with three options: i) rely on a small sample, ii) interpolate the missing observations through spatial krigging (Calderón, 2009 Park et al., 2019), or iii) use calculated temperature data. Since solutions We and ii would lead to severely biased and/or inconsistent estimates, we focus our efforts on the third option. It can use either remotely sensed data or data from a regional and global climate model.

Remotely sensed data offers great flexibility and availability, as it is continuously generated at various spatial and temporal resolutions. Improvements in the quality of remotely sensed data have also led to its increased use in economic analysis (Donaldson and Storeygard, 2016). Satellite imagery is often available at resolutions of 0.25° to 1° (Karger et al., 2017), with some images at the 0.05° resolution (Peres et al., n.d.). Building on remotely sensed data, a number of global climate models have further refined it with the addition of weather modeling results and ground and radiosonde observations (Fick and Hijmans, 2017; Karger et al., 2017). They offer a finer resolution than raw satellite imagery (up to 30 arc seconds or ~1 km at the Equator) with the potential downside of limited availability. For instance, WorldClim data is only available from 1970 to 2000, and CHELSA Version

1.2 is available from 1979 to 2013. Given the time frame of this study, CHELSA V.1.2 (Karger et al., 2017) is suitable for the analysis and is used for the estimations.

Table 3.1 presents the descriptive statistics for high and low altitude municipalities (above and below the mean altitude of 1518 m.a.s.l.). Temperature is, on average, nearly 6°C lower in the first group than in the second. Our results, displayed in the next section, indicate that altitude plays a significant role in coffee productivity. The choice to use August and March as the months of observation for temperature and precipitation is explained in the next Subsection.

Table 3.1. Descriptive statistics of main variables by altitude group.

	Low altitude municipalities				High altitude municipalities			
	Mean	**S.D.**	**Min.**	**Max**	**Mean**	**S.D.**	**Min.**	**Max**
				2007-2013				
Productivity (ton/ha)	0.72	0.52	0.00	8.97	0.71	0.36	0.00	8.79
Area planted (ha)	1291.85	1453.32	2.00	10073.00	1968.49	2498.03	3.00	20465.00
March precipitation (mm)	118.47	66.57	7.73	481.95	126.61	61.70	6.72	394.90
March temperature (°C)	22.29	2.09	17.66	28.52	16.90	2.28	10.11	22.55
August precipitation (mm)	109.81	85.30	1.68	491.66	109.22	84.69	1.95	434.23
August temperature (°C)	22.30	2.02	17.54	27.92	16.83	2.26	9.98	21.47
Altitude (m.a.s.l.)	1189.19	380.76	195.56	1758.01	2341.21	437.67	1765.42	3542.46
				RCP 2.6 2041-2060				
March precipitation (mm)	162	117	2.6	766	166.85	36.68	73.59	252.16
August precipitation (mm)	226	127	19	850	157.26	67.83	41.69	326.72
March temperature (°C)	24.1	2.26	17.10	46.2	15.46	2.72	7.59	20.59
August temperature (°C)	25.3	2.29	16.22	27.16	14.90	2.68	7.38	20.03

Table 3.1. Descriptive statistics of main variables by altitude group. (Cont.)

				RCP 4.5 2041-2060				
March precipitation (mm)	153	124	3.3	865	146	56	27	467
August precipitation (mm)	180	134	3.3	886	143	73	34	460
March temperature (°C)	26.1	2.33	20	29.7	16.6	3.3	3.5	34.9
August temperature (°C)	25.9	2.28	19.9	31.1	17.04	3.11	8.03	23.56
				RCP 6.0 2041-2060				
March precipitation (mm)	138	113	2.5	663	135	78	27	402
August precipitation (mm)	223	136	19	851	139	55	34	460
March temperature (°C)	25.8	2.3	19.9	29.6	16.9	2.95	8.4	22.3
August temperature (°C)	25.6	2.3	19.5	30.8	16.7	3.12	7.8	23.1

* Source: altitude data were obtained from the Shuttle radar topography mission (SRTM) (Werner, 2001), yield data were obtained from the National Agricultural Evaluations performed by the Colombian Ministry of Agriculture (see for example, Villalobos and Cifuentes, 2002), weather data were obtained from the CHELSA V.1.2 (Karger et al., 2017); ** Statistics for 2041-2060 are averaged over the 8 GCM models employed in this chapter: BCC-CSM2-MR, CNRM-CM6-1, CNRM-ESM2-1, CanESM5, IPSL-CM6A-LR, MIROC-ES2L, MIROC6, and MRI-ESM2-0.

In this chapter, we use future climate projections that rely on Global Circulation Models (GCMs) driven by three Representative Concentration Scenarios (RCP): 2.6, 4.5 and 6.0, described in the IPCC 5th Assessment Report (Stocker, 2013). Each prediction is retrieved from the CHELSA Future CMIP5 database at the 2.5-minute resolution. The local values for 2041 to 2060 are obtained from the GCMs: the Beijing Climate Center Climate System Model (BCC-CSM1), the Centre National de Recherches Météorologiques Circulation (CNRM-CM5, not available for the RCP 6.0), the Canadian Earth System Model version 2 (CanESM2 , not available for the RCP 6.0 scenario), the Institut Pierre-Simon Laplace Circulation Model 5A (IPSL-CM5A-LR), the Model for Interdisciplinary Research on Climate, Earth System (MIROC-ESM), the Earth System and Circulation Model (MIROC5) and the Meteorological Research Institute Earth System (MRI-CGCM3). On average, temperature and precipitation are expected to increase in Colombia's coffee-growing regions. The increase in precipitation in August is especially noteworthy, as it traditionally corresponds to a dry period.

A La Niña phenomenon was experienced at varying intensities between 2008 and 2011, increasing the prevalence of coffee leaf rust (*Hemileia vastatrix,* Henceforth CLR) in Colombia and Central America (Avelino et al., 2015). This event, aggravated by diminished flowering, resulted in a depression of coffee production and exports from Colombia (Bastianin et al., 2018). Figure 3.1 presents the time trends of temperature, precipitation and yield for the years 2007 to 2013:

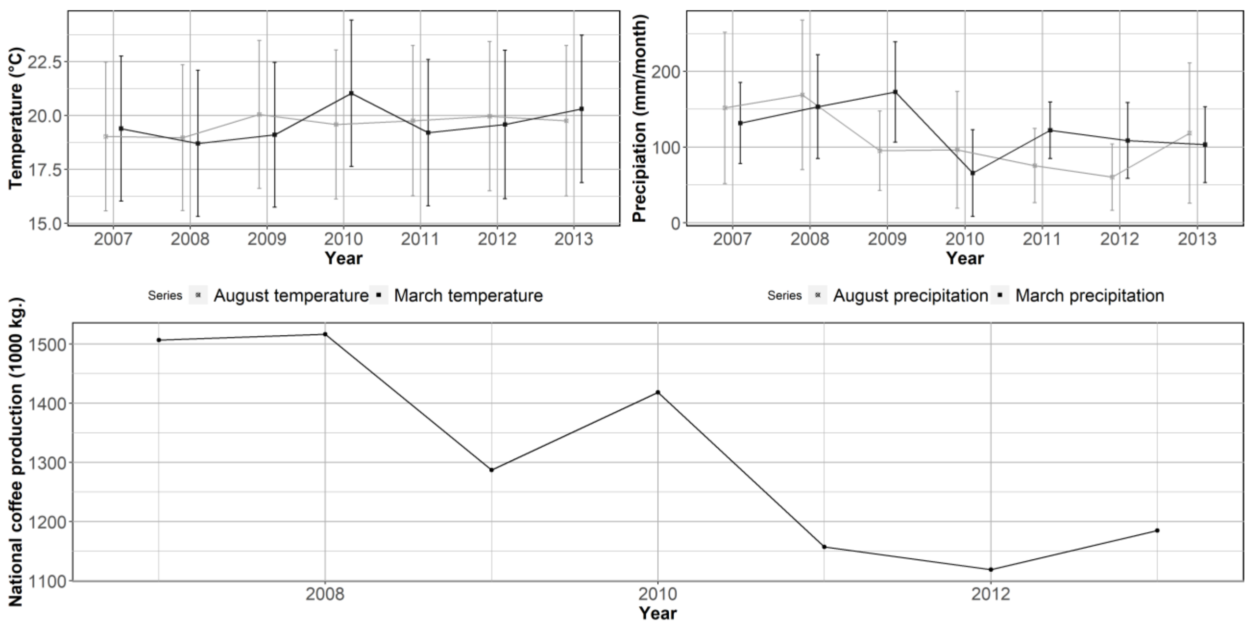

Figure 3.1. Time trends of: temperature (top left), precipitation (bottom left), and national yields bottom.

The graph shows a spike in precipitation, beginning in March 2008 and carrying on until March 2009. It was accompanied by a dip in total output of coffee in 2009, with a brief recovery in 2010 when precipitation decreased and mean temperature in March was high. This finding provides further evidence of the sensitivity of coffee productivity to varying weather conditions.

3.2.2 Theoretical framework

Changes in weather can have direct and indirect effects on coffee productivity. The direct effects refer to changes that modify the physiological processes of the plant and have an impact on the productivity realizations, which include induction of flowering and pollination as a result of short periods of hydric stress (Ramírez et al., 2014) or induction of vegetative growth as a result of extended rainy seasons (Carr, 2001). The indirect effects of changes in weather refer to changes in incidence of diseases, which include the CLR (Bastianin et al., 2018) and the distribution and reproduction patterns of both pests and pollinators. The latter include changes in the reproductive cycle of the Coffee Berry Borer (*Hypothenemus hampei*, Henceforth CBB) (Atallah et al., 2018; Iscaro, 2014; Jaramillo et al., 2010; Magina et al., 2007) and diminishing bee populations (Imbach et al., 2017).

We follow the example of Van Oijen et al. (2010) in considering that the complexity of models should be adjusted for the availability of data. We propose a simplified model for coffee production where the observable inputs of water and temperature have direct and indirect effects on five biological Submodels. Figure 3.2 presents the model's structure:

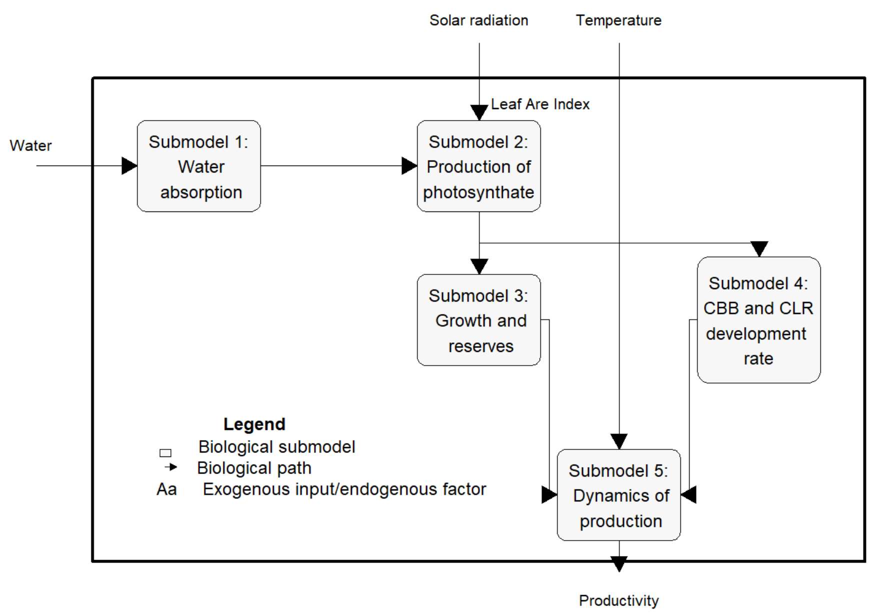

Figure 3.2. Proposed model for coffee productivity: relationship between coffee productivity, temperature, and precipitation.

The general model aims to demonstrate how one output—coffee yield—results from the dynamics of three exogenous inputs—water, photosynthetically active radiation (noted Io) and temperature—and one endogenous factor—Leaf Area Index (LAI). Five Submodels have been developed by Rodríguez et al. (2011) and Rodríguez et al. (2013) to describe the physiological processes of water absorption, production of photosynthate, growth and reserves, CBB and CLR development rate and dynamics of production. We take LAI and Io as constant due to our inability to observe them in our data. The first Submodel, water availability and absorption, is almost exclusively dependent on precipitation, as there is very little irrigated coffee cultivation. The water that is absorbed is broken apart in the photosynthetic process that transforms the carbon dioxide into photosynthate (Submodel 2). The photosynthate that is produced and is the focus of the second Submodel can be egested, respired, accumulated in reserves or used in growth. A fraction of the photosynthate accumulated in reserves or used in growth is used for reproduction and is directly related to productivity realization (Submodel 3).

Temperature is present in three Submodels. First, it has a direct effect on respiratory rates that occur at the expense of greater accumulation of reserves and growth, as well as on the increment of age due to the accumulation of thermic units (Submodel 3). Second, it has a direct effect on the increment of age of CBB due to accumulation of thermal units and on the infestation rate of CLR (model 4 in Appendix C.1.4). In turn, this impact has an effect on the dynamics of production (model 5), as CBB is the leading cause of loss due to herbivory (parasitism), and CLR has been found to severely affect yield realizations. In the latter case, there has been evidence of severe impacts of the la Niña phenomenon, which took place between 2008 and 2011 and is potentially affecting our results (Avelino et al., 2015). Additional details as well as the derivation of each model are presented in Appendix C.1.

Based on this model, we make inferences on three aspects of our econometric specification: i) $Y = f(T, T^2, P, P^2, T * P)$, where T and P stand for temperature and precipitation, ii) the observation of weather in March and August, and iii) the choice of a dynamic model specification to account for the effect of past productivity realizations on present yield. The choice of quadratic forms of temperature and precipitation considers two facts: degree-days measurements are not feasible with the data we are working on, which has a monthly temporal resolution, and temperatures above the upper bound of coffee growth (35°C) are rare in Colombia's coffee-growing region. Therefore, we favor a simpler functional form that assumes quadratic forms of temperature and precipitation to account for potential non-linear relationships among temperature, precipitation and yield.

One of the main challenges with the econometric modeling of production functions is the incongruence between the temporal scales of the variables, as indicated in Blanc and Schlenker (2017). Productivity data is usually available at yearly intervals, whereas weather data is observed over any given time period, from days to months. Furthermore, the inclusion of sequential observations of weather as regressors leads to an issue of multicollinearity, which can severely affect the efficiency of the estimators. We bridge this gap by building on the crop phenology literature: for any given crop, there exists a set of critical periods in which adverse environmental conditions can lead to a significant drop in yield (Zhao et al., 2013). Even though these periods do not preclude the importance of favorable weather conditions at other times during the production cycle, their predictive power over yield realizations outweighs that of other periods. In the case of coffee, DaMatta and Ramalho (2006) and DaMatta et al. (2007, 2018) identify the flowering and bean formation period as critically susceptible to adverse weather conditions. High temperatures during blossoming, especially if associated with a prolonged dry spell, may cause abortion of flowers. Prolonged dry spells can also lead to fruit drop, notably in the endosperm formation phase of bean filling (Alègre 1959; DaMatta et al., 2007, 2018). In the case of Colombia, Ramírez et al. (2014) identify March and August as the periods of most intense flowering, with the largest coffee-producing areas flowering in March. We adopt these two periods for the observation of temperature and precipitation, as flowers forming in March depend on the weather conditions of that month for blossoming and the conditions of August for bean filling, and vice versa for those forming in August.

Finally, we choose to model the dynamic nature of productivity to account for the fact that coffee is a perennial crop (DaMatta et al., 2007). The effect of past productivity realizations can be either positive or negative. If higher profits are invested in improved fertilization and pest control practices, farmers can expect better yields in the coming years. However, productivity can be affected when those investments are not made. Photosynthate reserves are exhausted after a heavy crop load, as described in Submodel 5. If they are not replenished, the number of fertilized flowers will be lower in the next flowering season (Drinnan and Mentzel 1985; DaMatta et al., 2007; DaMatta et al., 2018; DaMatta et al., 2019). This process is known as biennality of coffee productivity. We devote the next Subsection to the description of the econometric model to adequately capture the inferences described in this section.

3.2.3 Econometric model

The reduced form model for our econometric estimation is presented in equation (3.1). We capture the dynamic process of yearly productivity by regressing current productivity realizations y_{it} in tons/ha on last year's productivity realization y_{it-1}, on a set of weather variables $X = (T, T^2, P, P^2, T * P)$ and on c_i and μ_t that stand for spatial and time fixed effects, respectively and an error term ε_{it}:

$$y_{it} = \theta y_{it-1} + X_{it}\beta + c_i + \mu_t + \varepsilon_{it} \; with \; \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2), \qquad (3.1)$$

We expect that estimating this dynamic model using Least Squares Dummy Variable (LSDV) will yield a downward biased θ (Nickell, 1981). The reason is that the mean of the lagged dependent variable contains observations from time 0 to t-1 on y. The mean of the error captures the residuals from time 0 to t. Since y_{it-1} depends on ε_{it-1} and so does ε_{it}, the latter and y_{it-1} are not orthogonal; hence, θ is biased. In subsection 3.1. below, we will consider two alternatives to address this endogeneity. The first one is the Difference Generalized Method of Moments (GMM) proposed by Arellano and Bond (1991). It estimates a model based on the first differences of equation (3.1). This transformation expunges the time-invariant fixed effects c_i yet still suffers from endogeneity due to the dependence between y_{it-1} and ε_{it-1}. We address this problem by using previous realizations of the dependent variable as instruments for the first lag. The second alternative is the System GMM proposed by Arellano and Bover (1995) and Blundell and Bond (1998), where the lagged dependent variable in equation (3.1) is instrumented using the first differences as instruments. Compared to difference GMM, system GMM allows more instruments to be introduced and increases the efficiency of the estimates. Arellano and Bond (1995) have demonstrated that the latter point is especially true for panels with few time periods. This model requires the further assumption that the first difference instruments are uncorrelated with c_i.

Four conditions are necessary to correctly identify a dynamic panel model using either of the two GMM methods above (Blundell et al., 2000): i) the test of first order serial autocorrelation must be significant, ii) the test of second order autocorrelation must be non-significant, iii) the Hansen/Sargan test of over-identifying restrictions must be insignificant so that the null hypothesis of validity of the instruments is not rejected and iv) the coefficient of the lagged variable must fall within a credible range (Roodman, 2009). We work with the STATA Statistical Package version 15.1 (StataCorp, 2017). We use the xtreg command to estimate the static models and the xtdpdgmm command to estimate the GMM models (Kripfganz, 2019).

3.3 Results and discussion

3.3.1 Model fit

Table 3.2 below presents the results of the model described in equation (3.1). Column (1) presents the LSDV results of the quadratic static panel model without the time lag of the dependent variable. While this specification is akin to the specifications in Gay *et al.* (2006) and Sachs (2015), we report it for informative purposes, as the absence of y_{it-1} leads to an omitted variable bias (Chamberlain, 1978).

Table 3.2. Dynamic panel model estimation results.

VARIABLES	(1) LSDV	(2) Difference GMM	(3) System GMM	(4) System GMM	(5) Long-run System GMM[1]
(Lag of) coffee productivity		0.094***	0.572***	0.535***	
		(0.022)	(0.062)	(0.059)	
Mean temperature in March	0.083	0.190***	0.108*	0.414**	0.890**
	(0.0548)	(0.0615)	(0.0583)	(0.186)	(0.390)
Mean temperature in March sq.	-2.76×10^{-3}**	-4.42×10^{-3}***	-1.67×10^{-3}	-8.3×10^{-3}**	-0.018**
	(1.31×10^{-3})	(1.61×10^{-3})	(1.23×10^{-3})	(3.87×10^{-3})	(8.1×10^{-3})
Mean temperature in August	-0.168*	0.181	0.411*	0.099	0.214
	(0.092)	(0.211)	(0.239)	(0.317)	(0.680)
Mean temperature in August sq.	1.3×10^{-3}	-9.3×10^{-3}*	-0.0153**	-8.35×10^{-3}	-0.018
	(2.28×10^{-3})	(5.6×10^{-3})	(6.2×10^{-3})	(7.65×10^{-3})	(0.016)
Precipitation in March	-0.00126***	-1.3×10^{-3}*	-8.02×10^{4}	4.74×10^{-3}	0.010

Table 3.2. Dynamic panel model estimation results. (Cont.)

	(4.6×10^{4})	(6.73×10^{4})	(7.88×10^{4})	(3.23×10^{-3})	(6.8×10^{-3})
Precipitation in March sq.	3.52×10^{-6}***	6.96×10^{-6}***	3.63×10^{-6}**	4.16×10^{-6}**	8.96×10^{-6}**
	(1.24×10^{-6})	(1.70×10^{-6})	(1.85×10^{-6})	(1.74×10^{-6})	(6.39×10^{-6})
Precipitation in August	2.5×10^{-3}***	1.7×10^{-3}***	1×10^{-3}	-2.6×10^{-3}	-5.6×10^{-3}
	(3.45×10^{-4})	(5.31×10^{-4})	(6.8×10^{-4})	(2.2×10^{-3})	(4.64×10^{-3})
Precipitation in August sq.	-5.8×10^{-6}***	-4.09×10^{-6}***	-1.67×10^{-6}	-6.18×10^{-7}	-1.33×10^{-6}
	(8.06×10^{-7})	(1.11×10^{-6})	(1.58×10^{-6})	(1.74×10^{-6})	(3.74×10^{-6})
Precipitation in March × Mean temperature in March				-2.7×10^{-4}*	-5.8×10^{-4}*
				(1.42×10^{-4})	(3.01×10^{-4})
Precipitation in August × Mean temperature in August				1.52×10^{-4}*	3.27×10^{-4}*
				(9.07×10^{-5})	(1.9×10^{-4})
Mean altitude			-7.4×10^{-4}***	-8.1×10^{-4}***	-1.7×10^{-3}***
			(2.25×10^{-4})	(2.28×10^{-4})	(3.53×10^{-4})
Constant	2.885***	0.384	-2.029	-1.927	-4.144
	(0.974)	(2.214)	(2.038)	(1.785)	(3.846)
Observations	3,646	3,125	3,125	3,125	3,125
Adj. R-squared	0.212				
R*[ii]		0.289	0.148	0.152	0.152
Out-of-sample RMSE[iii]	0.639	0.830	0.508	0.474	0.474
Hansen-Sargan test		0.000	0.161	0.198	0.198
AR(1), p-value		0.000	0.000	0.000	0.000
AR(2), p-value		0.373	0.813	0.798	0.798

Notes:

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

i: Column (5) reports the long-run coefficients of the $(1-\theta)$ convergence estimation of the System GMM results displayed in column (4).

ii: R*, or squared correlation coefficient, is estimated as the correlation between the predicted and observed values of the dependent variable ($Corr(\hat{y}, y)^2$). It is akin to the estimation of R-squared in maximum likelihood estimators and it is conventionally reported in GMM models. See Bloom et al. (2001) for further details.

iii: Out-of-sample root mean squared error: out-of-sample estimations are completed by iteratively fitting each model on a subset of the sample that excludes one year. The fitted model is used to predict the productivity for the excluded year. The difference between the predicted and observed value (residual) is squared and averaged. The value reported corresponds to the square root of that value.

Columns (2) to (5) account for the perennial nature of the coffee plant and the fact that previous productivity realizations can be a good predictor of current productivity (DaMatta et al., 2007). The literature has demonstrated that including the time lag of the dependent variable requires a GMM approach to control for unobserved heterogeneity and avoid biased estimates (Nickell, 1981). As a result, we report the estimates based on difference GMM in column (2) (Arellano and Bond, 1991) and the estimates based on system GMM in columns (3) to (5) (Arellano and Bover 1995; Blundell and Bond 1998). Column (5) reports the long-run coefficients of column (4) and will be discussed further below.

Difference GMM transforms all the regressors by using their differences between t and t-1; hence, individual fixed effects c_i disappear as noted earlier. The tests for serial correlation reported at the bottom of table 3 show that there is serial correlation of order one (AR(1), p-value = 0.000) but not of order two (AR(2), p-value = 0.373), so the yield of only the previous year matters. However, the Hansen-Sargan test result is significant because it suggests that the lagged levels of the endogenous and exogenous variables are not adequate instruments. Arellano and Bover (1995) and Blundell and Bover (1998) argue that in panel settings spanning over a short time period, difference GMM estimates can be inefficient. Therefore, they suggest the system GMM. The results of columns (3) and (4) validate this hypothesis, as both the model with weather interactions and the one without them comply with the necessary conditions of a correctly identified GMM model (significant AR(1) test and non-significant Hansen-Sargan test). In terms of fit, the squared correlation coefficient (R*) of the system GMM models is a bit below the adjusted R-squared of the LSDV model. It does not surprise us given that GMM, unlike LSDV, is not an estimation strategy based on minimizing the residuals (Cameron and Trivedi, 2009). Yet, when we calculate the out-of-sample root mean squared error (RMSE) to test the predictive power of each model, our results show that the system GMM with weather interactions has the lowest RMSE. This result indicates that it is the most suitable option for the forecasting exercise undertaken in the next Subsection.

The results of column (4) highlight the importance of accounting for the dynamic nature of coffee production. The coefficient on the lagged dependent variable θ is positive and significant. We hypothesize that this positive coefficient comes from better yields that result in higher profits. These profits are re-invested in crop production in the form of better fertilization and pest control, which, in turn, lead to better yields in the following years (Chávez and Ridley, 2001). We also find a negative and significant coefficient associated with altitude. We believe the negative and significant coefficient captures the slower rate of accumulation of thermal units, which is due to cooler temperature at higher altitudes, that then results in lower accumulation of photosynthate (Arcila et al., 2007). Furthermore, the results of column (5) meet the expectations of the theoretical framework. Indeed, the statistically significant evidence of diminishing returns to temperature in March indicates that high or very high temperature is harmful for coffee during the flowering season, as stated by DaMatta et al. (2007). We also find that the effect of precipitation in March is positive and statistically significant. In line with the expectations derived in Submodel 2, coffee plants react favorably to increased water availability during the flowering period. We further argue that the monotonic relationship between March precipitation and coffee productivity observed in our model captures the fact that hydric excess and waterlogging is a rare occurrence in Colombia as coffee is planted in hilly areas, which results in significant surface runoff and in porous soils with adequate hydric conductivity (Poveda Jaramillo et al., 2002). Usually, excess rainfall is associated with a decrease in productivity (Ramírez et al., 2010) as the lack of a dry spell during the quiescent growth phase (about 2 to 4 months before flowering) stimulates flowering and results in scattered harvests (DaMatta et al., 2007, 2018). One limitation of this study is that we do not observe temperature and precipitation during the quiescent growth phase.

We also find that the results show no significant effect for temperature and precipitation in August. We believe this captures the fact that the main blooming season in Colombia's largest coffee-growing regions takes place during the first semester with a peak in March (Ramírez et al., 2014; Vélez et al., 2000). Weather conditions in August have a smaller impact on productivity, as the largest share of the yearly harvest is already at bean-filling stage, where beans are much more resilient to adverse weather conditions than flowers (DaMatta and Ramalho, 2006). Given the spatial and temporal resolution of our data, we fail to capture the smaller effect of weather during the sturdier bean-filling stage; however, these results do not rule out the importance of favorable weather during that stage.

It is also interesting to note the similar magnitude and opposing directions of the coefficients for the interaction between temperature and precipitation in each month. While high temperature and precipitation in March impact productivity negatively, the opposite is true for August. One possible explanation relates to the dynamics of CBB infestation. As described in Submodel 5, the number of CCB cohorts increases as temperature and precipitation increase. The impact of CBB on coffee productivity is also time-sensitive. If infestation occurs within the first two months after pollination, more than 50% of the berries are aborted; if it happens after the third month, that value drops to 23.5% (Bustillo Pardey, 2006). We believe that our model is capturing the opposing directions of the joint effect of temperature and precipitation on coffee productivity. Both the coffee plant and CBB develop optimally at temperatures of 24°C and benefit from soil and air humidity (Bustillo Pardey, 2006; Magrach and Ghazoul, 2015). When these favorable conditions coincide with pollination and initial bean formation, the damaging effect of greater CBB infestation outweighs the positive impact on the vegetative and reproductive development of the coffee plant. However, when those same optimal conditions happen in the latest stages of the reproduction process, CBB causes fewer losses, and bean filling is positively impacted by favorable temperature and precipitation. Given that the largest coffee-producing areas in Colombia flower in March, we argue that these results correctly reflect this fact. A similar effect has been observed for CLR (Avelino et al., 2015). In addition, note that the negative and significant coefficient for the interaction between temperature and precipitation in March can also relate to the importance of a hydric stress period that stimulates flowering (DaMatta et al., 2007, 2018).

The GMM coefficients reported in columns (2) to (4) correspond to the short-run marginal effects of the matrix of independent variables on the dependent variable (Arellano and Bond, 1991). We estimate the long-run effects by dividing the short-run estimates of the coefficients by the convergence rate $(1-\theta)$. We estimate the long-run coefficients of our preferred specification and present them in column (5). They will be used for the forecasting exercise of Subsection 3.2. However, before we proceed, we present further evidence of the validity of this estimation strategy. For that purpose, we run an exercise of productivity maximization at varying March temperatures. The optimal March temperature under the dynamic panel model is 19.5°C, which is within the optimal range for coffee production as estimated by Mosquera Sánchez et al. (2005) and DaMatta et al. (2007). Figure 3.3 plots the marginal effects of temperature, precipitation and associated productivity based on estimates from column (5). We plot separate curves for each altitude subset (above or below the median altitude) and evaluate the other covariates at their median value.

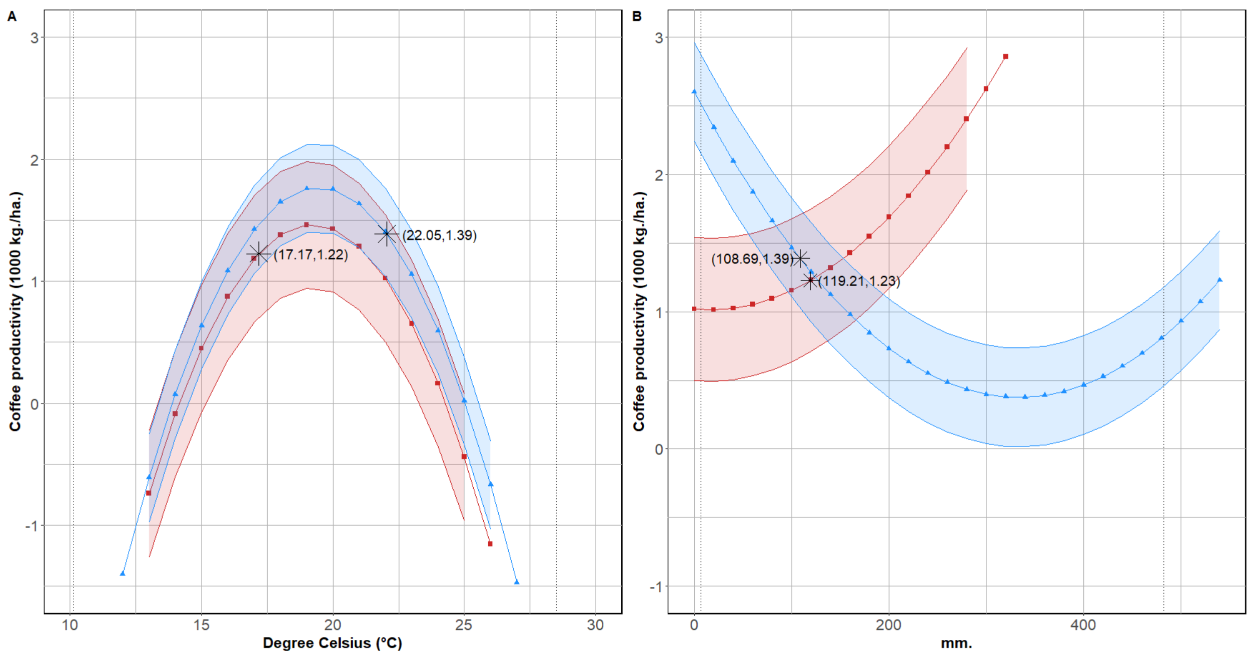

Figure 3.3. Marginal effects of (A) mean March temperature and (B) mean March precipitation by altitude group.

The stars in both curves represent the expected productivity evaluated at the median value of the corresponding weather variable for the period of 2007 to 2013. It is interesting to note that, despite average productivity being lower at higher altitudes, an increase in temperature in the future would have opposite effects for each group. Indeed, with an average increase of 1° to 2°C by 2050, as estimated by the National Institute of Hydrology, Meteorology and Environmental Studies of Colombia (IDEAM) (Ballesteros and Aristizabal, 2007), the high-altitude municipalities would see their productivity increase. In theory, they would move towards the optimum productivity level of temperature. On the other hand, low-altitude municipalities would experience a decrease in their median productivity, as they already are at the optimum mean temperature level (figure 3A). Similarly, high-altitude municipalities would benefit from higher precipitation in March, whereas low-altitude municipalities would benefit from a decrease (or a large increase) in precipitation (figure 3B). As a result, we expect that future weather conditions will reduce the productivity gap between high- and low-altitude municipalities, potentially reshaping the landscape of Colombia's coffee-growing regions.

In the case of our sample, the average increase in temperature forecasted by the GCM models is above the 2°C increment forecasted by IDEAM (See Table 3.1). More precisely, they suggest an increase of 4°C for the average temperature between 2041 and 2060. Under this scenario the mean March temperature in high altitude municipalities would be 27.27°C, which is well above the optimum level of 19.5°C found in our estimations. On the other hand, the projected temperature for high altitude municipalities is 20.78°C, which is very close to the aforementioned optimum. Furthermore, the 56 mm projected increase in precipitation in the low-altitude municipalities will accentuate the negative impact on their productivity while the 40 mm increase in the high-altitude municipalities is expected to boost their productivity.

3.3.2 Forecasting

In the case of the dynamic model proposed in equation (3.1), the first approximation to the predictor at future time $K = T + r$ is the expectation of $y_{i,K}$ conditional on the information set $I_K(y_{i,K-1}, X_{i,K}, c_i, \varepsilon_{i,K})$:

$$y_{i,K} = E[y_{i,T+r}|I_K] = E[\theta y_{i,K-1} + \beta X_{i,K} + c_i + \varepsilon_{i,K}], \tag{3.2}$$

$$y_{i,K} = \theta y_{i,K-1} + \beta X_{i,K} + c_i, \tag{3.3}$$

Because the expectation of future shocks of the idiosyncratic error term $\varepsilon_{i,K}$ is assumed zero, it is expunged through the conditional expectation. However, both $y_{i,K-1}$ and the time invariant fixed effects c_i remain. $y_{i,K-1}$ is incorporated through the $(1 - \theta)$ convergence transformation of the coefficients. c_i is the group-specific average of all the residuals. The predictions of future temperature and precipitation are extracted from the GCMs listed in section 3.2.1. Figure 3.4 reports the predicted average coffee productivity by 2041-2060 (dot) and the associated 95% confidence interval (whiskers).

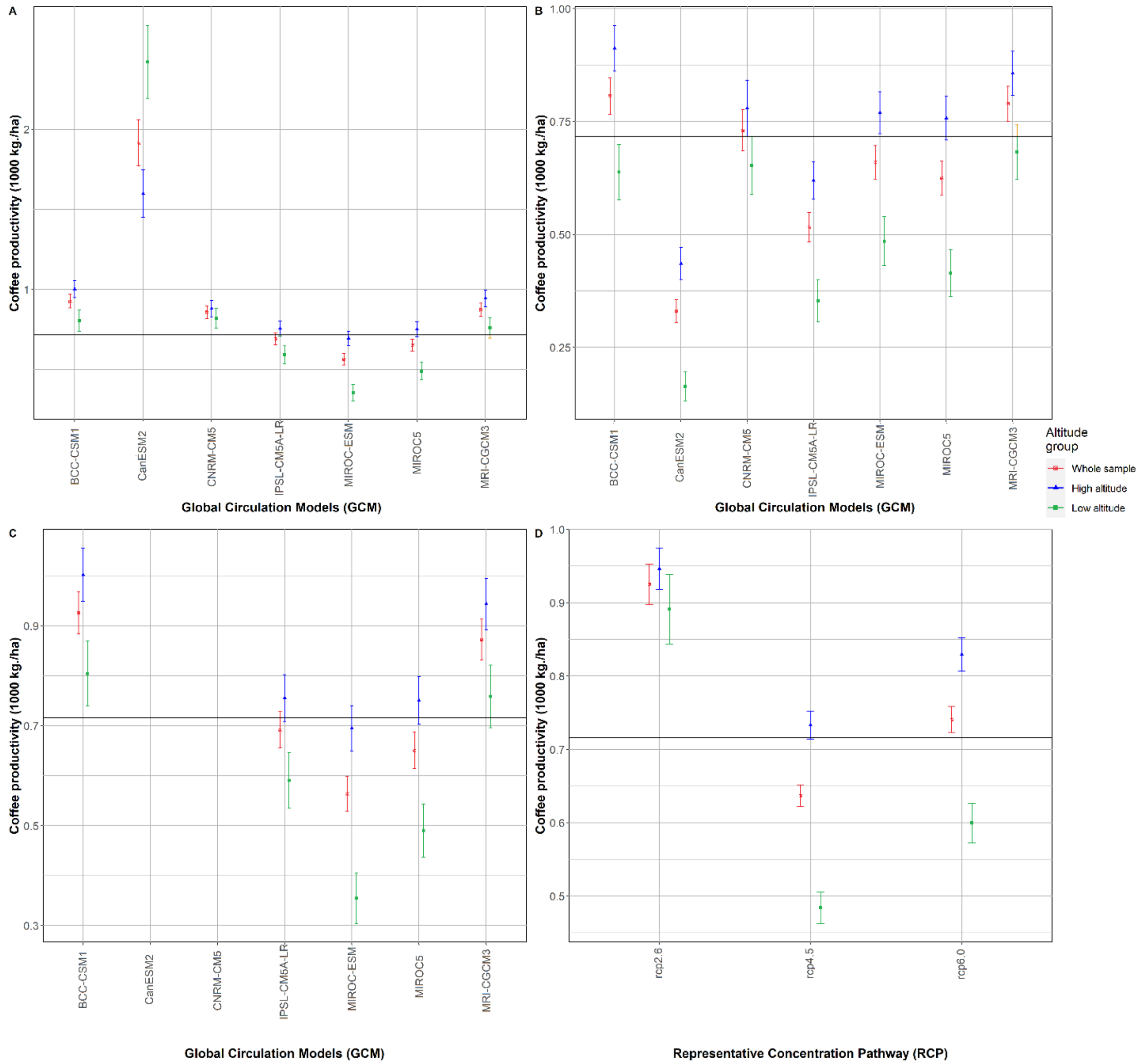

Figure 3.4. Projected coffee productivity in 2041-2060 for selected municipalities. The whiskers represent the 95% confidence interval of the mean. Whole sample: 521 municipalities; high altitude: 262 municipalities; low altitude: 259 municipalities. (A) Representative Concentration Path (RCP) 2.6, (B) RCP 4.5, (C) RCP 6.0, and (D) average prediction by RCP scenario.

The solid black line is the 2007 mean of coffee productivity, which stands at about 716 kg of coffee per hectare. The RCP 2.6 scenario, which predicts a likely increase in global temperature between 0.3°C and 1.7°C (Pachauri et al., 2014), suggests that the average coffee productivity will increase by 29% (confidence interval: [24.4, 34.9]). In this scenario, both the high- and low-altitude municipalities will experience an increase in average productivity (32% and 24% increases for high- and low-altitude municipalities, respectively). However, this result does not rule out a negative impact for a set of municipalities. Panel A of figure 3.5 shows the geographic distribution of change in productivity where the municipalities adjacent to the intra-Andean valleys and in the northeastern region are expected to experience a decrease in productivity.

RCP scenario 4.5 (figure 3.4B) assumes that global warming will range between 1.4°C and 3.1°C (Pachauri et al., 2014). Its results suggest a more heterogeneous impact of global warming. In this scenario, the productivity is expected to decrease by 11% (confidence interval: [13.1, 8.9]). The impact differs across altitude groups: high-altitude municipalities are expected to increase their productivity by 2.3% (confidence interval: [-0.4, 5.1]), and low-altitude municipalities are expected to decrease their productivity by 32.3% (confidence interval: [35.4, 29.4]).

Finally, under the RCP scenario 6.0, which predicts an increase in temperature between 2.6°C and 4.8°C (Pachauri et al., 2014), coffee production will increase by 4.46% on average (confidence interval: [0.97, 5.87]). Productivity in high-altitude municipalities will also increase by 16% (confidence interval: [12.6, 18.9]). The opposite is expected to happen in low-altitude municipalities, with a decrease in average productivity of 16.2% (confidence interval: [-20.4, 12.5]). We aim to show all scenarios in order to contribute to policy-making discussions. Therefore, we offer our municipal-level predictions for all three scenarios in Appendix C.3.

Figure 3.5 maps the expected change (positive or negative) at the municipality level for each of the three RCPs. The results indicate that Colombia's unique topography acts as a buffer that can mitigate most of the effects of climate variability on coffee productivity. Indeed, these findings indicate that negative impacts expected by low-altitude municipalities can be offset by increased productivity in high-altitude municipalities. The capacity of this shift in coffee cultivation to take place efficiently is highlighted by the fact that the area of coffee cultivation in high-altitude municipalities is already larger than it is in low-altitude municipalities (558,296 hectares vs. 352,114 hectares). Our findings suggest that this asymmetry will be accentuated in the future. As such, careful consideration and understanding of the large degree of spatial heterogeneity present in the country because of very different altitude levels is necessary. Any policy-making endeavors aiming to protect the livelihoods of Colombian coffee farmers will require place-tailored solutions.

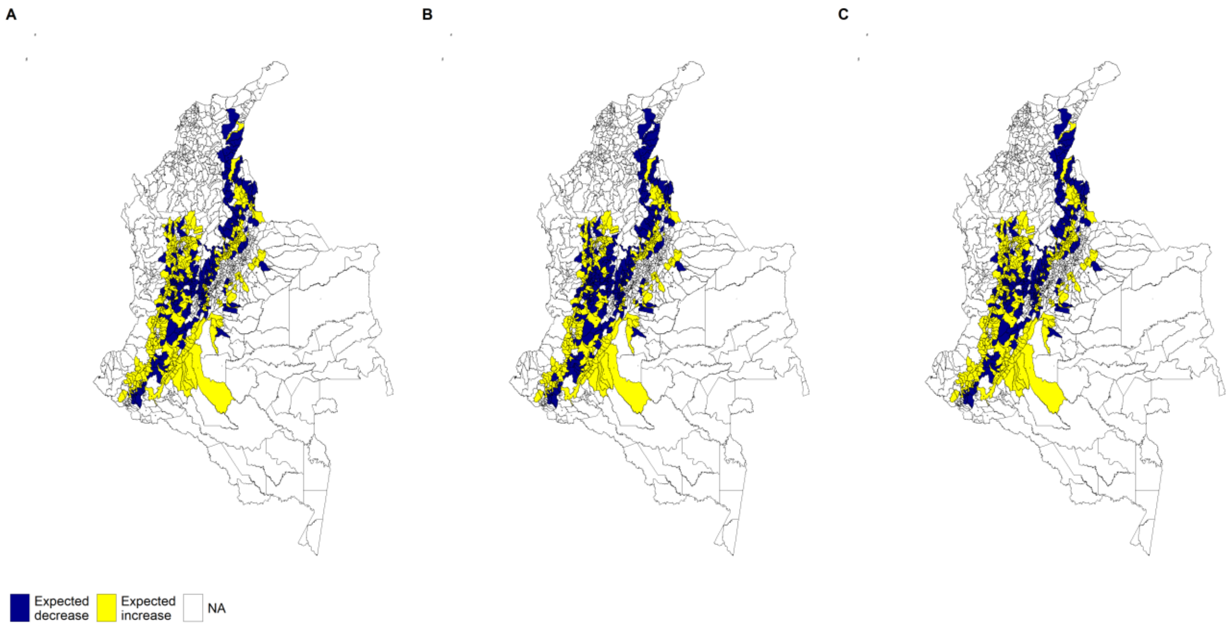

Figure 3.5. Expected changes in productivity across municipalities in 2041-2060 with respect to mean productivity from 2007-2013. (A) RCP 2.6, (B) RCP 4.5, and (C) RCP 6.0

Our set of predictions is subject to a couple of limitations. First, our model is not sensitive to the various types of adaptation strategies farmers can undertake that would mitigate the magnitude of our predictions. These options have been documented in the literature and include shading (Jaramillo et al., 2011), crop diversification (Rahn et al., 2014), irrigation and fertilization (Fares et al. 2016; DaMatta et al. 2018) and eventually shifting crops to more resistant species, such as *Coffea canephora*, or other crops better suited to the new conditions (Adjei-Nsiah and Kermah, 2012; Krishnan, 2017). If the data were available, we believe they would enrich our estimates and forecast. Finally, our model ignores the technological progress that could make coffee plants more resilient to future weather conditions. One such example is the development and diffusion of CLR-resistant varieties that have decreased the susceptibility of Arabica coffee to the pathogen (Alvarado, et al., 2013). Even though the effort to develop a CBB-resistant variety has yet to be successful, some avenues of research suggest it might be possible in the future (Romero et al., 2015). Similar efforts have been conducted to develop drought-resistant coffee plants (Silva et al., 2018). In the absence of information on adaptation and technological progress, we believe our estimates provide coffee growers and policymakers with meaningful and accurate insights on the consequences of not addressing the challenges posed by future climate conditions.

3.4 Conclusions

This chapter uses a panel data approach and a novel data set to measure the effect of climate variability within the framework of a crop production function that is built on elements from the crop physiology literature

(Rodríguez et al., 2011, 2013). This approach allows us to go further than previous key references on the analysis of coffee yield realizations (Gay et al., 2006; Sachs et al., 2015), as we include the biennial productivity of coffee and provide results at the municipal, instead of only national, level. Since most policy-making institutions in Colombia operate at the sub-national level, it is important to produce estimates and forecasts at the local level to adequately address the magnitude and the spatial variability of the challenges that arise from climate change. Furthermore, this chapter makes use of high-resolution global climate models. This approach is increasingly popular when focusing on climate variability in developing countries where the network of field weather stations is limited and accurate surface weather data are scarce (Bunn et al., 2015; Läderach et al., 2017; Magrach and Ghazoul, 2015).

A key finding of our study relates to the importance of accounting for the dynamic component of coffee productivity, in which the lagged productivity realizations have a positive and significant predictive power on current productivity realizations. We relate this finding to the perennial nature of the coffee plant and argue that positive yields in the previous year improve the economic conditions of the farmer. As a result, this improvement leads to more investments in fertilizers and pest control in the current year. Modeling this process allows us to increase the accuracy of our estimates (measured by the out-of-sample RMSE) and to offer more appropriate recommendations than past approaches that ignored the dynamic nature of coffee productivity have.

Based on estimates calibrated over the past, as well as data from eight global climate models and three representative concentration scenarios, we also forecast coffee productivity by 2041-2060. These results show that Colombia's unique topography is a buffer that can mitigate most of the effects of climate variability on coffee productivity. Indeed, our findings indicate that the negative impacts expected in low-altitude municipalities could be offset by increased productivity in high-altitude municipalities. In addition, these results display an even greater heterogeneity when calculated at the local level. As such, any policy-making endeavors aiming to protect the livelihoods of Colombian coffee farmers will require solutions that differ across municipalities.

Future research will focus on lifting a set of limitations that are common in the crop production function literature (Gay et al., 2006) and that we have adopted here too. For instance, the use of a constant technology and the assumption of linear climate adaptation strategies deserve to be challenged. Huffman et al. (2018) and Caetano et al. (2018) provide recent efforts in this direction on the corn and soybean productions, respectively. In the case of Colombia, we believe that novel adaptation strategies (Cavatte et al., 2012; Jaramillo et al., 2011) could support coffee production on land parcels that, until now, have been classified as unsuitable and hence were not included in our estimation. In addition, improvements in technology such as drought-resistant cultivars could help keep some cropland productive (Romero et al., 2015), as could the development of more efficient methods for irrigation and fertilization (Fares et al. 2016; DaMatta et al. 2018). These recent advances provide the foundations for some exciting avenues of research for the years to come.

3.5 Chapter 3 References

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APPENDIX A

SUPPLEMENTARY MATERIAL FOR CHAPTER 1

A.1 Baseline estimations including criminal gangs (Bacrim) presence.

Table A.1. Difference-in-Difference including criminal gangs (Bacrim) presence.

	Economic activity	Violence	Coca cultivation
POST	1.51 *	-32.28 ***	3.14 ***
	(0.91)	(3.49)	(1.07)
POST X ELN	-3.47	-4.88	0.13
	(2.14)	(3.66)	(0.52)
POST X FARC	3.05 **	-10.02 ***	1.05 **
	(1.44)	(1.41)	(0.41)
POST X Bacrim	0.20	-14.24 ***	0.32
	(2.01)	(3.27)	(0.41)
POST X FARC/ELN	-1.23	-8.56	13.39 **
	(1.52)	(5.77)	(6.64)
POST X FARC/Bacrim	5.58	-28.34 ***	4.18
	(4.20)	(4.22)	(4.11)
POST X ELN/Bacrim	-4.60 **	-31.69 ***	1.71
	(1.85)	(7.55)	(1.57)
POST X All	10.61	-7.44 **	-1.02
	(11.78)	(3.35)	(0.76)
Observations	366	2013	2013

Source: Author's calculations

Notes: The unit of observation is the municipality-year. The specification includes municipality and department-by-year fixed effects. Standard errors clustered at the municipal level are presented in parenthesis. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

A.2 Baseline estimations controlling for PDET municipalities.

Table A.2. The effect of the conflict resolution process on the outcomes of interest including a control for municipalities with Territorial Development Plans (PDET)

	Economic activity	Violence	Coca cultivation
POST	-6.41	-49.63 ***	1.63
	(4.28)	(7.19)	(3.18)
POST X FARC	9.53 ***	-2.23	0.89
	(3.43)	(4.55)	(1.32)
POST X FARC/ELN	6.32	1.27	8.38 *
	(4.23)	(6.03)	(4.99)
POST X PDET	-0.40	-7.27 **	4.09 ***
	(2.89)	(2.97)	(1.49)
Observations	366	2013	2013

Source: Author's calculations

Notes: The unit of observation is the municipality-year. The sample is restricted to municipalities that had reports of presence of at least one armed group. All specifications include municipality and department-by-year fixed effects. Standard errors clustered at the municipal level are presented in parenthesis. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

APPENDIX B

SUPPLEMENTARY MATERIAL FOR CHAPTER 2

B.1 Ex-Post power calculations

Table B.1. Ex-Post power calculations.

Group	Dependent variable	Power
Students	MIPA Technical	0.9994693
	MIPA Accounting	0.9911339
Parents	MIPA Technical	0.9844399
	MIPA Accounting	0.9739868
	Access to credit	0.7607648
	Adoption of technology	0.8280655

Source: Authors' calculations from surveys and tests.

B.2 Attrition bias by baseline characteristics

Table B.2. Attrition balance by baseline characteristics.

Baseline characteristic	Treat	Control	P-Value
Household size	4.4172662	4.2272727	0.4760941
Male-headed household	0.6330935	0.6818182	0.4971113
Educational level of parent	1.660819	1.527273	0.6350655
Landholding	4.842105	4.672727	0.8147287

Source: Authors' calculations from surveys and tests.

B.3 The effect of SATec on outcomes not targeted by the program.

Table B.3. Treatment effect on outcomes not targeted by SATec: students.

	Students			
	Access to savings	Adoption of technology: livestock	Adoption of technology: Marketing	Adoption of technology: Natural resources
A. Comparison of means				
Treat	0.04	0.01	0.03	-0.08
	(0.04)	(0.03)	(0.04)	(0.09)
Observations	226	226	226	226
B. Difference-in-differences				
Treat x time	0.05	-0.05	-0.00	-0.20 *
	(0.04)	(0.05)	(0.06)	(0.10)
Treat	0.06	0.12 *	0.10 *	0.22 **
	(0.05)	(0.06)	(0.06)	(0.10)
Time	0.06	0.06	0.05	0.04
	(0.05)	(0.04)	(0.06)	(0.12)
Observations	226	226	226	226

Source: Authors' calculations from surveys and tests.

Notes: Each column and panel correspond to separate OLS regressions that control for individual- and household level attributes (gender, age, schooling, household size and male-headed household). Standard errors clustered at the school level in parenthesis; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table B.4. Treatment effect on outcomes not targeted by SATec: parents.

	Parents		
	Adoption of technology: livestock	Adoption of technology: Marketing	Adoption of technology: Natural resources
A. Comparison of means			
Treat	0.02	0.04	-0.11 **
	(0.02)	(0.05)	(0.04)
Observations	184	184	184
B. Difference-in-differences			
Treat x time	0.02	0.02	-0.00
	(0.04)	(0.09)	(0.08)
Treat	0.19	-0.05	-0.08
	(0.14)	(0.06)	(0.06)
Time	-0.00	0.02	0.05
	(0.02)	(0.05)	(0.06)
Observations	184	184	184

Source: Authors' calculations from surveys and tests.

Notes: Each column and panel correspond to separate OLS regressions that control for individual- and household level attributes (gender, age, schooling, household size and male-headed household). Standard errors clustered at the school level in parenthesis; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

APPENDIX C

SUPPLEMENTARY MATERIAL FOR CHAPTER 3

C.1 Agronomic model of the effect of temperature and precipitation on coffee productivity

C.1.1 Submodel 1. Water absorption

Rodríguez et al. (2011) model water absorption through the roots, S_w, using a so-called Type III response function as follows:

$$S_w = D_w[1 - e^{\frac{-\alpha_w W)}{D_w}}]$$

where D_w is the demand for water, which also sets the upper bound for water uptake, Φ_w, such that $0 \leq Phi_w = S_w/D_w < 1$. $W(t)$ is the water available to the roots at time t (i.e. $W(t) = W_{soil}(t) - W_{PWP}(t)$) where $W_{PWP}(t)$ is the permanent wilting point, $W_{soil}(t)$ is the current level of water available in the soil, and α_w is the fraction of the root zone that can be searched by the roots calculated as a function of the whole plant Leaf Area Index, $LAI(t)$ and the light extinction coefficient k:

$$\alpha_w = 1 - e^{-kLAI(t)}$$

An example of how the area explored by the roots is calculated using real values is as follows: for a full-grown plant, the light extinction coefficient k is 0.446 and LAI oscillates between 7 and 8 meters per meter of land. Therefore, the average fraction of the root zone explored by a full-grown plant is 0.967 or 96.7% of the volume occupied by the roots. The relationship between demand for water and available water can be derived using the implicit function theorem:

$$\frac{\partial D_w}{\partial W} = -\frac{\alpha_w e^{-\frac{\alpha_w W}{D_w}}}{1 - e^{-\frac{\alpha_w W}{D_w}} - \alpha_w e^{-\frac{\alpha_w W}{D_w}} W}.$$

The numerator is always positive. The denominator has only one plausible case given that W is a non-negative value. If $W > 0$ the denominator is always positive, and therefore $\frac{\partial D_w}{\partial W}$ is negative, which means that demand for water decreases as water availability increases. It indicates satiation by the plant. The case of $W = 0$ is ruled out since at this point the denominator of the exponentials is 0 and therefore the partial derivative evaluated at this value of W is undefined. This process concurs with agronomic theory in that if the soil is at permanent wilting point, there is no recovery for the plant and death is inevitable.

C.1.2 Submodel 2. Production of photosynthate

The modeling of production of photosynthate follows a similar Type III response function written as follows:

$$S = D[1 - e^{\frac{-\alpha_w W - \alpha(LAI)*c*I}{D}}]$$

S is the per capita photosynthetic rate, demand D is the genetical maximum per plant under conditions of non-limiting resource, $\alpha LAI(t)$ is identical to α_w, I_o is the photosynthetically active radiation hitting the canopy of the plantation, and the constant c is the rate of conversion from Io to photosynthate, all of which are assumed to be positive. If the non-limiting resource condition holds for all inputs but demand for water D_w, then:

$$\frac{\partial S}{\partial D_w} = 1 - e^{-\frac{\alpha(LAI)\cdot c\cdot I_o}{D_w}} - \frac{\alpha(LAI) e^{-\frac{\alpha(LAI)\cdot c\cdot I_o}{D}} \cdot c \cdot I_o}{D_w}$$

which is always positive for $D_w > 0$. However, demand of water has to be compounded with the demand for oxygen, as water and oxygen compete for space within the porosities of the soil. When precipitation exceeds surface runoff, evapotranspiration, and infiltration, waterlogging can have detrimental efects on production of photosynthate. In particular, under oxygen deficiency, plants recur to anaerobic fermentative processes in detriment of aerobic metabolism, with a significant loss in the efficiency of ATP generation (Sousa and Sodek 2002; Silveira et al. 2014), and therefore diminishing the photosynthate available for growing and building of reserves.

C.1.3 Submodel 3. Growth and reserves

Plants produce photosynthate S and allocate it in priority order to egestion $(1 - \beta)$, to respiration $(i.e. Q_{10})$, or with conversion efficiency λ to reproductive and vegetative growth and reserves (GR):

$$GR = (S\beta - Q_{10})\lambda$$

It is very straightforward to see that $\frac{\partial GR}{\partial S}$ is non-negative given that $0 < \beta < 1$. In other words, the more photosynthate produced the larger the reproductive and vegetative growth reserves are.

C.1.4 Submodel 4. CBB development rate

Rodríguez et al. (2013) model development rate of CBB, $R(T(t))$, is specificed as:

$$R(T(t)) = \lambda - e^{\rho T(t)} - e^{\rho T_{max} - \frac{T_{max} - T(t)}{T_u}}$$

The effect of temperature T on the development rate can be estimated by the partial derivative:

$$\frac{\partial R(T(t))}{\partial T(t)} = \rho e^{\rho T(t)} - e^{\rho T_{max} - \frac{T_{max} - T(t)}{T_u}} \cdot T_u^{-1}$$

which is always positive for $\infty < T(t) < Tm$. Given that development rates are non-negative for living organisms, the previous functional form implies that the development rate can be modeled through a piecewise function:

$$R(T(t)) = \begin{cases} 0 & T(t) \leq T_{min} \\ \lambda - e^{\rho T(t)} - e^{\rho T_m - \frac{T_m - T(t)}{T_u}} & T_{min} \leq T(t) \leq T_{max} \\ 0 & T_{max} \leq T(t) \end{cases}$$

The values for λ, rho, T_m and T_u have been estimated by Jaramillo and Chaves (2000) and validated for the Colombian case in both experimental and productive settings. Their research finds: $\lambda = -1.0551$, $\rho = 0.00358$, $T_m = 34.2548°C$ and $T_u = 0.1537°C$ which in turn sets the minimum temperature, T_{min}, for positive development rates of CBB at 14.9°C.

C.1.5 Submodel 5. Dynamics of production

The general model for the i-th class of an age structured population proposed by Gutierrez et al. (1998) can be used to describe the process of production in coffee. The model links density of a cohort N_i (in mass or numbers i.e. yields in kg./ha.), to the number of age classes k, the expected mean development time Δ, the increment in age during one day $\Delta x(T(t))$ in degree days and the proportional net loss rate that includes biological factors such as herbivory (or CBB parasitation) μ_i so that:

$$\frac{dN_i(t)}{dt} = \frac{k\Delta x(T(t))}{\Delta}[N_{i-t} - N_i] - \mu_i N_i$$

Two previous submodels enter in action in submodel 5: the reproductive and growth reserves GR which are positively correlated with N_i and N_{i-1} , and the CBB development rate which is positively correlated with the cohort density variables. This result stems from the fact that the shorter the reproductive period, the larger the population of egg-laying females and the more severe the net loss from CBB infestation.

Similarly, temperature has two opposing effects on yields: a positive direct effect through $\Delta x(T(t))$ and a negative indirect effect through μ_i. The relative strength of the effects has important implications on the functional form that captures the effect of temperature on yields and the expected signs of the coefficients associated with it. Some intuition for this question can be gauged from Rodríguez et al. (2013): the number of newly attacked coffee berries at time $t, S_b(t)$ is a function of the number of searching CBB females $N_b(t)$, the demand for berries $B(t)$ and the female search rate α_b, such that:

$$S_b(t) = B(t)\left[1 - e^{\left(\frac{-N_b(t)(1-e^{(-\alpha_b(t)B(t)/N_b(t))})}{B(t)}\right)}\right]$$

If the search is imperfect: $0 \leq \Phi = S_b(t)/B(t) < 1$, it means that some females ($1 - \Phi$) fail to find a host or are lost to the local population due to emigration. We argue that the failure of CBB to completely infest all new coffee berries implies that temperature still has an overall positive effect on yield realization even if it is dampened by the increased parasitization due to larger and more frequent cohorts of CBB.

C.2 Omitted variable bias: proof

True population model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + u$$

Estimated model (omitting x_2)

$\tilde{y} = \widetilde{\beta_0} + \widetilde{\beta_1} x_1$

Therefore,

$$\widetilde{\beta_1} = \widehat{\beta_1} + \widehat{\beta_2}\tilde{\delta}$$

Where $\widehat{\beta_1},\ \widehat{\beta_2}$ are the slope estimates from regressing y on x_1 and x_2, respectively, and $\tilde{\delta}$ is the slope estimate of regressing x_2 on x_1.

Under the assumption that $\widehat{\beta_1},\ \widehat{\beta_2}$ are unbiased estimates of $\beta_1,\ \beta_2$, then:

$E\left(\widetilde{\beta_1}\right) = E(\widehat{\beta_1} + \widehat{\beta_2}\tilde{\delta})$

$E\left(\widetilde{\beta_1}\right) = E(\widehat{\beta_1}) + E\left(\widehat{\beta_2}\right)\tilde{\delta} = \beta_1 + \beta_2\tilde{\delta}$

$$\Rightarrow Bias\left(\widetilde{\beta_1}\right) = E\left(\widetilde{\beta_1}\right) - \beta_1 = \beta_2\tilde{\delta}$$

C.3 Projected changes in coffee productivity for selected municipalities, 2041-2060

Zip code	Municipality	RCP 2.6	RCP 4.5	RCP 6.0
5001	Medellin	0.634	0.587	0.645
5002	Abejorral	0.707	0.673	0.755
5004	Abriaqui	0.631	0.529	0.59
5021	Alejandria	1.006	0.883	1.003
5030	Amaga	0.73	0.755	0.833
5031	Amalfi	0.852	0.816	0.93
5034	Andes	0.784	0.685	0.795
5036	Angelopolis	0.63	0.618	0.677
5038	Angostura	0.957	0.701	0.773
5040	Anori	0.93	0.856	0.996
5042	Santa Fe de Antioquia	1.161	1.116	1.255
5044	Anza	1.087	1.054	1.185
5055	Argelia	0.373	0.436	0.482
5059	Armenia	0.379	0.507	0.541
5079	Barbosa	0.924	0.848	0.951
5088	Bello	0.528	0.456	0.492
5091	Betania	1.415	1.229	1.434
5093	Betulia	1.013	0.957	1.078
5101	Ciudad Bolivar	1.113	1.012	1.163
5107	Briceno	1.033	0.938	1.063
5113	Buritica	1.416	1.283	1.453
5125	Caicedo	0.511	0.421	0.46
5129	Caldas	0.554	0.514	0.566
5134	Campamento	1.348	1.128	1.286
5138	Canasgordas	0.814	0.762	0.841
5142	Caracoli	0	0.016	0.023
5145	Caramanta	0.955	0.924	1.047
5148	El Carmen de Viboral	0.764	0.677	0.777
5190	Cisneros	0.921	0.868	0.981
5197	Cocorna	0.606	0.646	0.72
5206	Concepcion	0.75	0.584	0.651
5209	Concordia	0.946	0.929	1.045
5212	Copacabana	0.753	0.718	0.795
5237	Don Matias	0.776	0.646	0.714
5240	Ebejico	0.566	0.723	0.713
5282	Fredonia	0.456	0.554	0.603
5306	Giraldo	1.076	0.92	1.037
5308	Girardota	0.775	0.734	0.812

5310	Gomez Plata	1.024	0.919	1.037
5313	Granada	0.876	0.707	0.807
5315	Guadalupe	1.17	0.986	1.112
5321	Guatape	0.97	0.805	0.944
5347	Heliconia	0.763	0.764	0.842
5353	Hispania	0.505	0.606	0.659
5364	Jardin	0.487	0.433	0.491
5368	Jerico	0.853	0.839	0.945
5376	La Ceja	0.652	0.569	0.641
5380	La Estrella	0.548	0.521	0.581
5411	Liborina	0.56	0.565	0.608
5425	Maceo	0.136	0.265	0.299
5440	Marinilla	0.725	0.627	0.711
5467	Montebello	0.674	0.681	0.752
5483	Narino	0.477	0.536	0.606
5501	Olaya	0.289	0.397	0.415
5541	Penol	0.867	0.739	0.846
5543	Peque	1.27	1.044	1.166
5576	Pueblorrico	0.835	0.823	0.926
5607	Retiro	0.464	0.363	0.4
5628	Sabanalarga	0.588	0.627	0.685
5631	Sabaneta	0.733	0.922	0.819
5642	Salgar	1.187	1.05	1.201
5647	San Andrãˆs	0.663	0.526	0.573
5649	San Carlos	0.288	0.336	0.375
5652	San Francisco	0	0.037	0.035
5656	San Jeronimo	0.738	0.772	0.848
5660	San Luis	0.033	0.111	0.119
5667	San Rafael	0.659	0.667	0.756
5670	San Roque	0.559	0.598	0.674
5679	Santa Barbara	0.583	0.633	0.697
5686	Santa Rosa de Osos	0.314	0.144	0.116
5690	Santo Domingo	0.962	0.826	0.935
5756	Sonson	0.353	0.431	0.468
5761	Sopetran	0.498	0.598	0.646
5789	Tamesis	0.899	0.951	0.996
5792	Tarso	0.418	0.746	0.561
5809	Titiribi	0.563	0.65	0.712
5819	Toledo	0.815	0.807	0.902
5842	Uramita	1.023	0.986	1.106
5856	Valparaiso	0.098	0.642	0.2
5858	Vegachi	0.49	0.573	0.646
5861	Venecia	0.299	0.414	0.434

5885	Yali	0.432	0.521	0.583
5887	Yarumal	0.882	0.587	0.633
15022	Almeida	0.879	0.757	0.84
15090	Berbeo	0.891	0.883	1
15106	Briceno	0.71	1.177	0.829
15109	Buenavista	0.552	0.891	0.643
15185	Chitaraque	0.989	1.067	1.07
15212	Coper	0.393	0.97	0.51
15325	Guayata	0.717	0.651	0.718
15377	Labranza Grande	1.131	1.003	1.128
15401	La Victoria	0.539	0.648	0.696
15442	Maripi	0.084	0.686	0.161
15455	Miraflores	1.011	0.863	0.96
15469	Moniquira	0.733	1.026	0.814
15480	Muzo	0.017	0.752	0.061
15507	Otanche	0	0.407	0
15514	Paez	1.163	1.077	1.237
15531	Pauna	0.276	0.945	0.385
15533	Paya	0.91	0.953	1.099
15550	Pisba	1.073	0.959	1.075
15580	Quipama	0.044	0.597	0.119
15660	San Eduardo	0.893	0.765	0.845
15664	San Jose de Pare	0.933	1.139	1.035
15681	San Pablo de Borbur	0.005	0.562	0.051
15686	Santana	0.938	1.206	1.061
15690	Santa Maria	0.996	0.997	1.168
15761	Somondoco	0.824	0.783	0.876
15816	Togãœi	0.75	0.997	0.829
15897	Zetaquira	0.721	0.635	0.695
17001	Manizales	0.516	0.826	0.617
17013	Aguadas	0.697	0.962	0.801
17042	Anserma	0.389	0.752	0.526
17050	Aranzazu	0.605	0.81	0.687
17088	Belalcazar	0.252	0.76	0.381
17174	Chinchina	0.229	0.782	0.348
17272	Filadelfia	0.193	0.709	0.321
17388	La Merced	0.298	0.764	0.416
17433	Manzanares	0.83	0.802	0.977
17442	Marmato	0.656	1.025	0.808
17444	Marquetalia	0.557	0.818	0.728
17446	Marulanda	0.013	0	0
17486	Neira	0.586	0.835	0.685
17513	Pacora	0.516	0.714	0.617

17524	Palestina	0.148	0.714	0.274
17541	Pensilvania	0.879	0.811	1.003
17614	Riosucio	0.738	0.659	0.767
17616	Risaralda	0.318	0.745	0.449
17653	Salamina	0.277	0.384	0.332
17662	Samana	0.004	0.261	0.073
17665	San Jose	0.214	0.651	0.337
17777	Supia	0.634	0.78	0.761
17867	Victoria	0	0.56	0
17873	Villamaria	0	0.071	0
17877	Viterbo	0.046	0.509	0.136
18001	Florencia	1.739	1.673	1.974
18247	El Doncello	1.406	1.43	1.701
18256	El Paujil	1.396	1.422	1.692
18410	La Montanita	0.546	0.672	0.802
18592	Puerto Rico	1.487	1.49	1.754
18753	San Vicente del Caguan	0.862	1.005	1.17
19001	Popayan	0.923	1.413	1.073
19022	Almaguer	0.614	0.943	0.743
19050	Argelia	2.254	2.059	2.465
19075	Balboa	1.341	1.928	1.512
19100	Bolivar	0.809	1.229	0.96
19110	Buenos Aires	1.08	1.513	1.268
19130	Cajibio	1.133	1.548	1.331
19137	Caldono	0.687	1.223	0.845
19142	Caloto	0.363	1.089	0.503
19212	Corinto	0.79	1.21	0.919
19355	Inza	0.329	0.635	0.425
19364	Jambalo	0.395	0.773	0.525
19392	La Sierra	0.648	1.191	0.804
19397	La Vega	0.368	0.657	0.481
19450	Mercaderes	0.316	1.018	0.445
19455	Miranda	0.774	1.267	0.911
19473	Morales	1.418	1.32	1.647
19517	Paez	0.674	1.029	0.805
19532	Patia	0.529	1.376	0.699
19548	Piendamo	0.778	1.406	0.95
19585	Purace (Coconuco)	0	0.159	0
19622	Rosas	0.668	1.257	0.825
19693	San Sebastian	0	0.016	0
19698	Santander de Quilichao	0.466	1.255	0.629
19760	Sotara (Paispamba)	0.047	0.253	0.056
19780	Suarez	1.471	1.379	1.672

19785	Sucre	0.64	1.229	0.805
19807	Timbio	0.812	1.392	0.967
19821	Toribio	0.057	0.31	0.074
19824	Totoro	0	0.195	0
20001	Valledupar	0.087	0.18	0.197
20011	Aguachica	0	0	0
20013	Agustin Codazzi	0.052	0.118	0.115
20045	Becerrill	0	0	0
20175	Chimichagua	0	0	0
20178	Chiriguana	0	0	0
20228	Curumani	0	0	0
20310	Gonzalez	0.762	0.769	0.843
20383	La Gloria	0	0	0
20400	La Jagua de Ibirico	0	0	0
20517	Pailitas	0	0	0
20550	Pelaya	0	0	0
20614	Rio de Oro	0	0	0
20621	La Paz	0.265	0.384	0.4
20710	San Alberto	0	0.172	0
20770	San Martin	0	0	0
25019	Alban	0.315	0.841	0.445
25035	Anapoima	0	0.458	0
25040	Anolaima	0.574	1.026	0.703
25053	Arbelaez	0.676	0.871	0.789
25086	Beltran	0	0.545	0
25095	Bituima	0.211	0.887	0.309
25120	Cabrera	0	0.144	0
25123	Cachipay	0.346	0.79	0.483
25148	Caparrapi	0	0.618	0
25151	Caqueza	0.974	0.913	1.032
25168	Chaguani	0	0.629	0
25245	El Colegio	0.245	0.537	0.358
25258	El Penon	0.19	0.892	0.286
25281	Fosca	0.534	0.453	0.503
25290	Fusagasuga	0.63	0.905	0.772
25293	Gachala	0.859	0.698	0.775
25297	Gacheta	0.529	0.453	0.486
25299	Gama	0.876	0.723	0.808
25320	Guaduas	0	0.724	0
25328	Guayabal de Siquima	0.274	0.855	0.382
25335	Guayabetal	1.12	0.913	1.035
25368	Jerusalen	0	0.614	0
25372	Junin	0.101	0.042	0.024

25386	La Mesa	0.028	0.52	0.082
25394	La Palma	0.263	0.831	0.376
25398	La Pena	0.005	0.73	0.033
25402	La Vega	0.216	0.811	0.316
25426	Macheta	0.081	0.062	0.038
25436	Manta	0.728	0.668	0.74
25438	Medina	1.036	1.003	1.176
25488	Nilo	0	0.575	0
25489	Nimaima	0	0.699	0
25491	Nocaima	0.012	0.753	0.039
25506	Venecia	0.432	0.606	0.52
25513	Pacho	0.483	0.881	0.592
25518	Paime	0.159	0.855	0.246
25524	Pandi	0.502	0.94	0.656
25580	Puli	0	0.594	0
25592	Quebradanegra	0.105	0.894	0.175
25594	Quetame	0.782	0.65	0.72
25596	Quipile	0.486	1.21	0.642
25599	Apulo	0	0.589	0
25645	San Antonio del Tequendama	0.495	0.61	0.614
25649	San Bernardo	0	0.013	0
25653	San Cayetano	0.42	0.746	0.505
25658	San Francisco	0.306	0.707	0.421
25662	San Juan de Rio Seco	0	0.577	0
25718	Sasaima	0.089	0.708	0.159
25743	Silvania	0.687	0.909	0.793
25777	Supata	0.449	0.86	0.561
25797	Tena	0.604	0.938	0.753
25805	Tibacuy	0.429	1.118	0.57
25807	Tibirita	0.331	0.316	0.325
25815	Tocaima	0	0.614	0
25823	Topaipi	0.246	0.921	0.349
25862	Vergara	0.164	0.875	0.255
25867	Viani	0.543	1.242	0.708
25871	Villa Gomez	0.575	1.094	0.709
25875	Villeta	0.016	0.784	0.03
25878	Viota	0.145	0.583	0.227
25885	Yacopi	0	0.475	0
25898	Zipacon	0.454	0.799	0.555
27245	El Carmen	0.592	0.404	0.473
41001	Neiva	0.63	1.416	0.811
41006	Acevedo	1.316	1.365	1.466
41013	Agrado	0.509	1.308	0.692

41016	Aipe	0.044	0.901	0.04
41020	Algeciras	0.955	1.413	1.119
41026	Altamira	0.819	1.476	1.026
41078	Baraya	1.153	1.731	1.318
41132	Campoalegre	0.604	1.397	0.777
41206	Colombia	0.853	1.265	0.994
41244	Elias	1.176	1.69	1.361
41298	Garzon	1.325	1.795	1.485
41306	Gigante	1.248	1.821	1.423
41319	Guadalupe	1.197	1.643	1.362
41349	Hobo	0.414	1.143	0.562
41357	Iquira	1.438	2.022	1.609
41359	Isnos	0.489	0.729	0.6
41378	La Argentina	0.023	0.201	0.042
41396	La Plata	0.871	1.294	1.016
41483	Nataga	0.96	1.51	1.124
41503	Oporapa	1.302	1.627	1.435
41518	Paicol	0.802	1.536	0.992
41524	Palermo	0.249	1.146	0.341
41530	Palestina	1.443	1.596	1.568
41548	Pital	1.349	1.967	1.53
41551	Pitalito	1.244	1.553	1.393
41615	Rivera	0.886	1.592	1.064
41660	Saladoblanco	0	0.123	0
41668	San Agustin	0.252	0.443	0.331
41676	Santa Maria	1.337	1.808	1.534
41770	Suaza	0.865	1.238	1.036
41791	Tarqui	1.194	1.776	1.374
41797	Tesalia	0.402	1.186	0.557
41799	Tello	0.93	1.601	1.111
41801	Teruel	1.383	1.817	1.546
41807	Timana	0.967	1.436	1.141
50001	Villavicencio	0.073	0.155	0.217
50223	Cubarral	0.989	0.841	1.001
50226	Cumaral	0	0.02	0.028
50251	El Castillo	0.913	0.976	1.14
50270	El Dorado	0.518	0.618	0.734
50330	Mesetas	0.363	0.644	0.55
50400	Lejanias	1.325	1.21	1.424
50606	Restrepo	0.592	0.647	0.778
50683	San Juan de Arama	0.005	0.055	0.078
52001	Pasto	0	0	0
52019	Alban (San Jose)	0.942	1.174	1.064

52036	Ancuya	1.149	1.37	1.263
52051	Arboleda	1.105	1.481	1.241
52110	Buesaco	0.209	0.334	0.266
52203	Colon	1.013	1.253	1.135
52207	Consaca	0.319	0.356	0.4
52233	Cumbitara	0.745	1.458	0.934
52240	Chachagãœi	0.809	0.936	0.919
52256	El Rosario	0.784	1.588	0.97
52258	El Tablon de Gã"Mez	0.305	0.423	0.355
52260	El Tambo	0.925	1.239	1.055
52287	Funes	0	0.043	0
52320	Guaitarilla	0.43	0.587	0.507
52378	La Cruz	0	0.027	0
52381	La Florida	0.653	0.782	0.754
52399	La Union	0.891	1.267	1.04
52405	Leiva	0.797	1.497	0.971
52411	Linares	0.988	1.361	1.134
52418	Los Andes	1.169	1.172	1.399
52435	Mallama (Piedrancha)	0.56	0.87	0.683
52540	Policarpa	0.867	1.732	1.048
52565	Providencia	0.055	0.11	0.062
52683	Sandona	0.772	0.841	0.88
52685	San Bernardo	0.482	0.669	0.57
52687	San Lorenzo	1.016	1.415	1.157
52693	San Pablo	0.594	0.807	0.702
52694	San Pedro de Cartago	0.645	0.986	0.77
52699	Santa Cruz (Guachaves)	0.952	1.38	1.092
52786	Taminango	0.571	1.135	0.741
52788	Tangua	0	0	0
52885	Yacuanquer	0.174	0.198	0.226
54001	Cucuta	0	0.594	0
54003	Abrego	0.62	0.634	0.655
54051	Arboledas	0.562	0.699	0.58
54099	Bochalema	0.5	0.71	0.603
54109	Bucarasica	0.774	0.98	0.834
54128	Cachira	0.765	0.974	0.823
54172	Chinacota	0.597	0.639	0.684
54174	Chitagã€	0.12	0.039	0.018
54206	Convencion	0.075	0.182	0.188
54223	Cucutilla	0.404	0.458	0.401
54239	Durania	0.052	0.529	0.128
54245	El Carmen	0.468	0.55	0.6
54261	El Zulia	0	0.6	0

54313	Gramalote	0.505	0.868	0.596
54344	Hacari	0.164	0.294	0.291
54347	Herran	0.474	0.38	0.39
54377	Labateca	0.622	0.503	0.54
54398	La Playa	0.647	0.657	0.707
54405	Los Patios	0	0.242	0
54418	Lourdes	0.578	1.025	0.668
54520	Pamplonita	0.561	0.557	0.595
54599	Ragonvalia	0.738	0.714	0.777
54660	Salazar	0.675	0.922	0.736
54670	San Calixto	0.259	0.372	0.382
54673	San Cayetano	0	0.535	0
54680	Santiago	0	0.53	0
54720	Sardinata	0	0.321	0
54800	Teorama	0.122	0.253	0.269
54820	Toledo	0.999	0.84	0.933
54871	Villa Caro	0.438	0.528	0.425
54874	Villa del Rosario	0	0.259	0
63001	Armenia	0.165	0.858	0.285
63111	Buenavista	0.111	0.701	0.211
63130	Calarca	0.522	0.995	0.65
63190	Circasia	0.458	1.044	0.607
63212	Cordoba	0.403	0.724	0.502
63272	Filandia	0.582	1.083	0.73
63302	Genova	0.143	0.39	0.215
63401	La Tebaida	0.074	0.797	0.142
63470	Montenegro	0.17	0.921	0.297
63548	Pijao	0.114	0.366	0.182
63594	Quimbaya	0.152	0.844	0.27
63690	Salento	0.108	0.341	0.155
66001	Pereira	0.568	1.041	0.699
66045	Apia	1.009	0.922	1.072
66075	Balboa	0.216	0.739	0.349
66088	Belen de Umbria	0.749	0.804	0.864
66170	Dosquebradas	0.527	0.934	0.675
66318	Guatica	0.768	0.729	0.837
66383	La Celia	0.793	0.848	0.912
66400	La Virginia	0.205	0.917	0.358
66440	Marsella	0.241	0.792	0.361
66456	Mistrato	0.201	0.221	0.234
66572	Pueblo Rico	0.717	0.734	0.83
66594	Quinchia	0.479	0.538	0.599
66682	Santa Rosa de Cabal	0.209	0.425	0.288

66687	Santuario	1.241	1.153	1.332
68001	Bucaramanga	0.094	0.622	0.171
68013	Aguada	1.311	1.141	1.338
68020	Albania	0.743	1.049	0.817
68051	Aratoca	0.619	0.942	0.766
68077	Barbosa	0.989	0.952	1.085
68079	Barichara	0.32	0.584	0.453
68092	Betulia	0.006	0.54	0.028
68101	Bolivar	0	0.058	0
68121	Cabrera	0.046	0.346	0.155
68167	Charala	0.928	1.056	1.021
68169	Charta	0.338	0.426	0.372
68176	Chima	1.027	0.923	1.062
68209	Confines	0.902	0.949	0.994
68211	Contratacion	1.019	0.911	1.055
68217	Coromoro	0.245	0.43	0.258
68229	Curiti	0.898	1.056	0.996
68235	El Carmen de Chucuri	0.078	0.419	0.184
68245	El Guacamayo	0.739	0.714	0.816
68255	El Playon	0.27	0.778	0.391
68264	Encino	0.144	0.343	0.157
68271	Florian	1.232	1.577	1.354
68276	Floridablanca	0.421	0.79	0.526
68296	Galan	1.046	1	1.13
68298	Gambita	0.649	0.902	0.706
68307	Giron	0.017	0.633	0.052
68320	Guadalupe	0.666	0.89	0.797
68322	Guapota	0.519	0.926	0.663
68324	Guavata	0.877	0.826	0.959
68344	Hato	1.243	1.067	1.225
68368	Jesus Maria	1.076	1.164	1.168
68370	Jordan Sube	0.161	0.635	0.307
68377	La Belleza	0.075	0.564	0.169
68397	La Paz	0.537	0.593	0.66
68406	Lebrija	0	0.614	0
68418	Los Santos	0.515	0.931	0.677
68444	Matanza	0.615	0.861	0.672
68464	Mogotes	0.786	1	0.868
68498	Ocamonte	0.748	0.97	0.858
68500	Oiba	0.947	0.912	1.047
68502	Onzaga	0.059	0.199	0.056
68524	Palmas del Socorro	0.517	0.889	0.664
68533	Paramo	0.948	1.003	1.051

68547	Piedecuesta	0.732	0.902	0.815
68549	Pinchote	0.713	0.947	0.849
68572	Puente Nacional	0.661	0.967	0.74
68615	Rionegro	0	0.378	0
68669	San Andres	0.113	0.104	0.081
68673	San Benito	0.706	0.971	0.856
68679	San Gil	0.731	0.858	0.86
68682	San Joaquin	0.872	1.092	0.93
68684	San Jose de Miranda	0.384	0.428	0.443
68689	San Vicente de Chucuri	0	0.378	0
68745	Simacota	0.006	0.031	0.038
68755	Socorro	0.601	0.894	0.745
68770	Suaita	0.815	0.896	0.919
68773	Sucre	0.714	0.797	0.836
68780	Surata	0.013	0.077	0.018
68820	Tona	0	0	0
68855	Valle de San Jose	0.745	1.051	0.862
68861	Velez	0.76	0.793	0.897
68872	Villanueva	0.499	0.856	0.652
68895	Zapatoca	0.647	1.01	0.779
73001	Ibague	0.63	0.98	0.748
73024	Alpujarra	0.481	1.261	0.632
73026	Alvarado	0	0.638	0
73043	Anzoategui	0.013	0.14	0.035
73055	Armero	0	0.792	0
73067	Ataco	0.123	0.909	0.191
73124	Cajamarca	0.01	0.185	0.022
73152	Casabianca	0.248	0.474	0.333
73168	Chaparral	0.865	1.397	1.033
73226	Cunday	0.029	0.795	0.044
73236	Dolores	0.786	1.504	0.965
73270	Falan	0	0.544	0
73283	Fresno	0.363	0.734	0.504
73347	Herveo	0.197	0.246	0.27
73352	Icononzo	0.553	1.191	0.714
73408	Lerida	0	0.748	0
73411	Libano	0.149	0.652	0.251
73443	San Sebastian de Mariquita	0	0.573	0
73449	Melgar	0	0.608	0
73483	Natagaima	0	0.836	0
73504	Ortega	0	0.715	0
73520	Palocabildo	0.259	0.679	0.382
73555	Planadas	0.023	0.311	0.041

73563	Prado	0	0.795	0
73616	Rioblanco	0.315	0.488	0.418
73622	Roncesvalles	0	0.126	0
73624	Rovira	0.6	1.024	0.732
73675	San Antonio	0.534	0.945	0.66
73678	San Luis	0	0.703	0
73686	Santa Isabel	0	0.03	0
73854	Valle de San Juan	0	0.633	0
73861	Venadillo	0	0.695	0
73870	Villahermosa	0.206	0.334	0.3
76001	Cali	1.212	1.689	1.35
76020	Alcala	0.164	0.835	0.289
76036	Andalucia	0.291	1.019	0.426
76041	Ansermanuevo	0.445	0.95	0.596
76054	Argelia	0	0.173	0
76100	Bolivar	0.594	1.036	0.733
76111	Buga	0.563	0.857	0.656
76113	Bugalagrande	0.109	0.758	0.198
76122	Caicedonia	0.063	0.639	0.13
76147	Cartago	0.182	0.9	0.326
76233	Dagua	1.57	1.64	1.701
76243	El Aguila	0.887	0.865	0.971
76246	El Cairo	0.134	0.159	0.177
76248	El Cerrito	0.858	1.329	0.99
76250	El Dovio	0.184	0.546	0.283
76275	Florida	0.526	0.875	0.639
76306	Ginebra	0.584	1.009	0.706
76318	Guacari	0.347	0.957	0.483
76364	Jamundi	1.192	1.728	1.351
76377	La Cumbre	0.634	1.007	0.769
76400	La Union	0.386	0.989	0.534
76403	La Victoria	0.155	0.908	0.277
76497	Obando	0.19	0.92	0.331
76520	Palmira	0.741	1.171	0.871
76563	Pradera	0.619	1.041	0.747
76606	Restrepo	1.174	1.492	1.306
76616	Riofrio	0.71	1.083	0.839
76622	Roldanillo	0.567	1.118	0.718
76670	San Pedro	0.45	1.062	0.601
76736	Sevilla	0.777	1.196	0.895
76823	Toro	0.472	1.034	0.632
76828	Trujillo	0.486	0.827	0.599
76834	Tulua	0.994	1.371	1.106

76845	Ulloa	0.181	0.848	0.308
76863	Versalles	0.027	0.26	0.076
76869	Vijes	0.49	0.925	0.63
76890	Yotoco	0.594	1.083	0.753
76892	Yumbo	0.803	1.264	0.955
85162	Monterrey	0.19	0.264	0.37
85225	Nunchia	0.011	0.041	0.057
85315	Sacama	1.165	1.105	1.253
85400	Tamara	0.948	0.977	1.12
86001	Mocoa	1.597	1.483	1.759

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