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Essays on Socioeconomic Shocks and Policies in Agriculture

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ESSAYS ON SOCIOECONOMIC SHOCKS AND POLICIES IN AGRICULTURE

by

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The three chapters of this doctoral dissertation estimate the responses of agricultural productivity, production value of agriculture, and crop supply to some external shocks and policies. Using unique panel datasets for Colombia and the United States, this research provides new insights regarding the responsiveness of agriculture to some socioeconomic effects and related market policies.

Chapter 1 studies the effect of armed conflicts in rural areas on agricultural productivity in Colombia by using a production function that includes violence shocks such as the forced intra-national displacement of the rural population from 1995 to 2017. Although the relevance of the agricultural sector to the Colombian economy, the annual growth rate of the value of agricultural production has fluctuated significantly over the last two decades with a relatively low growth rate. Therefore, it is of imperative interest to understand how violence and the internal displacement of persons have affected the use of resources and productivity in Colombian agriculture.

Chapter 2 investigates the effect of anti-drug strategies implemented under a joint US-Colombia policy (*Plan Colombia*) on the value of agricultural production of Colombian regions with coca crops. This chapter uses a difference-in-difference approach to evaluate the impact of the anti-drug policies on the GDP of agriculture in the coca-growing areas.

Chapter 3 examines the effects of a policy in the ethanol market on the supply of biomass from corn production at the extensive and intensive margins. This chapter employs a profit function framework, simultaneous equations panel models, and instrumental variables approach to analyze the land allocation and crop yield responses to the US 2007's Renewable Fuel Standard (RFS). This policy mandated specified quantities of total biofuels creating exogenous market shocks to corn prices in several counties along the US Great Plains. It is of particular interest to assess the corn supply and cropland allocation responsiveness to the price increase structurally generated by the mandates.

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CHAPTER 1
THE COST OF VIOLENCE FOR LEGAL AGRICULTURAL PRODUCTIVITY: EVIDENCE FROM COLOMBIAN ARMED CONFLICT

1.1. Introduction

The violence from armed conflict in Colombia has been costly to agriculture. In the last fifty years, violence shocks mainly affected the Colombian rural population through forced intra-national displacement and war-related casualties. Previous studies have found that the Colombian armed conflict has internally displaced 4.7 million people since 1996, killed nearly a quarter of a million since the late 50s, and kidnapped around 27 thousand since 1970 (Arias *et al.*, 2019; Morales, 2018; Dueñas *et al.*, 2014). These violence shocks displacing people alter rural labor and the agricultural enterprise's risk and uncertainty, leading to reductions in investments and technology adoption that significantly reduce the sectorial productivity[1]. Studies of productivity growth in Colombia should consider this issue to understand economic sectors' evolution and the characteristics of their technical change.

The agricultural sector has traditionally been crucial to the Colombian economy.[2] However, annual growth rates of the production value of agriculture fluctuated significantly over the last two decades, with a relatively low growth rate of 1.6% since 1990 (see Jiménez *et al.*, 2018, for more details, and Figure 1.2 for a visual perspective of Colombian agricultural GDP and its growth rate evolution in 1995-2017). This research

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[1] Because productivity might be an ambiguous concept, the term "productivity" used in this study refers to any potential change in output from a given level of inputs. A productivity variation may occur due to a technology change or fluctuations in the technical efficiency with which the inputs are used (Dogramaci *et al.*, 1988; Fulginiti and Perrin, 1993).

[2] Colombia's agriculture consists of 4 sub-sectors: farming, livestock, forestry, and fisheries, where the latter two sectors are relatively small. Although the agricultural sector has historically been one of the major engines of Colombian economic development, the share of agriculture in Colombia's gross domestic product (GDP) has almost fallen consistently since 1995, especially after 1999 (see Figure 1.1). Figure 1.1 indicates that the average value-added in the agricultural sector as a percentage of Colombia's GDP during 1995-2017 was 8.25 percent, with a minimum of 5.39 percent in 2013 and a maximum of 14.02 percent in 1995. The latest value from 2017 is 6.39 percent (see Figure 1.1).

employs a production function that includes violence shocks at the department level[3] from 1995 to 2017. The objective is to explore the effect of the armed conflict on the agricultural productivity of Colombia. This chapter examines the conflict effects through internally displaced persons (IDP)[4] and the number of war-related casualties on Colombian agricultural productivity.

One essential assumption here is that agricultural productivity may be affected by IDP and casualties, which are two of the most relevant outcomes of violence shocks and uncertainty generated by the armed conflict. We examine this issue using a unique panel dataset consisting of 26 departments of Colombia. The conceptual framework implemented was an aggregate agricultural production function where conflict-related variables are assumed to significantly contribute to determining the productivity of traditional inputs such as labor and capital. This relationship implies that the conflict imposes costs on economic productivity through two broad channels. First, armed combats and terrorist attacks destroy capital and assets that reduce the productive capacity of firms (including farms and households) and food security, especially in rural areas (Blattman and Miguel, 2010; George *et al*., 2019; Collier, 1999; Ibáñez and Moya, 2010; Justino, 2011; Arias *et al.*, 2019). This mechanism hence affects incentives to innovate. Second, the presence of non-state armed actors prompts individuals to run away from rural areas as they experience shocks such as aggression against the civilian population deteriorating the labor supply through abductions, killings, and maiming (Camacho, 2008; Arias *et al.*, 2019; George *et al*., 2019). This channel thus affects incentives to invest in human capital.

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[3] Colombia consists of 1,123 municipalities grouped into 32 departments (31 continental departments and the Island of San Andrés and Providencia). The continental departments constitute five major administrative regions (Amazon, Andean, Caribbean, Orinoco, and Pacific). Municipalities are analogous to counties in the U.S., whereas departments are political divisions like states in the U.S.

[4] The Inter-American Commission on Human Rights (1999) describes a displaced person as "… anyone who has been forced to migrate within the national boundaries, leaving aside his/her residence or his/her habitual economic activities because either his/her life, his/her physical integrity or his/her freedom have been either violated or threatened by situations such as armed conflict, generalized violence, violation of human rights, and any other situation that may alter public order…". Moreover, IDP should not be confused with refugees because they do not cross-national frontiers. Thus their protection is primarily the responsibility of the national State concerned (Office of the United Nations High Commissioner for Refugees –UNHCR-, 2007).

The main research question addressed by this chapter is: Have violence shocks from armed conflict in rural areas of Colombia affected agricultural productivity? It is relevant to consider the relationship between factors of production and the armed conflict for productivity analysis of the Colombian agricultural sector. There is an expected negative link between violence shocks from armed conflict and the productivity of factors used in agricultural production. For instance, Dube and Vargas (2013) show that commodity price shocks affect the dynamic of armed rural conflicts in Colombia by changing the amount of labor supplied to conflict activity. The authors examine exogenous changes in the world price of agricultural commodities and found that income shocks induced by those changes are negatively related to rural conflicts because of an opportunity cost effect on Colombian agriculture.[5]

We analyze the relationship between agricultural inputs and violence shocks as they affect agricultural productivity. That is to say, the intensification of armed conflicts leads to outcomes such as forced IDP from rural to urban areas of Colombia that directly affect both the availability and the productivity of inputs in agriculture. The increased risk and uncertainty introduced by violence from such conflicts may indirectly affect innovation investments in the sector. Violence shocks can discourage investments in human capital that may lead to adverse shocks in productivity by affecting the marginal productivity of inputs.

Colombian rural areas have been scenarios of persistent violence, armed conflicts, social tensions, poverty traps, and thus extreme vulnerability of their population's socioeconomic activities. However, armed conflicts and violent events triggered by the war between insurgent groups and the government forces in the rural regions are the main reason for the departure of people from rural to urban areas in Colombia. Economic literature related to this issue has focused on identifying whether violence or armed conflicts impact economic growth. This impact is associated with (a) changes in productive factors accumulation by reducing labor supply (Odozi and Oyelere, 2021;

[5] The opportunity cost effect here implies that positive agricultural income shocks increase Colombian agriculture wages and reduce violence from the conflict in rural areas by reducing the labor supplied to criminal activities (Dube and Vargas, 2013).

Blattman and Miguel, 2010a), (b) lifetime labor productivity (Blattman and Miguel, 2010a,b) or (c) increasing capital costs (Gaviria and Vélez, 2001; Riascos and Vargas, 2004; World Bank, 2009; Pshisva and Suarez, 2010; Thomson, 2011; Dube and Vargas, 2013; Maher, 2015a,b). However, there is little evidence about the effects of violence expressed in irreversible outcomes such as the armed conflict-related casualties and internal displacement of the rural population on the productivity of Colombian agriculture. This study provides insights into how such violence shocks may have affected Colombia's agricultural sector yields and productivity. Blattman and Miguel (2010) pointed out that an economic growth theory framework may help in analyzing the consequences of conflicts. They assert that: "*...If conflict affects economic performance, it must be because it affects a factor of production (physical capital, labor, or human capital), the technology, institutions, and culture that augment these factors, or prices (e.g., costs of capital). The growth framework also clarifies the possible nature of the impacts, not only on income levels and economic growth in equilibrium, but also out-of-equilibrium dynamics*...." (Blattman and Miguel, 2010b, p. 38).

The remainder of the chapter organizes as follows. Section 1.2 provides background on the context of the Colombian armed conflict. Section 1.3 describes how past conflict outcomes shocks can affect current levels of agricultural productivity. Section 1.4 describes the data and the methodology for estimating the productivity elasticities using department panel data. Section 1.5 presents and discusses the main results. Section 1.6 concludes.

1.2. The Colombian Conflict

Colombia provides a scenario for analyzing the effects of violence shocks from armed conflict on agricultural productivity.[6] This violence impacts mainly the rural areas

[6] Political violence in Colombia is rooted in the conflict about an unequal and exclusionary agrarian system in which land ownership inequality represents a key explanatory factor for the country's history of violence (Engel and Ibáñez, 2007; González and López, 2007). Other crucial elements explaining the history of Colombian violence in rural areas have been poverty, weak institutional factors such as ineffective government intervention in marginal areas as well as the rent-seeking motives by nonstate armed actors

in Colombia. As Bejarano (1997) pointed out, about 93% of the municipalities affected by the actions of non-governmental armed groups are primarily rural, where these actions impact negatively and particularly agricultural activities. Moreover, there is a wide-ranging variation in the incidence of violence from the armed conflict across Colombian rural areas (Echandia, 2003; Brauer *et al.*, 2004) that provides a case study to analyze the effects of the armed conflict on agricultural productivity.

The rural armed conflict in Colombia started with the launch of a communist insurgency in the 1960s. Three main groups have been involved in this conflict: the state, the guerrillas, and the paramilitaries. The guerrillas are represented mainly by the Armed Revolutionary Forces of Colombia (FARC by its Spanish acronym) and the National Liberation Army (ELN by its Spanish acronym). These groups engaged in the conflict with the ideological motivation to force a redistribution of land by overthrowing the government (Engel and Ibáñez, 2007; Fajardo, 2002; González and López, 2007). However, the guerrillas were also motivated by their profitable involvement in the conflict and rent-seeking activities regarding illegal but profitable drug production (Rubio, 2005; Dube and Vargas, 2013; Richani, 1997). A salient example of such assertion is that the FARC and the ELN had an estimated income of 800 million US dollars in 1996 when the FARC was considered the worldwide richest guerrilla army (Richani, 1997).

During the 1980s, the Colombian conflict was relatively low, and the conflict escalated dramatically during the 1990s. The armed conflict intensified sharply because of the guerrilla defeat of narcotraffickers and the rise of paramilitary groups. Although the organization of anti-insurgent self-defense groups (known today as paramilitaries) by rural landowners and drug barons arose as a response to guerrilla extortions, since the late 1980s, paramilitarism did not emerge as an organized third force with a significant regional presence until the mid-1990s (Dube and Vargas, 2013). The United Self-Defense Groups of Colombia (AUC by its Spanish acronym) appeared specifically in 1997 through the official coalition of the earlier fragmented paramilitary groups. The entry of

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related to drug and oil production and distribution (González and López, 2007; Rubio, 2005). For a more detailed review of the determinants of violence in Colombia, see Martinez (2001).

the AUC is linked to a severe intensification in overall casualties mainly because the paramilitaries also targeted civilians that they perceived to be allied with the guerrillas (For more details, see Restrepo *et al.*, 2003 and Acemoglu *et al.*, 2020).

In the 1995-2003 period, the armed conflict in Colombia was technically three-sided, with all the groups fighting one another, but, in some cases, there was collusion between the government army and the paramilitaries in countering the guerrilla groups (Dube and Vargas, 2013; Gutiérrez and Barón, 2005). Paramilitarism has gone beyond the military alliance between the government and the AUC. There is evidence of an episode of Colombian history known as the "para-politics" scandal. This incident consists of the involvement of paramilitary groups with politicians that accepted illegal assistance in getting elected through both eliminations of opponents and paramilitary coercion of voters in exchange for policies favoring ex-paramilitary members (Acemoglu *et al.*, 2013). Fergusson *et al*. (2014) prove that significant defeats for the insurgents reduce the probability that some politicians fight them, especially in electorally salient places. Their conclusion supports the hypothesis that the Colombian armed conflict is political to the extent that politicians need to keep enemies alive to maintain their political advantage.

A noteworthy event occurred in 2003 when the AUC declared a partial cease-fire, and many paramilitary units started to participate in a demilitarization program. However, the demobilization process did not disarm all blocks, which led to a short-term decline in paramilitary violence along with the formation of a new generation of paramilitaries (Human Rights Watch, 2005). Figure 1.3 shows a remarkable structural trend change in the number of armed conflict-related casualties after 2002 that could be somewhat related to such demobilization. We can also observe in Figure 1.3 that the time series regarding forced IDP follows a similar trend, with significant structural changes in 2002 and 2007.

As violence shocks in Colombia involve armed conflicts among the government, the guerrillas, and the paramilitaries, the non-governmental armed groups have had alternate periods of dramatic expansion and decline in the number of fronts. One key feature attributed to these variations has been the enlargement of the illegal armed activity responsible for expanding the production of illicit crops such as coca and poppies

(Díaz and Sánchez, 2004). Because of this, the Colombian government intensified aerial spraying of glyphosate on coca plantations and conducted counterinsurgency actions that increased the expansion of non-governmental actors' fronts fostering further criminal and violent acts (González and López, 2007).

Although several factors account for the overall productivity of the Colombian agricultural sector, the present study aims to identify the role of violence shocks from the armed conflict. Since conflict imposes costs on economic productivity (e.g., through devastation and uncertainty caused by violence shocks), this research seeks to estimate the violence effects on agricultural productivity as the responsiveness of a meta-production function to the armed conflict shocks. For this purpose, we also provide background on the factors used to identify these shocks in the next section.

1.3. Effects of Violence shocks and Illegal Crops on Agricultural Productivity

Agricultural productivity can be affected directly and indirectly by the violence from the armed conflict. The direct effects can result from farms or agricultural production units caught in the armed conflict that could account for significant disruptive impacts that lower productivity (González and López, 2007). The indirect effects can result from diverting resources into unproductive uses (Collier 1999), reducing the returns of productive activities such as legal agriculture by making more attractive rent-seeking, corruption, and criminality, among other illegal activities. Thus, more resources allocated to illegal activities indirectly detract productive investments in either physical or human capital by reducing the accumulation of capital inputs, knowledge, and skills that lower productivity in legal agriculture.

The rural areas of Colombia (where mainly the armed conflict occurs) face the war effects directly through the disruptions in agricultural activities. These disruptions could materialize in high constraints to the sale and transportation of outputs, destruction of productive assets, killing of farmers or potential workers, and disturbing vandalic acts. These direct impacts would imply additional costs to exert the economic activities as more resources have to be employed to sell outputs or acquire inputs in the areas of conflict (González and López, 2007). If the armed conflict results in many casualties, the fear of death may prompt forced displacement of the rural population and the consequent abandonment of agricultural land and productive assets (Morrison 1993). Colombia has ranked second in the number of IDPs because of decades of armed conflict compounded by a high prevalence of drug trafficking.

The paramilitaries and guerrillas are not only involved in the appropriation of resources through criminal activities (e.g., predation on public funds, kidnapping, and extortion) but also in the cocaine trade (see, e.g., Angrist and Kugler, 2008; Dube and Vargas, 2013; Mejia and Restrepo, 2013, 2016; Rincón-Ruiz *et al.*, 2013). Angrist and Kugler (2008) provide evidence that violence increased in Colombian rural areas where coca cultivation increased, generating non or few economic benefits for residents as the profits from coca-growing are practically taxed away by combatants dissipated through nonproductive activities. On the other hand, many agricultural areas have been rendered unfit for agriculture because of the government's aerial herbicide spraying of coca plantations that unintentionally affected neighboring legal crops (González and López, 2007; Rozo, 2014). As the presence of coca cultivation leads to aerial spraying, side effects in rural areas with coca plantations reflect in alleged harmful impacts on health, legal crops, the environment, and the socio-economic conditions of coca-producing areas (Camacho and Mejía, 2015; Relyea, 2005; Rozo 2014; Mejía *et al.*, 2017).

In the areas cultivated with coca, the eradication efforts and military interventions aimed at disrupting the production of cocaine impose additional costs to agricultural productivity. These costs can appear as losses resulting from conventional agriculture disturbed by government fights with drug producers over the effective control of the land used for illegal crop production. These conflicts take the form of both forced eradication campaigns and confrontations between government forces and the non-state armed groups involved in coca cultivation and cocaine production. The misallocation of productive resources can also distort agricultural productivity, for example, when money laundering and drug traffickers' investment in land endorse land used for livestock in areas suitable for crops (the Republic of Colombia, 2000).

Although the distortion of market prices may be relevant in the areas affected by the conflict, this research focuses on the productivity effects of violence due to the rural armed conflict. As pointed out by Alvarez (1995): "*coca cultivation per se may do little to enrich the cultivators, since—as with the relationship between the farmgate price of coffee and the beans we buy at Starbucks—the price of raw coca leaf makes up a small fraction of the price of cocaine*" (Angrist and Kugler, 2008, p. 192). However, some previous studies suggest that cocaine plays a crucial role in the Colombian economy due mainly to shifts in the demand for coca leaves to have a perceptible economic effect (See Angrist and Kugler, 2008 and the references therein). Steiner (1998) estimated the Colombian income from illegal drugs at 4%–6% of GDP in the first half of the 1990s. This financial resource has a significant impact on violence by increasing the resources available to insurgent groups and coca production and reducing the overall level of economic activity (Suárez, 2000; Angrist and Kugler, 2008). The link between agricultural productivity with violence and illegal crop production is especially relevant in Colombia, which has experienced striking adverse shocks related to the armed conflict, primarily in rural areas.

1.4. Methodology and Data

1.4.1. Theoretical Framework

To account for external factors such as the effect of violence shocks, we define a production function for Colombian agriculture as $Y = f(\boldsymbol{X}; \boldsymbol{\beta})$. This is a real-valued function characterizing the maximum amount of output Y produced from any given set of conventionally measured inputs $\boldsymbol{X} = (X_1, \dots, X_n)$, and $\boldsymbol{\beta}$ represents the vector of all parameters. The production function is assumed to be continuous and twice differentiable implying that $f_{X_i} > 0$, and $f_{X_i X_i} < 0 \; \forall \; X_i$, $i = 1, \dots, n$. A relevant assumption is that places with a greater incidence of violence due exclusively to the armed conflict led to more casualties, higher presence of internally displaced persons (IDP), and lower availability of inputs to produce Y. The parameters in $\boldsymbol{\beta}$ are assumed to be variable and determined at any place and time by previous choices as well as the current technological, natural, and institutional environment, i.e., $\beta_i = G_i(v_1, \dots, v_m)$, where variables v_k, $k = 1, \dots, m$, represent the technology changing variables as in Fulginiti and Perrin (1993). Following Fulginiti and Perrin (1993), we use the concept of elasticity of productivity for the v_k: $\varphi_k = \partial Y/\partial v_k(v_k/Y)$ which indicates the percentage by which output would change with inputs fixed in response to a 1% change in v_k. The focus of this study is mainly on the effect of violence shocks as technology-changing variables.

1.4.2. Empirical Approach

This study estimates agricultural productivity in Colombia at the level of the Department by estimating a production function for the sector. At this level of aggregation, we assume constant returns-to-scale (CRS) −dividing the output and the inputs by the agricultural land area− and specify yields (y) as a function of inputs (per unit of land) and technology:

$$y(\boldsymbol{x}; \boldsymbol{\beta}) = A(\boldsymbol{v}) \prod_{i=1}^{n} x_i^{\beta_i(\boldsymbol{v})} \qquad (1)$$

where

$$\ln A = \alpha_0 + \sum_{k=1}^{m} \gamma_k v_k + \delta_0 \tau + u_0, \qquad k = 1, \dots . m \qquad (1a)$$

$$\beta_i = \alpha_{i0} + \sum_{k=1}^{m} \alpha_{ik} v_k + \delta_i \tau + u_i, \qquad i = 1, \dots . n \qquad (1b)$$

where v_k's are the technological changing variables all contained in vector $\boldsymbol{v}$=$(v_1, \dots, v_m)$; τ denotes time (or a trend) as a proxy for exogenous technical change[7];

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[7] Besides the technology changing variables used here for Colombia, the model allows the introduction of the trend τ as well as time-invariant unobserved heterogeneity (α_{0d}, where d indicates the unit of analysis, let us say a department or region) and unobserved time-variant factors, let us say in the form of $\alpha_d \times \tau$. This could be appealing if one has strong reasons to believe that the omission of those factors is relevant enough to bias the results of the structural model by attributing the effect of the omitted variables to those that were included. This concern can be useful to test for sensitivity of the results to other relevant-omitted sources of technological change that affect a particular region's agricultural productivity, given that agricultural technology could be highly sensitive to local environmental\institutional conditions and spillovers of technology. Otherwise, all other more general factors (either time-invariant or time-variant) would affect all units of study in a similar way through τ.

the α's, γ's and δ's represent fixed parameters to be estimated; u_0 represents a random variable distributed independently of the x's, τ, and the v's; u_i's are random variables independent of the v_k's, and τ, with mean zero and finite positive semi-definite covariance matrix. The β's are the elasticities of production concerning each of the variable inputs x's. These output elasticities are thus affected by the technology-changing variables in the sense that these variables are taken by the decision-makers as parameters (or state variables) for the current production period (Fulginiti and Perrin, 1993; Mundlak *et al.*, 2012). We obtain the following convenient econometric model by expressing equation (1) in natural logs as

$$\ln y = \alpha_0 + \sum_{i=1}^{n} \alpha_{i0} \ln x_i + \sum_{i=1}^{n} \sum_{k=1}^{m} \alpha_{ik} (v_k \cdot \ln x_i) + \delta_0 \tau + \sum_{i=1}^{n} \delta_i (\tau \cdot \ln x_i)$$
$$+ \sum\nolimits_{k=1}^{m} \gamma_k v_k + \sum_{i=1}^{n} u_i \ln x_i + u_0 \quad (2)$$

With this specification, it is feasible to directly estimate the technological impacts of violence shocks from armed conflict and the presence of illicit but profitable crops that compete for resources with legal agriculture. For simplicity, the technology changing variables are expressed in logs as $v_k = \ln z_k, \forall k = 1, \dots m$. Using (2), the elasticity of productivity for z_k is

$$\varphi_k = \frac{\mathrm{d}\ln y}{\mathrm{d}\ln z_k} = \sum_{i=1}^{n} \alpha_{ik} \ln x_i + \gamma_k \quad (3)$$

The effect of violence shocks and illegal crop production activities on current productivity could be thus summarized by the productivity elasticities given by (3). The exogenous rate of technical change can be similarly obtained by $\mathrm{d}\ln y/\mathrm{d}\tau = \delta_0 + \sum_i \delta_i \ln x_i$. This analytical framework is used to measure the effect of violence shocks on agricultural productivity for Colombian agriculture represented by 26 departments that are traditionally agricultural.[8]

[8] The information used in this research is based on surveys whose scope of study consists mainly of 26 departments in continental Colombia that are considered as "traditionally agricultural". These departments are Antioquia, Arauca, Atlántico, Bolívar, Boyacá, Caldas, Caquetá, Casanare, Cauca, Cesar, Córdoba, Cundinamarca, Chocó, Huila, La Guajira, Magdalena, Meta, Nariño, Norte de Santander, Quindío,

1.4.3. Data and Empirical Estimation

1.4.3.1. Data on Production

Data are from several sources. We use the publicly available annual data on agricultural outputs and inputs from 1995 to 2017 at the department level based on the National Survey of Agriculture (ENA), the Large Integrated Household Survey (GEIH), and the Vital Statistics microdata obtained from the National Administrative Department of Statistics (DANE).

The ENA estimates the total land use, size, distribution of sampling segments, and the number and size of Agricultural Production Units (APUs).[9] The universe of the ENA consists of the total rural area of Colombia with potential agricultural use. Hence, large areas not used for agricultural purposes corresponding to the extensions of natural forests and bodies of water are all excluded. The survey provides aggregated data on agricultural land, production, and yields of major temporary and permanent crops, pasture area, milk production, and livestock inventory. We use the department-level figures available for 2010-2016 and published by the DANE. We then combine this information with the statistics per departments and municipalities from the survey of agricultural evaluations (EVA)[10] of the Ministry of Agriculture and Rural Development (MADR) for the period 1995-2009 related to the number of APUs, area planted and harvested, production and yields of permanent and transitory crops. Regarding livestock activity, ENA and EVA provide information on the inventory of cattle and other animal species such as horses and sheep. After matching the data in ENA and EVA, eliminating incomplete

Putumayo, Risaralda, Santander, Sucre, Tolima, and Valle del Cauca. The Island of San Andrés and Providencia is also classified as a “traditionally agricultural department”, but the surveys did not collected information on agricultural activities in such insular department during most of the years analyzed in the present study. Thus, the “traditionally non-agricultural departments” of Amazonas, Guainía, Guaviare, Vichada, and Vaupés as well as the Island of San Andrés and Providencia are not included in the analysis.

[9] An Agricultural Production Unit (APU) or enterprise is an economic production unit with a clearly defined management that includes all agricultural or/and fishing activities exerted in it, regardless of its property title, legal status, or size.

[10] The municipalities’ survey of agricultural evaluations are investigations carried out since 1970 by the Ministry of Agriculture and Rural Development. These evaluations record the productive activities of crop production, livestock, forestry, and aquaculture in Colombia.

information, and linearly interpolating missing data, the sample consists of 598 observations (26 departments × 23 years).

Information about the population in rural areas is from the GEIH and the Population and Demography Series from the DANE. The DANE specifically provides national, departmental, and municipal estimates (projections) of the population by urban/rural area and age groups for the 1985-2020 period. The Colombian rural working-age population was calculated here as the number of people aged ten years and over in rural areas of each department.

The data for the specification of the variables used in the estimation are: the output (Y) as the value of agricultural production in millions of 2005 US dollars; land (X_0) as thousands of hectares of arable and permanent cropland, and permanent pastures; labor (X_1) as thousands of individuals in the working-age population in rural zones; livestock (X_2) as the number of cow equivalent livestock units as calculated by Hayami and Ruttan (1970); and, finally, a year fixed effect or trend (τ) as a proxy for exogenous technological change in the agricultural sector.[11]

1.4.3.2. Data on Violence Shocks

The displacement data are from the Colombian government's Unique Registration System (URS) -*Sistema Único de Registro*-. We used consolidated statistical information from CODHES-SISDES (Information System on Human Rights and Displacement) on the number of forced internally displaced persons that exited the municipality/department from year to year. The Colombian government compiles the URS with non-governmental agencies and the Catholic Church. IDP refers to migrants forced to abandon their physical residence and employment (economic) activity because of the Colombian armed conflict, generalized violence, massive human rights violations, or other circumstances that threaten or drastically alter public order. The URS distinguishes between municipalities/departments where the displacements occurred and the

[11] We also use a control variable for farm size measured as the average APU size calculated as the total number of hectares covered by the UPAs divided by the total number of UPAs.

municipalities/departments where displaced persons relocated. We use specific information on the number of armed conflict victims classified as displaced due to the violence from armed conflicts. In areas with high-level displacement, we expect cultivation to decline due to the disruption of agricultural activities and the local labor markets. For this study, the variable z_1 (Internally Displaced Persons- IDP) measures the ratio between the annual number of displaced persons and the total population in the department of origin per 100 thousand inhabitants. More specifically, we construct z_1 as the (one-year) lagged ratio of the annual number of IDP to the total population per one hundred thousand inhabitants in the department where the displacement occurred.

To specify the variable z_2 (Casualties), we employ a unique event-based dataset from the Uppsala Conflict Data Program (UCDP) of the Department of Peace and Conflict Research at Uppsala University in Sweden. The dataset contains four measures of the violence from the armed conflict across Colombian municipalities from 1975 to 2019: guerrilla attacks, paramilitary attacks, clashes, and war-associated casualties. We aggregate the annual number of armed conflict-related deaths of civilians and fighters to the department-year level and use these aggregated figures to proxy for direct political violence. The variable z_2 is specified then as the one-year lagged ratio of the annual number of casualties to the total population in the department of the recorded deaths per 100 thousand inhabitants. According to our data, the Colombian civil war resulted in at least 78,560 deaths and 7,053,250 IDPs from 1995 to 2017 in the twenty-six Colombian departments we are studying. Although the chapter focuses on the effect of violent shocks from the rural armed conflict, other factors are also included, such as environmental, institutional, and the effect of past prices as technology-changing variables.

1.4.3.3. Data on Coca Cultivation and Cocaine Prices

To measure the effects of coca cultivation, we use a 23-year panel of the 26 Colombian departments (19 of which grew coca at some point during the 1995–2017 period). The panel dataset uses the United Nations Office on Drug and Crime (UNODC) information. The UNODC has conducted satellite surveys of coca crops in every municipality of the country since 1999[12]. These surveys use satellite photography and measure the number of hectares of coca in a given area (usually a municipality) at the end of each year.

Because the UNODC and the Colombian government achieved full national coverage in the year 2001, the data on coca leaves cultivation for the period 1995-1998 comes from information in Angrist and Kugler (2007), “Cuadro 1.” in Ramírez (2002), and Uribe (1997). The UNODC and the Colombian government use satellite imagery and verification flights over coca-growing areas to monitor the location and spread of coca cultivation. In 2005, for example, the area within each department with active coca cultivation was between 28 and 17,305 hectares, with seven departments having no reportable levels of coca cultivation.

The UNODC also provides information on illicit drugs' estimated prices and purity. To specify the variable proxy of illegal crop production, we use the international retail cocaine prices (street prices) in 2018 US dollars per gram. The price time series for cocaine (inflation-adjusted to 2018 US$) used in the present study is an average weighted by population (in Europe and USA) available for the period 1990-2018.

The variable z_3 (past cocaine price) is specified such that it may capture potential cross-sectional effects of annual exogenous changes in the cocaine price on Colombian illicit drug cultivation. This variable is a proxy for the annual value of coca cultivation (or economic relevance of cocaine production) for the areas growing coca leaves. Thus, z_3 is equal to the one-year lagged retail cocaine price weighted by the ratio between the area planted with coca in each department/year to the total (national) area cultivated with coca in the corresponding year. An increase in the international retail cocaine price or a higher area proportion devoted to coca cultivation would reflect a higher incentive to invest in (or more productive resources allocated to) cocaine production and, consequently, coca-growing instead of legal agriculture.

[12] Although there is no precise data on the amount of coca cultivated or the amount of cocaine produced and subsequently exported, both the UNODC and the U.S. State Department make annual estimations of the size of the illicit industry. The present study uses those estimations that are available at https://www.unodc.org/unodc/en/crop-monitoring/?tag=Colombia.

1.4.3.4. Data on Weather

Additional department-level technology-changing variables include rainfall (z_4) and temperature (z_5). These weather variables were constructed based on the data regarding the Agrometeorological Indicators produced on behalf of the Copernicus Climate Change Service. This dataset covers the world time series daily surface meteorological data from 1979 to 2020. The dataset relies on the hourly ECMWF-ERA5 data geo-localized and available at a spatial (horizontal) resolution of $0.1° \times 0.1°$ (about $10km^2$). More specifically, we use the information on (1) *2m temperature*, indicating the daily average air temperature at the height of 2 meters above the surface; and (2) *precipitation flux*, defined as the total volume of liquid water (mm3) precipitated over the period 00h-24h local time per unit of area (mm2), per day. The data were subsequently averaged to the monthly/municipality level using a shapefile[13] for all the Colombian municipalities.

Because we carry out a department-year analysis of the effect of potential weather shocks on the agricultural productivity, each year, temperature (z_4) and rainfall (z_5) are measured as an (annual/department) average of the municipality-monthly values of *2m temperature* and *precipitation flux*, respectively. The use of rainfall and temperature as technology-changing variables relies on the fact that weather shocks can lead to more prolific or lean harvests that can be directly associated with changes in profits from rural activities, potentially affecting incentives to invest in agriculture.[14] Thus, as the focus here is on rural areas in Colombia, weather shocks are among the most critical risk factors faced by rural households because of the potentially harmful effects of weather

[13] A *shapefile* is a geospatial vector data format for storing geometric locations suitable to geographic information system (GIS) software.

[14] Colombia has been particularly affected by rainfall and temperature shocks. According to the Global Climate Risk Index (Harmeling, 2011), the country ranked third (after Pakistan and Guatemala) in 2010 among the countries most affected by weather-related events such as droughts, floods, and heatwaves. Moreover, the number of disaster events registered in Colombia in the first decade of the 2000s increased by more than 60% with respect to the number in 1970–99 (Campos *et al.*, 2011; Andalón *et al.*, 2016).

shocks on the agricultural activities on which the rural population generally relies (Giné *et al.*, 2008; Andalón *et al.*, 2016).

1.4.3.5. Data on Output Price

Following Fulginiti and Perrin (1993), we also include a technology-changing variable related to past price expectations z_6 (output prices).[15] At least two theoretical reasons can justify the inclusion of the past output prices as an argument for the agricultural production function. First, output price is a crucial mechanism for the adoption of new production techniques, and they also create strong incentives for innovation such that the price regime of one period could significantly affect the technology relevant to a subsequent period (Mundlak, 1988; Fulginiti and Perrin, 1993; Mundlak *et al*., 2012). Second, any technical change (expressed as a new production technique) can have an equivalent unique combination of inputs defined in a production function (Fulginiti and Perrin, 1993; Mundlak *et al*., 2012). As a proxy for z_6, we use a three-year moving average of Törnqvist-Theil indexes of prices received for the main agricultural products of Colombia. These indexes were constructed for each department, using deflated price series for the relevant commodities. The Törnqvist index here is the weighted geometric mean of the relative prices using averages of the value shares in the two periods as weights. The data used are the prices received by producers and quantities produced in metric tons every two years, $(t-1)$ and (t), for each of m crops indexed by j. Denoting the price of crop j at year $t-1$ by $p_{j,t-1}$, and, analogously, defining $q_{j,t}$ as the amount of crop j produced in year t, then, the Törnqvist price index P_t at the year t can be calculated as follows:

[15] Fulginiti and Perrin (1993) developed a model involving a production function specification that posits that past prices can determine current productivity levels. Output prices are among the technology-changing variables that can determine the choice of techniques and thus productivity. This link between prices and productivity implies that the higher (lower) are prices in agriculture, the faster (slower) the rate of both technological innovation and productivity growth (Schultz, 1978; Fulginiti and Perrin, 1993; Anderson, 2009).

$$\frac{P_t}{P_{t-1}} = \prod_{j=1}^{m} \left(\frac{p_{j,t}}{p_{j,t-1}}\right)^{\frac{1}{2}\left[\frac{p_{j,t-1}q_{j,t-1}}{\sum_{j=1}^{m}(p_{j,t-1}q_{j,t-1})}+\frac{p_{j,t}q_{j,t}}{\sum_{j=1}^{m}(p_{j,t}q_{j,t})}\right]} \tag{8}$$

The information on the prices came from the Producer Prices (in 2005 US$) per ton of the Colombian agricultural commodities available for the 1991-2018 period. The Food and Agriculture Organization of the United Nations (FAO) provides annual data on Agriculture Producer Prices. These Prices are prices received by farmers for primary crops, live animals, and primary livestock products as collected at the point of initial sale (price paid at the farm gate). To complete the series for some agricultural products, we use data from the Colombian Confederation of Agricultural Producers Associations (FEDEAGRO) and MADR (deflated prices converted to dollars at the 2005 official exchange rate). The primary transitory and permanent crops production data are from the EVA and are available for the 1985-2017 period. The transitory crops used are sesame, cotton, rice, barley, beans, corn, potatoes, soy, sorghum, and wheat. The perennial crops include banana, coffee, cocoa, sugarcane, yam, palm oil, tobacco, and cassava. We calculate a cross-department price index from a Törnqvist index value for each department in 1999 relative to a base consisting of the 26-departments average price and quantity for each commodity. Finally, we divided the price index series for each department by the 1999 cross-department index value.

Another reason for including past output prices as a technology-changing variable is that they can reflect crucial changes in the incentives to invest in the sector producing such output. These investments may take the form of both physical and human capital, production techniques enhancement, or technology and infrastructural development that have a significant role in improving productivity.[16] The prices in the production function is different from specifying a supply function in which variation in output prices

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[16] In agriculture, these investments can take the form of either physical capital stock (land, equipment, irrigation, machinery, storage facilities, livestock) or human capital (stock of knowledge, expertise, or management ability). Also, other investment type closely linked to agricultural productivity are public investments, such as infrastructural development, R&D, extension/training and technical assistance system, technology, or sustainable natural resources management. These public investments also promote and complement private investment in the agricultural sector, fostering technology adoption and increasing productivity.

generates a spread of points on a given production function used to identify the supply function (Mundlak, 1988). However, the inclusion of the price in the production function here implies changes in output given the inputs, i.e., shifts of that production function that create a different set of implemented functions affecting productivity. Therefore, the assumption is that past prices are among the technology-changing variables that can determine the techniques available and thus the production function and productivity. This assumption implies that the higher (lower) are prices in agriculture, the faster (slower) the rate of both technological innovation and productivity growth (Schultz, 1979; Schuh, 1974; Fulginiti and Perrin, 1993). An econometrical reason is to mitigate concerns about reverse causality regarding the indirect effects of agricultural income shocks on violence. In the economics literature, the prices of agricultural commodities are associated negatively with armed conflict: output price increases lead to a decline in violence from armed conflicts in regions that produce more of the corresponding output (see, e.g., Dube and Vargas, 2013; Bazzi and Blattman, 2014).

1.4.4. Empirical Estimation

Table 1.1 presents a simple description and summary statistics of the key empirical variables used in the analysis. The CRS assumption has been imposed by dividing the output (Y) and input variables X_1 and X_2 by land (X_0). This results in yield ($y = Y/X_0$) and the vector of relative inputs $\boldsymbol{x}$ = (x_1,x_2), where $x_i = X_i/X_0$, i =1,2. The following baseline structure is estimated by department d (= 1…, 26) and year t (= 1995…, 2017):

$$\ln y_{dt} = \alpha_0 + \sum_{i=1}^{2} \alpha_{i0} \ln x_{idt} + \sum_{i=1}^{2} \sum_{k=1}^{6} \alpha_{ik} (v_{kdt} \cdot \ln x_{idt}) + \delta_0 \tau + \sum_{i=1}^{2} \delta_i (\tau \cdot \ln x_{idt}) + \sum_{k=1}^{6} \gamma_k v_{kdt} + \sum_{i=1}^{2} u_{idt} \ln x_{idt} + u_{0dt} \tag{9}$$

We have specified the technology-changing variables in logs for the productivity elasticities calculation: $v_k = \log{(z_k)}$. Pooling all departments and years together in a single equation of the form specified in (9) gives 598 observations. We estimate the parameters in equation (9) with OLS. Unobservable factors that jointly determine violence and agricultural decisions may vary smoothly across departments and could be potentially relevant omitted variables. In some specifications, we include region-fixed effects (α_{0d}) and region-specific time trends ($\alpha_d \times \tau$).[17] An essential hypothesis in this chapter is that rural areas with more violence intensity from the armed conflict are more likely to exhibit a higher presence of both war-related outcomes (such as casualties and IDP from rural to urban zones) and illegal drug production. Consequently, all of this would alter both the use of inputs and productivity in agricultural activities.

1.5. Empirical Results and Discussion

Table 1.2 shows the estimated coefficients of the parameters in equation (4). This table contains twenty-two coefficients, seven of which are significant at the 1% level, three at the 5% level, and four at the 10% level. We use the estimates in Table 1.2 to calculate the average production and productivity elasticities evaluated at the mean of all the observations.[18] All the technology-changing variables are in logs. Hence, each elasticity of productivity for any of these variables represents the percentage by which productivity (percentage output change with inputs fixed) would change in response to a 1% change in the corresponding variable. Overall, the mean values of the estimated coefficients in Table 1.3 show significant effects of the technology-changing variables.

The productivity elasticities of most interest here are the elasticities related to violence shocks from armed conflict and illegal crop cultivation. The coefficients for the technology-changing variables IDP and cocaine price are negative and significantly

[17] The Colombian regions considered are: Amazon containing the departments of Caquetá and Putumayo; Andean consisting of Antioquia, Boyacá, Caldas, Cundinamarca, Huila, Norte de Santander, Quindío, Risaralda, Santander, and Tolima; Caribbean including Atlántico, Bolívar, Cesar, Cordoba, La Guajira, Magdalena, and Sucre; Orinoco that is constituted by Arauca, Casanare, and Meta; and Pacific which group the departments of Cauca, Chocó, Nariño, and Valle del Cauca. We include the region-fixed effects (α_{0d}) and region-specific time trends ($\alpha_d \times \tau$) to control for time-invariant and time-variant unobservable factors of the analyzed regions, respectively.

[18] See Table A.1.1 for sensitivity analysis of the baseline model to some alternative specifications of equation (9).

different from zero. The productivity elasticity for war-related casualties is negative but not statistically significant. The estimated coefficient for the IDP indicates that a 1% increase in the ratio of IDP to the total population per 100,000 people due to the armed conflict (averaging 1,296) would produce a 0.041% downward permanent shift in the annual production function. Similarly, an increase of 1% in the ratio of war-related casualties (averaging 19) to the total population per 100,000 inhabitants and the past cocaine price shocks would shift the annual production function down by 0.012% and 0.611%, respectively.[19]

The technology-changing variables related to weather indicate that a 1% increase in the mean annual temperature would temporarily lower the productivity of Colombian legal agriculture by approximately 1.578%. A 1% increase in the yearly mean precipitation would increase Colombian agricultural productivity by about 0.235%. The productivity elasticity for the past output price indicates that a 1% increase in the previous three-year average output price would cause an approximated 0.416% temporary upward shift of the Colombian agricultural production function. This price effect implies that a boom in agricultural commodity prices like that in the 2000-2007 period or the first five years of the 2010s created incentives to invest in Colombia's agriculture. These incentives would promote the innovation and adoption of new production techniques because the price regime during the boom would positively affect the technology relevant to subsequent periods. However, a downturn in the price of agricultural goods could counterbalance those productivity enhancements during such a boom or even reduce them if the decline in the price of commodities from agriculture cancels out the effects of past periods of high output prices.

[19] It is worth mentioning that the magnitude of the estimated productivity elasticities for violence shocks are relatively small because the regressions control for crucial factors affecting both productivity and violence. Some of these factors include the weather and income shocks that may explain changes in violence through mechanisms related to variations in economic incentives to invest in the agricultural sector. Once the regressions include some of these factors, the estimations mitigate endogeneity concerns. Therefore, the estimated productivity effects may be attributed mainly to variations in the violence and not those other factors affecting the Colombian agricultural sector. Moreover, the productivity effects of violence shocks estimated here represent permanent changes in agricultural productivity or shifts in the meta-production function of Colombia's agriculture.

The second panel in column 2 of Table 3 displays the production elasticities evaluated at the average values of the variables and the semielasticity related to τ. All the estimated average production elasticities are statistically significant between 0 and 1. We find that the mean (averaged over the 26 departments and the period 1995-2017) production elasticity for the inputs, i.e., labor and livestock are 0.52 and 0.40, respectively. The trend coefficient suggests that the average rate of exogeneous technical change in the Colombian agricultural sector is 1% per year.

The last column of Table 3 shows the estimates of a conventional Cobb-Douglas production function.[20] From this model, the elasticity of production for labor is 0.73 and for livestock is about 0.12. The estimated annual exogenous technical change from this model is around 0.8%. We can note that the elasticity of labor input is somewhat lower relative to that estimated from the variable coefficients model, even though it is still higher than the elasticity of livestock. This result is reasonable because Colombian agriculture is labor-intensive, and the agricultural output is relatively highly responsive to changes in the rural labor force potentially used in agriculture. By contrast, the inclusion of technology-changing variables increases the estimated livestock production elasticity. The magnitude of the estimated coefficient for the exogenous technical change slightly increased, but its statistical significance decreased with the inclusion of the technology-changing variables. These changes in the production elasticities and the exogenous technical change come basically from the impact of the included technology-changing variables.

One of the main differences between the results of this study and related previous literature is that we attribute higher production elasticities to labor. Some previous studies estimate labor elasticity in the range of 0.14-0.46[21] compared to our 0.52 (see, e.g., the

[20] This model is equivalent to impose the constraint $\alpha_{ik} = \gamma_k = 0$, for all i=1,2 and k=1…,6 in equation (4), which implies that both the total factor productivity (A) and the output elasticities (β_i, for the inputs i=1,2) do not depend on the technology-changing variables v_k, for k=1…,6. The overall R^2 of this model is 0.62, while it is 0.85 for the variable coefficients model in Table 2. This difference could imply that the unexplained error in the fixed coefficients model reduces up to 61% when including the technology-changing variables. An F-test, with F(31, 514)=114.61, indicates that this addition is significantly different from zero.

[21] See Fulginiti and Perrin (1993), Table 2 in Fuglie (2008), Mundlak *et al.* (2012), and Trindade and Fulginiti (2015) for the comparisons to previous estimates.

cost shares for labor input of 0.46 in Everson and Fuglie, 2010; and the average production elasticity of 0.14 for labor in Trindade and Fulginiti, 2015). The Cobb-Douglas production function estimates for Colombia's agriculture from 1975-to 2013 by Jiménez *et al.* (2018) indicate that the labor elasticity ranges from 0.07 and 0.44 when assuming constant technological change. The average livestock elasticity estimated here is thus within the range established by some previous estimates. For instance, the average production elasticities using a stochastic frontier model are 0.55 for livestock in Trindade and Fulginiti (2015); 0.24 in Bharati and Fulginiti (2007); and 0.14-0.25 in Everson and Fuglie (2010). Moreover, Jiménez *et al.* (2018) find that the livestock production elasticity is 0.927 for Colombia's agricultural sector.

A noteworthy result is that the past output price coefficient is positive while the past cocaine price coefficient is negative. These estimations are consistent with a positive productivity response to output price changes and inverse productivity response to the risk of conflict and diverted agricultural resources to illegal drug production. The former is in line with the inference of a positive response of productivity to the implemented technology insofar as higher output prices create incentives to invest in the sector. The latter is consistent with previous studies documenting that to the extent that coca finances the Colombian armed conflict, increased coca cultivation may have reduced the overall level of economic activity, especially in agriculture (see Angrist and Kugler, 2007; Dube and Vargas, 2013).

The elasticity of productivity for the past output prices is about 0.42, and the cocaine price is −0.61. These are sizable values. Using the same framework, Fulginiti and Perrin (1993) report a past price elasticity of productivity of 0.13 for a group of 18 countries in the period 1961-1984 (0.028 for Colombia), whereas by using a somewhat different framework, Mundlak *et al.* (2012) compute a price elasticity of productivity of 0.2. The price elasticity of productivity estimated here is slightly more than double that of Mundlak *et al.* (2012) and is significantly larger than that of Fulginiti and Perrin (1993). This is because these previous studies conducted cross-country analysis such that aggregated data generally produces lower elasticity estimates, as does when controlling for unit-level fixed effects in panel data analysis (Miller and Alberini, 2016). For the coca price elasticity of productivity, there is both suggestive and quantitative evidence that illegal resources such as coca cultivation increase the duration of civil conflicts (Angrist and Kugler, 2008; Ross, 2004). Angrist and Kugler (2008) provide empirical evidence on this issue from a quasi-experimental research design that studies the impact of demand shocks for illicit resources on rural economic conditions and civil conflict. Their paper shows that an exogenous upsurge in coca prices and cultivation in Colombia implies that the rural areas that saw accelerated coca production became considerably more violent. This link is evidence that the financial opportunities that coca provides and the rent-seeking by combatants limit the economic gains from coca production to the detriment of main productive activities such as legal agriculture in rural areas.

The productivity effects calculated here can be crucial for studying Colombian agriculture as the technology-changing variables used here reflect some of the main events that affected the sector from 1995 to 2017. These events include not only profitability/macroeconomic crisis or unstable agricultural policies, but mainly the country's crisis related to the armed conflict, drug traffic/illicit crop production, agricultural commodity price shocks, and some weather effects.[22]

We computed elasticities for each observation in the sample and show the average elasticities of the model per department from 1995-to 2017 in Table 1.4 and the 26 departments' average elasticities per year in Table 1.5. Note that all 26 departments have been negatively affected in agricultural productivity terms by the internal displacement of people due to the violence from the armed rural conflict (see Table 4). The departments with the highest productivity elasticities of IDP are La Guajira, Meta, Casanare, Arauca, Cauca, Norte de Santander, Huila, Putumayo, Caquetá, Tolima, Santander, Bolívar, Nariño, and Valle del Cauca. Consistent with this, *Defensoría del Pueblo* (2016) pointed out that 40% of the Colombian IDPs come from the departments of Nariño, Cauca, Chocó, and Valle del Cauca. This is also consistent with the fact that at most 70% (18 of the 26 departments) of the productivity elasticities for casualties in Table 1.4 indicate a

[22] See Appendix A in Jiménez *et al.* (2018) for a detailed list of the most remarkable events in Colombia's agriculture from 1975-to 2013, and Chapter 8 (about Colombia) of the series of annual reports on Agricultural Policy Monitoring and Evaluation for 2015-2018 from the OECD available at https://www.oecd-ilibrary.org/agriculture-and-food/agricultural-policy-monitoring-and-evaluation_22217371.

permanent downward shift of the production function, being the most sensitive La Guajira, Cauca, Nariño, Putumayo, Huila, Norte de Santander, Risaralda, Valle del Cauca, Tolima, Meta, Quindío, Caldas, Bolívar, Santander, Chocó, and Antioquia. These findings are consistent with reports (see, e.g., Gallego, 2020) showing that the departments with more than 46% of the total armed conflict victims in Colombia are Cauca, Antioquia, Nariño, Chocó, Bolívar, and Caldas. These are also departments where the highest prevalence of murders of social leaders and former guerrillas occur (Gallego, 2020).

Regarding past cocaine prices, the productivity elasticities coefficients averaged over 1995-2017 have all a negative sign, indicating significant downward production function shifts in the agriculture of Córdoba, Sucre, Boyacá, Chocó, Cundinamarca, Cesar, Magdalena, Antioquia, Caldas, Bolívar, and Valle del Cauca. These results are consistent with the departmental exposure to international cocaine price shocks (with its intensity measured as the value of cocaine production weighted by coca cultivation). The higher the value of coca cultivation to a department (either because of increases in the international cocaine prices creating incentives to invest in coca production or relatively more relevant participation of a department in the national coca cultivation), the lower the legal agricultural productivity.

The productivity elasticities for the annual mean temperature are negative everywhere. They indicate that a 1% change in temperature would temporarily shift the production function down by at least 1% (in Córdoba) and up to 2% (in Meta). The elasticities of productivity concerning annual rainfall show positive effects across the departments. These results are somewhat consistent with Lachaud *et al.* (2017) assessing the agricultural productivity in Latin America in the presence of weather shocks. First, their study points out that a gap in the (agricultural) productivity literature is still the omission of climatic variables as regressors in the models used to derive TFP measures. Second, the authors developed climate-adjusted TFP measures to estimate random parameter stochastic production frontier models and assess the impact of climatic variability on TFP. Finally, they find that adverse weather socks harm productivity with an average reduction in output across the region ranging between 0.02 and 22.7% over the period 2000-2012 relative to 1961–1999. This estimate would reveal an adverse impact of climatic variability on agricultural output and productivity in the region. However, their results do not indicate a negative climatic effect on Colombia. The present study also accounts for climatic effects in analyzing Colombian agriculture. However, our results show that an increase in temperature (or a decrease in precipitation) would reduce the productivity of Colombian agriculture. The last column in Table 1.4 shows that the output price productivity elasticities are all positive across the departments, being the most elastic Arauca, Casanare, and Meta.

Table 1.5 shows that the productivity elasticities for IDP, casualties, (past) cocaine price, and temperature were negative for each year from 1995 to 2017, reflecting an increasingly higher estimated responsiveness of agricultural productivity to such technology-changing variables. The rainfall and price productivity elasticities are estimated to be positive for the 1995-2017 period. These estimated elasticities show a relatively stable trend in magnitude for rainfall and those estimated coefficients on past output price elasticities within the range between 0.38 in 1999 and 0.45 in 1997.

The last three columns of Tables 1.4 and 1.5 present the estimated production elasticities and exogenous technical change at the department and year levels, respectively. We calculate the production elasticities concerning each input as the β's in equation (1b) and the exogenous rate of technical change as the semielasticity given by $\mathrm{dln}y/\mathrm{d}\tau = \delta_0 + \sum_i \delta_i \mathrm{ln}x_i$. The input elasticities for labor and livestock range across departments between $0.27-0.70$ and $0.03-0.76$, respectively (see Table 1.4). The last column of Table 1.4 shows that the exogenous rate of technical change varies among the 26 departments from -0.93% to 1.9%. The estimates of the annual production elasticities presented in Table 1.5 for labor and livestock concentrated in the range of 0.41-0.64 and 0.20-0.55, respectively. The last column of Table 1.5 indicates that the annual rate of exogeneous technical change for the agriculture of the 26 departments varies across years from 0.75% to 1.17% during 1999-2017, which overlaps with the interval 0.8-1.3% for the period 1975-2013 estimated by Jiménez *et al.* (2018).

3.1. Estimated Cost of Violence in Terms of Productivity Effects

One of the main implications of our results is the implicit economic costs imposed by the armed conflict in terms of agricultural productivity loss. We attempt to compute a lower bound monetary measure of this productivity loss due to violence shocks from the armed conflict using the estimates in Tables 1.4 and 1.5. We assume that the productivity of Colombian agriculture is highly affected by violence causing direct and indirect costs to the sector. In general, we estimate a monetary measure (a shadow cost or gain) in agricultural productivity terms from any percentage change in the technology-changing variables for any department d in any year t as

$$Cost_{kdt} = \varphi_{kdt} \times \%\Delta v_{kdt} \times Y_{dt} \tag{10}$$

where φ_{kdt} is the elasticity of productivity for v_k of d at t; $\%\Delta v_{kdt}$ is the coefficient of variation (CV) for v_k of d at t, and Y_{dt} is the value of agricultural production in millions of 2005 US dollars for a department d at year t. Table 1.6 displays the estimated average costs (gains) from the percentage change of each technology-changing variable given by its CV at the department level for the whole period of study. We can observe that the cost of violence (IDP and casualties) from the armed conflict was specially and significantly constraining for the departments of Córdoba, Cesar, Sucre, Magdalena, Caquetá, Casanare, and Atlántico. The shadow cost of violence shocks for these departments is between 1.3%-6.8% of their mean annual agricultural GDP. Although in less intensity, we can observe that the other departments that bear a significant shadow cost of IDP in terms of their agricultural GDP are La Guajira, Casanare, Meta, Cauca, Arauca, Huila, Putumayo, Nariño, Norte de Santander, Caquetá, Tolima, Santander, Bolívar, Valle del Cauca, Caldas, Atlántico, Cesar, and Magdalena. For these departments, the cost of this violence shock is between 0.6% and 2% of their agricultural GDP per year. The rural areas of some of these departments are historically the most affected by the armed conflict because of the persistent presence of guerrilla groups and paramilitaries and conflict-related events.[23] [24]

Regarding the cost of past cocaine prices to agricultural productivity in coca-producing departments, we can infer from Table 1.6 that the illegal drug crop cultivation has represented a loss in productivity that ranges from 22% (in Meta) to eleven-tenths (in Caldas) of their mean annual agricultural GDP. The shadow cost of coca crops to agricultural productivity has significantly constrained the departments of Caldas, Chocó, Córdoba, Valle del Cauca, Cundinamarca, Boyacá, Cesar, Magdalena, Arauca, and Santander, whereas in less intensity the departments of Caquetá, Antioquia, Nariño, Norte de Santander, Bolívar, Cauca, and Putumayo.

Table 1.7 presents the estimated costs (gains) from each technology-changing variable at the annual level for Colombian agriculture. We can observe that the cost of violence across the years analyzed here has been quite persistent in terms of the GDP of agriculture from the 26 traditionally agricultural departments considered in the analysis. The cost of violence measured as a loss of agricultural productivity (due to IDP and war-related casualties) could vary from 1% to 7% of the GDP of Colombian agriculture during the 1995-2017 period. From 1996 to 1998 and the last six years in the sample since 2012, violence imposed the highest costs in terms of productivity loss measured as a proportion of the agricultural GDP (more than 2.9%). In addition, violence shocks impacted productivity in a slightly less intensive but still highly substantial way, the Colombian agricultural GDP in 2000 and 2004 (more than 2%). To provide some context

[23] Although the armed conflict has extended to several areas of rural Colombia, it is critical to point out that leading paramilitary groups emerged from the Magdalena Medio Region (constituted by the departments of Antioquia, Bolívar, Boyacá, Cesar, and Santander) and Córdoba department. The main guerrilla groups, FARC and ELN, originated from the Southern departments (Cauca and Tolima) and the department of Santander, respectively. See Dube and Vargas (2013) for more details on the origin of non-state armed actors in Colombia.

[24] Historically, the departments with the most violent presence of the FARC are Cauca, Huila, Nariño, Meta, Tolima, Antioquia, Bolívar, Córdoba, La Guajira, Norte de Santander, and Putumayo; with the ELN are Nariño, Cauca, Risaralda, Chocó, Antioquia, Arauca, Santander, Norte de Santander, Bolívar, and Cesar; and with paramilitaries Antioquia, Nariño, Cauca, Valle del Cauca, Bolívar, Chocó, La Guajira, Magdalena, Atlántico, Putumayo, and Risaralda. Regarding force displacement, the departments of Colombia with the historical highest number of displaced people victims of the armed conflict are Nariño, Antioquia, Cauca, Chocó, Norte de Santander, and Valle del Cauca, and in less proportion Caquetá, Tolima, Huila, and Putumayo. For more details on historical presence of nonstate armed groups and forced internal displacement of persons in Colombia, see CERAC (2011), López (2011), Ibáñez (2009), and *Defensoría del Pueblo* (2016).

for these percentages, we can point out some remarkable events related to Colombia's agriculture during the analyzed period following Jiménez *et al.* (2018) and the reports on Agricultural Policy Monitoring and Evaluation from 2015 to 2018 elaborated by the OECD. The 1990-1997 period exhibited unstable agricultural policies, increased drug traffic, and the armed conflict intensification, all of which discouraged the spread of environments for productivity and private investments. Among the most remarkable events affecting Colombian agriculture during 1998-2002: (1) the armed conflict intensity prompting many people to leave rural areas discouraging even more private investment; and (2) the Colombian government did not prioritize the agricultural development because of an ongoing macroeconomic crisis and the armed conflict intensification. Although the 2003-2013 period was characterized by a boom in agricultural commodity prices worldwide from 2006 to 2011 and by the security policy focused on restoring confidence to invest in the Colombian economy, there were also a series of shocks that could have lessened the beneficial effects of such striking events. First, violence was still a crucial problem in rural areas. Second, Colombian legal agriculture exhibited a lack of innovation and technological development that projected a profitability crisis due partially to the decrease in worldwide agricultural commodity prices from 2010-to 2013.

Finally, during the last period of our sample (2014-2017), the agricultural sector in Colombia faced significant constraints to hinder productivity. Agriculture operates in an environment with underinvestment in public goods and services, poor land management, and unsuccessful land tenure reforms. This latter aspect reflects that more than 40% of land ownership continues to be informal. The long-running armed conflict also relates to drug trafficking generating millions of victims and IDP, which has deeply affected the performance of the Colombian agricultural sector. From Table 1.7, we can also estimate the total cost of violence and the presence of drug crop production as a monetary measure of the loss in agricultural productivity. The estimated cost of violence from 1995 to 2017 would be approximately $6.6 billion (2005 USD), while the (shadow) cost generated by coca cultivation (historically and significantly linked to the armed conflict persistence) in the same period could be around $129.2 billion (of 2005 USD). Alternatively, using the coefficient of variation (CV) for IDP and casualties, we could have a more consistent computation of the total effect of violence on the production function. We use the means and standard deviations in Table 1.1 for IDP and casualties and the corresponding average productivity elasticities for these technology-changing variables in Table 1.3. From these calculations, we can infer that the violence in Colombia would have shifted downward the Colombian agricultural production function by 20.1% from 1995 to 2017.

4. Conclusions

The central issue addressed by this study is whether violence has a significant effect on the productivity of agricultural resources. We use a production function for Colombian agriculture, where violence shocks and other "technology-changing variables" determine the productivity of inputs in legal agriculture. We provide quantitative evidence of a significant negative association of violence shocks and illegal crop production incidence with the productivity of the agricultural sector of Colombia. We also find that the past agricultural output prices and current productivity of Colombian agriculture are positively correlated. Other results imply that weather shocks such as higher mean temperatures and lower rainfall conditions reduce the productivity of agricultural activities on which rural areas generally rely. Overall, we can distinguish two primary blocks of effects: the productivity effect and the scale effect. The productivity effect implies that a 1% increase in the armed conflict-related internally displaced people and casualties permanently lower productivity in Colombian agriculture by around 0.041% and 0.012%, respectively. We also find that the past cocaine price incidence (given coca cultivation intensity) and mean temperature can temporarily reduce agricultural productivity by approximately 0.61% and 1.58%, respectively. A 1% increase in past output price expectations and mean precipitation would temporarily shift the production function of Colombian agriculture upward by 0.42% and 0.24%, respectively. Exogenous technical change is approximately 1%, on average, and it varies across departments from -0.92% in Arauca to almost 2% in Chocó. The scale effect indicates a significant variation of the input elasticities due to the inclusion of the technology-changing variables. Production elasticities, on average, are 0.52 for labor and 0.40 for livestock but have a wide range across departments depending on the level of the departmental productivity changing variables. In particular, the violence from the armed conflict in rural areas of Colombia was costly to agriculture because it implied a downward shift in the production function or a productivity reduction of almost 20.1% from 1995 to 2017. The estimated cost of this violence for legal agriculture in Colombia would have been approximately 2005 USD 6.6 billion from 1995 to 2017 (only through the violence shocks considered here and in terms of productivity loss). In a post-conflict Colombian context, it is thus imperative to understand how and why the armed conflict hindered access to crucial factors of production and affected yields and agricultural productivity.

Table 1. 1– Definition and Descriptive Statistics of the Variables in the Sample, 26 departments from 1995 to 2017

	Short Description	Mean	SD	Min	Max
Production Variables:					
Y	Output (million USD$)	1.53	1.37	69	7.11
X_0	Land (thousand ha)	1,393.4	1,080	50.24	5,221.2
X_1	Labor (thousand persons)	311.4	236.3	11.97	1,116.2
X_2	Livestock (thousand animals)	909.5	790	30.93	9,249.5
Technology Changing Variables:					
v_1	IDP per 100,000 inhabitants	1,296	1,967	1	17,798
v_2	Casualties per 100,000 inhabitants	19	215	0	5,065
v_3	Cocaine price per gram ($) weighted by coca cultivation	2.61	5.33	0	35.31
v_4	Mean temperature (Celsius)	21.04	3.89	13.67	27.55
v_5	Mean precipitation (mm)	9.56	5.67	1.83	28.87
v_6	Lagged output Price (Törnqvist index, average of past three years)	1.26	0.32	0.43	2.44
τ	Unexplained exogeneous technological change (time trend)	12	6.64	1	23
Other Variables:					
Farm Size	Average farm size (ha per UPA)	48.93	58.44	0.81	362.06
Region 1	Amazon region	0.08	0.27	0	1
Region 2	Andean region	0.38	0.49	0	1
Region 3	Caribbean region	0.27	0.44	0	1
Region 4	Orinco region	0.12	0.32	0	1
Region 5	Pacific region	0.15	0.36	0	1

Notes: The output (Y) is the value of agricultural production in millions of 2005 US dollars; land (X_0) is in thousands of hectares of arable and permanent cropland and permanent pastures; labor (X_1) is in thousands of individuals in the working-age population in rural zones; livestock (X_2) represents the number of cow equivalent livestock units; the variable v_1 is the (one-year) lagged ratio of the annual number of IDP to the total population per one hundred thousand inhabitants in the department where the displacement occurred; the variable v_2 is the (one-year) lagged ratio of the annual number of conflict-related casualties to the total population in the department of the recorded deaths per 100 thousand inhabitants; the variable v_3 (past cocaine price) is the (one-year) lagged retail cocaine price weighted by the ratio between the area planted with coca in each department/year to the national area cultivated with coca in the corresponding year; the variable v_4 is the (annual/department) mean of the municipality-monthly values of temperature; the variable v_5 is the (annual/department) mean of the municipality-monthly values of precipitation flux; and the variable v_6 is the a cross-department price index (a Törnqvist index) relative to a base consisting of a 1999 cross-department index value. The other variables used in the analysis are Farm Size as the average APU size (total number of hectares covered by the UPAs divided by the total number of UPAs) and the dummy variables Region 1, 2, 3, 4, and 5 equal to 1 (0 otherwise) for the Amazon, Andean, Caribbean, Orinoco, and Pacific region, respectively.

Table 1. 2 − Ordinary Least Squares Estimates of Equation (9) with dependent variable $\ln y$, 26 departments

	Inputs		Intercept
	Labor ($\ln x_1$)	Livestock ($\ln x_2$)	(α_0, γ_k, δ_0)
Linear terms (α_{i0})	-0.5642	-1.7590	-4.1469
	[0.5347]	[0.7528]**	[0.7062]***
IDP (α_{i1})	0.0112	0.0497	
	[0.0092]	[0.0291]*	
Casualties (α_{i2})	-0.0104	0.0570	
	[0.0144]	[0.0343]*	
Past Cocaine Price (α_{i3})	-0.0378	-0.3762	-0.8501
	[0.0490]	[0.1967]*	[0.1568]***
Temperature (α_{i4})	0.1770	0.4609	-1.0925
	[0.1616]	[0.2527]*	[0.2156]***
Rainfall (α_{i5})	0.2042	0.2087	0.6383
	[0.0463]***	[0.0829]**	[0.0737]***
Past Output Price (α_{i6})	-0.2035	-0.1540	0.0403
	[0.0781]***	[0.1622]	[0.1456]
Trend (τ) (δ_i)	0.0064	0.0100	0.0243
	[0.0028]**	[0.0072]	[0.0055]***

Notes: Robust standard errors in brackets. The estimates are based on 546 observations during the years 1995 and 2017. Overall R^2=0.85, between R^2=0.90, and within R^2=0.33..
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 1. 3 − Productivity and Production Elasticities, 26 departments during 1995-2017

	Regression Model	
	Variable Elasticity[a]	Fixed Elasticity[b]
Productivity elasticity for technology-changing variable:		
IDP (φ_1)	-0.0408	
	[0.0176]*	
Casualties (φ_2)	-0.0123	
	[0.0230]	
Past Cocaine Price (φ_3)	-0.6112	
	[0.1259]**	
Temperature (φ_4)	-1.5784	
	[0.2224]***	
Rainfall (φ_5)	0.2349	
	[0.0716]*	
Past Output Price (φ_6)	0.4161	
	[0.1272]**	
Production elasticity for input variable and trend:		
Labor ($\ln x_1$)	0.5153	0. .7333
	[0.0556]***	[0.0357]***
Livestock ($\ln x_2$)	0.4034	0.1194
	[0.1192]*	[0.0271]***
Trend (Exogeneous Technical Change)	0.0100	0.0082
	[0.0051]	[0.0012]***

Notes: The elasticities are evaluated at the mean of all the observations. Standard errors in brackets are computed with the delta method provided by Papke and Wooldridge (2005).

[a] Equation (4). [b] Equation (4) restricted by $\alpha_{ik} = \gamma_k = 0$ for all i and k.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 1. 4 − Estimated Productivity Elasticities at the Department Level, 1995-2017

Department	Productivity elasticity for						Production elasticity for		Trend
	IDP (φ_1)	Casualties (φ_2)	Past Cocaine Price (φ_3)	Temperature (φ_4)	Rainfall (φ_5)	Past Output Price (φ_6)	Labor ($\ln x_1$)	Livestock ($\ln x_2$)	(τ)
Antioquia	-0.027	-0.006	-0.693	-1.427	0.353	0.308	0.526	0.311	0.014
	[0.013]**	[0.017]	[0.133]**	[0.163]***	[0.059]**	[0.110]**	[0.049]***	[0.104]*	[0.005]**
Arauca	-0.076	0.015	-0.479	-2.123	-0.375	1.021	0.428	0.518	-0.009
	[0.033]**	[0.053]	[0.172]**	[0.533]***	[0.158]**	[0.256]***	[0.037]***	[0.139]***	[0.009]
Atlántico	-0.017	0.005	-0.768	-1.330	0.401	0.271	0.412	0.305	0.016
	[0.012]	[0.016]	[0.134]***	[0.155]**	[0.058]***	[0.108]**	[0.072]***	[0.153]	[0.004]***
Bolívar	-0.036	-0.009	-0.642	-1.530	0.267	0.388	0.555	0.498	0.011
	[0.012]***	[0.015]	[0.092]***	[0.136]***	[0.047]***	[0.082]***	[0.060]**	[0.100]***	[0.003]***
Boyacá	-0.018	0.003	-0.762	-1.328	0.411	0.260	0.274	0.044	0.017
	[0.010]**	[0.014]	[0.128]***	[0.149]**	[0.055]***	[0.104]**	[0.096]**	[0.136]	[0.004]***
Caldas	-0.026	-0.010	-0.692	-1.403	0.387	0.273	0.602	0.486	0.015
	[0.010]*	[0.012]	[0.106]***	[0.141]***	[0.049]***	[0.093]**	[0.049]***	[0.115]***	[0.004]***
Caquetá	-0.053	0.003	-0.581	-1.779	-0.012	0.665	0.467	0.384	0.002
	[0.020]**	[0.031]	[0.112]**	[0.282]***	[0.087]	[0.138]***	[0.037]***	[0.139]**	[0.005]
Casanare	-0.079	-0.002	-0.430	-2.108	-0.298	0.934	0.402	0.412	-0.007
	[0.030]**	[0.045]	[0.164]**	[0.453]***	[0.137]*	[0.226]***	[0.039]***	[0.120]***	[0.008]
Cauca	-0.063	-0.057	-0.404	-1.723	0.273	0.344	0.659	0.438	0.009
	[0.029]**	[0.033]*	[0.136]**	[0.271]***	[0.077]**	[0.144]**	[0.067]***	[0.121]***	[0.007]
Cesar	-0.029	0.016	-0.729	-1.518	0.182	0.489	0.563	0.571	0.010
	[0.018]	[0.028]	[0.134]***	[0.220]***	[0.073]**	[0.119]***	[0.049]***	[0.093]***	[0.005]**
Chocó	-0.014	-0.007	-0.762	-1.249	0.521	0.147	0.700	0.763	0.020
	[0.010]	[0.014]	[0.137]***	[0.197]***	[0.067]***	[0.127]	[0.055]***	[0.151]***	[0.005]***
Córdoba	-0.001	0.026	-0.901	-1.182	0.454	0.238	0.558	0.551	0.019
	[0.016]	[0.024]	[0.187]***	[0.189]***	[0.073]***	[0.140]*	[0.062]***	[0.085]***	[0.006]***
Cundinamarca	-0.020	-0.002	-0.744	-1.338	0.418	0.250	0.442	0.252	0.017
	[0.008]*	[0.011]	[0.117]***	[0.134]***	[0.050]***	[0.096]**	[0.062]***	[0.116]	[0.004]***
Guajira	-0.094	-0.062	-0.230	-2.113	-0.071	0.670	0.524	0.518	-0.003
	[0.034]***	[0.037]	[0.188]	[0.318]***	[0.100]	[0.186]***	[0.060]***	[0.089]***	[0.008]
Huila	-0.057	-0.034	-0.483	-1.717	0.190	0.442	0.453	0.339	0.007
	[0.020]***	[0.021]	[0.094]***	[0.182]***	[0.056]***	[0.100]***	[0.059]***	[0.087]**	[0.004]
Magdalena	-0.028	0.007	-0.715	-1.477	0.256	0.411	0.482	0.513	0.012
	[0.013]*	[0.021]	[0.118]***	[0.162]***	[0.057]***	[0.097]***	[0.046]***	[0.107]***	[0.004]***
Meta	-0.087	-0.016	-0.362	-2.155	-0.284	0.909	0.440	0.316	-0.008
	[0.027]***	[0.038]	[0.154]*	[0.407]***	[0.125]**	[0.208]***	[0.036]***	[0.115]*	[0.007]
Nariño	-0.035	-0.040	-0.585	-1.416	0.494	0.146	0.482	0.030	0.017
	[0.021]*	[0.025]	[0.110]***	[0.267]***	[0.075]***	[0.137]	[0.058]***	[0.181]	[0.006]***
N. Santander	-0.060	-0.032	-0.472	-1.761	0.140	0.492	0.375	0.165	0.006
	[0.020]***	[0.022]	[0.100]**	[0.190]***	[0.060]*	[0.105]***	[0.060]***	[0.111]	[0.004]
Putumayo	-0.056	-0.040	-0.474	-1.695	0.232	0.398	0.507	0.263	0.008
	[0.021]***	[0.023]*	[0.100]***	[0.197]***	[0.058]**	[0.107]***	[0.049]***	[0.164]	[0.005]
Quindío	-0.027	-0.014	-0.679	-1.401	0.405	0.252	0.646	0.492	0.016
	[0.010]*	[0.012]	[0.104]***	[0.152]***	[0.051]***	[0.096]**	[0.059]***	[0.134]***	[0.004]***
Risaralda	-0.026	-0.029	-0.657	-1.329	0.533	0.118	0.604	0.480	0.019
	[0.015]*	[0.018]*	[0.109]***	[0.241]***	[0.070]***	[0.130]	[0.056]***	[0.131]***	[0.005]***
Santander	-0.037	-0.007	-0.640	-1.549	0.244	0.412	0.520	0.363	0.011
	[0.012]***	[0.017]	[0.094]***	[0.143]***	[0.050]***	[0.084]***	[0.048]***	[0.097]**	[0.003]***
Sucre	-0.012	0.016	-0.818	-1.303	0.381	0.299	0.589	0.584	0.016
	[0.013]	[0.020]	[0.152]***	[0.160]***	[0.062]***	[0.114]**	[0.073]***	[0.097]***	[0.005]***
Tolima	-0.049	-0.022	-0.548	-1.657	0.199	0.443	0.482	0.402	0.008
	[0.015]***	[0.018]	[0.083]***	[0.157]***	[0.050]***	[0.086]***	[0.049]***	[0.088]***	[0.004]**
V. Cauca	-0.031	-0.022	-0.641	-1.427	0.412	0.239	0.704	0.491	0.016
	[0.013]**	[0.014]	[0.113]**	[0.182]***	[0.058]**	[0.110]*	[0.061]***	[0.128]**	[0.005]**

Notes: The elasticities are evaluated at the mean. Standard errors in brackets are computed with the delta method provided by Papke and Wooldridge (2005).

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 1. 5 – Annual Productivity Elasticities for Colombian Agriculture, 26 departments

Year	Productivity elasticity for						Production elasticity for		Trend
	IDP (φ_1)	Casualties (φ_2)	Past Cocaine Price (φ_3)	Temperature (φ_4)	Rainfall (φ_5)	Past Output Price (φ_6)	Labor ($\ln x_1$)	Livestock ($\ln x_2$)	(τ)
1995	-0.035	-0.006	-0.655	-1.525	0.259	0.399			0.011
	[0.016]	[0.022]	[0.125]***	[0.211]***	[0.069]*	[0.122]**			[0.005]
1996	-0.040	-0.011	-0.615	-1.577	0.233	0.419			0.010
	[0.019]	[0.025]	[0.140]*	[0.234]***	[0.076]*	[0.136]**			[0.006]
1997	-0.054	-0.027	-0.514	-1.696	0.184	0.453	0.416	0.200	0.008
	[0.024]	[0.029]	[0.157]	[0.265]***	[0.084]	[0.154]**	[0.065]***	[0.127]	[0.006]
1998	-0.043	-0.015	-0.594	-1.596	0.230	0.418	0.471	0.278	0.010
	[0.019]	[0.024]	[0.132]**	[0.232]***	[0.074]*	[0.134]*	[0.059]***	[0.120]	[0.005]
1999	-0.034	-0.006	-0.660	-1.507	0.277	0.381	0.523	0.340	0.012
	[0.019]*	[0.025]	[0.144]***	[0.240]**	[0.078]*	[0.142]*	[0.059]***	[0.112]*	[0.006]
2000	-0.043	-0.014	-0.593	-1.607	0.217	0.432	0.521	0.344	0.009
	[0.018]*	[0.023]	[0.119]***	[0.221]***	[0.070]*	[0.124]**	[0.057]***	[0.109]	[0.005]
2001	-0.039	-0.009	-0.627	-1.567	0.232	0.421	0.479	0.323	0.010
	[0.021]	[0.027]	[0.148]**	[0.248]**	[0.080]*	[0.145]*	[0.057]***	[0.105]	[0.006]
2002	-0.040	-0.010	-0.620	-1.576	0.229	0.424	0.488	0.377	0.010
	[0.018]	[0.024]	[0.140]**	[0.231]***	[0.076]**	[0.136]*	[0.059]***	[0.104]	[0.005]
2003	-0.043	-0.013	-0.600	-1.603	0.214	0.436	0.503	0.395	0.009
	[0.018]	[0.023]	[0.127]**	[0.225]***	[0.073]**	[0.129]**	[0.057]***	[0.110]*	[0.005]
2004	-0.042	-0.012	-0.605	-1.600	0.212	0.439	0.479	0.354	0.009
	[0.017]*	[0.022]	[0.122]**	[0.219]***	[0.071]*	[0.124]**	[0.056]***	[0.112]	[0.005]
2005	-0.041	-0.009	-0.615	-1.593	0.210	0.442	0.476	0.408	0.009
	[0.017]*	[0.023]	[0.122]***	[0.218]***	[0.070]**	[0.124]**	[0.051]***	[0.106]*	[0.005]*
2006	-0.039	-0.008	-0.627	-1.570	0.227	0.427	0.477	0.415	0.010
	[0.016]*	[0.022]	[0.122]**	[0.216]***	[0.070]**	[0.124]**	[0.049]***	[0.105]*	[0.005]*
2007	-0.039	-0.008	-0.628	-1.571	0.227	0.427	0.483	0.408	0.010
	[0.016]*	[0.022]	[0.120]***	[0.212]***	[0.069]**	[0.121]**	[0.049]***	[0.112]*	[0.005]*
2008	-0.040	-0.010	-0.622	-1.574	0.228	0.425	0.531	0.462	0.010
	[0.016]*	[0.022]	[0.117]**	[0.211]***	[0.068]**	[0.119]**	[0.050]***	[0.120]*	[0.005]
2009	-0.037	-0.008	-0.638	-1.549	0.245	0.410	0.522	0.437	0.011
	[0.016]*	[0.022]	[0.121]***	[0.212]***	[0.069]*	[0.121]**	[0.051]***	[0.110]*	[0.005]
2010	-0.036	-0.008	-0.645	-1.533	0.259	0.397	0.559	0.490	0.011
	[0.016]*	[0.021]	[0.118]***	[0.211]***	[0.068]*	[0.119]**	[0.049]***	[0.109]**	[0.005]
2011	-0.037	-0.010	-0.635	-1.539	0.262	0.392	0.539	0.463	0.011
	[0.015]*	[0.020]	[0.117]**	[0.208]***	[0.067]*	[0.119]*	[0.048]***	[0.117]*	[0.005]
2012	-0.042	-0.015	-0.602	-1.581	0.242	0.408	0.532	0.441	0.010
	[0.017]**	[0.022]	[0.116]**	[0.213]***	[0.068]*	[0.120]**	[0.052]***	[0.120]*	[0.005]
2013	-0.041	-0.015	-0.602	-1.580	0.243	0.406	0.591	0.497	0.010
	[0.017]*	[0.022]	[0.113]***	[0.212]***	[0.067]*	[0.118]*	[0.058]***	[0.124]*	[0.005]
2014	-0.041	-0.014	-0.608	-1.569	0.251	0.399	0.522	0.460	0.010
	[0.016]*	[0.021]	[0.118]**	[0.213]***	[0.068]**	[0.121]*	[0.058]***	[0.125]*	[0.005]
2015	-0.043	-0.017	-0.590	-1.591	0.243	0.405	0.557	0.472	0.010
	[0.018]*	[0.022]	[0.119]**	[0.219]***	[0.069]**	[0.123]*	[0.059]***	[0.134]*	[0.005]
2016	-0.043	-0.018	-0.589	-1.588	0.247	0.400	0.641	0.558	0.010
	[0.017]*	[0.022]	[0.117]**	[0.217]***	[0.069]*	[0.122]*	[0.057]***	[0.143]**	[0.005]
2017	-0.045	-0.020	-0.573	-1.612	0.232	0.413	0.511	0.350	0.010
	[0.019]*	[0.024]	[0.122]**	[0.230]***	[0.072]*	[0.128]**	[0.066]***	[0.179]	[0.005]

Notes: The elasticities are evaluated at the mean. Standard errors in brackets are computed with the delta method provided by Papke and Wooldridge (2005).

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 1. 6 – Productivity Cost (Gain) per Department for the 1995-2017 Period

Department	AGDP	IDP	Casualties	Cocaine Price	Temperature	Rainfall	Output Price
Antioquia	2,106	-6.7	11.2	-888.1	-331.1	473.7	5.2
		[3.0]**	[33.8]	[163.6]**	[36.2]***	[76.2]**	[1.8]**
Arauca	299	-3.3	21.3	-153.4	-73.2	-26.0	1.3
		[1.4]**	[74.2]	[52.1]**	[17.9]***	[11.5]**	[0.3]***
Atlántico	119	-0.8	-0.8	-	-48.6	118.7	0.2
		[0.5]	[4.3]	-	[5.5]**	[16.9]***	[0.1]**
Bolívar	421	-3.1	6.6	-133.8	-99.0	-269.1	0.9
		[1.0]***	[11.5]	[19.2]***	[8.8]***	[47.5]***	[0.2]***
Boyacá	855	-3.7	-4.2	-642.4	-129.2	112.8	1.2
		[2.1]**	[30.6]	[107.2]***	[14.3]**	[15.1]***	[0.5]**
Caldas	464	-3.2	7.8	-512.7	-42.6	110.0	0.9
		[1.2]*	[10.3]	[78.7]***	[4.3]***	[14.0]***	[0.3]***
Caquetá	174	-1.4	-1.3	-82.8	-32.0	-0.9	0.6
		[0.5]**	[13.4]	[15.9]***	[5.1]***	[5.4]	[0.1]***
Casanare	372	-5.5	0.1	-	-108.4	-26.7	1.3
		[2.1]**	[54.2]	-	[23.4]***	[12.7]*	[0.3]***
Cauca	573	-7.6	45.2	-156.5	-55.5	-100.4	1.2
		[3.5]**	[25.9]*	[51.2]*	[8.7]***	[27.6]**	[0.5]**
Cesar	494	-3.1	-16.3	-366.1	-104.6	164.0	1.5
		[2.0]	[28.5]	[67.6]***	[15.3]***	[65.9]***	[0.4]***
Chocó	219	-0.3	8.8	-188.3	-19.1	37.6	0.2
		[0.2]	[14.9]	[34.0]***	[3.1]***	[4.9]***	[0.2]
Córdoba	643	0.0	-43.8	-501.2	-111.6	-188.5	0.8
		[1.3]	[39.1]	[104.4]***	[17.9]***	[30.3]***	[0.5]*
Cundinamarca	2,419	-13.2	9.1	-1,835.4	-201.6	401.9	2.9
		[5.1]*	[48.4]	[288.8]***	[20.1]***	[48.2]***	[1.1]**
La Guajira	170	-3.4	20.1	-40.2	-68.2	26.6	0.6
		[1.2]***	[12.2]	[31.2]	[10.2]***	[37.9]	[0.2]***
Huila	684	-7.4	35.7	-	-165.8	132.5	1.5
		[2.6]***	[22.2]	-	[17.6]***	[38.2]***	[0.3]***
Magdalena	613	-3.8	-6.9	-389.6	-157.2	104.0	1.5
		[1.8]*	[20.8]	[64.1]***	[17.3]***	[23.2]***	[0.4]***
Meta	611	-8.6	32.9	-137.1	-141.0	-60.2	2.5
		[2.7]***	[76.5]	[56.2]*	[26.4]***	[26.9]**	[0.6]***
Nariño	615	-5.9	24.2	-219.7	-44.7	90.1	0.6
		[3.5]*	[14.7]	[41.4]***	[8.4]***	[13.7]***	[0.6]

Table 1. 7 – (continued)

Department	AGDP	IDP	Casualties	Cocaine Price	Temperature	Rainfall	Output Price
N. Santander	469	-4.4	22.7	-164.3	-160.6	31.7	1.4
		[1.4]***	[16.0]	[33.4]**	[17.1]***	[12.8]*	[0.3]***
Putumayo	78	-0.8	15.2	-19.6	-12.6	15.4	0.2
		[0.3]***	[8.8]*	[4.2]***	[1.5]***	[3.8]**	[0.1]***
Quindío	400	-2.4	25.4	-	-34.9	103.3	0.8
		[0.9]*	[22.1]	-	[3.8]***	[12.9]***	[0.3]**
Risaralda	306	-1.4	25.8	-	-23.5	102.2	0.3
		[0.8]*	[15.6]*	-	[4.3]***	[13.4]***	[0.3]
Santander	1,258	-9.5	15.0	-629.8	-117.9	150.7	2.7
		[3.1]***	[36.3]	[91.8]***	[10.9]***	[30.8]***	[0.6]***
Sucre	220	-0.5	-5.3	-	-48.3	-40.7	0.4
		[0.6]	[6.5]	-	[5.9]***	[6.6]***	[0.2]***
Tolima	1,001	-7.7	25.4	-	-229.4	148.5	2.2
		[2.4]***	[21.0]	-	[21.6]***	[37.4]***	[0.4]***
V. del Cauca	1,546	-10.9	28.8	-1,178.8	-111.5	955.9	2.4
		[4.4]**	[18.4]	[205.6]**	[14.2]***	[131.9]**	[1.1]*

Notes: The values are in 2005 US$1 million. The exchange rate in 2005 was approximately US$1 = 2,321.5 COP Colombian Peso. AGDP indicates the Annual Average Agricultural GDP. Standard errors in brackets are computed with the delta method provided by Papke and Wooldridge (2005).

Table 1. 8 – Annual productivity cost (gain) for technology-changing variable, 26 departments

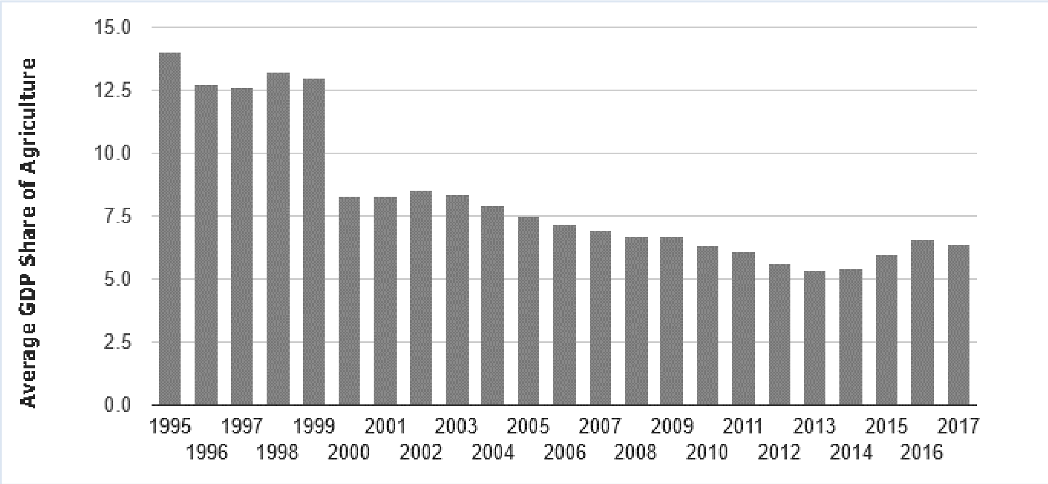
Year	AGDP	IDP	Casualties	Cocaine Price	Temperature	Rainfall	Output Price
1995	10,020.9	-55.47	34.06	-5,178.99	-1,518.21	1,774.65	19.35
		[0.95]	[15.01]	[48.63]**	[7.39]***	[17.15]*	[0.25]**
1996	9,917.8	-72.87	272.75	-4,594.30	-1,664.59	1,228.57	22.94
		[1.35]	[18.41]	[61.50]**	[9.88]***	[21.05]*	[0.36]**
1997	9,929.5	-111.60	580.74	-3,465.62	-1,710.61	777.33	23.96
		[1.84]	[20.39]	[58.80]	[9.45]***	[23.15]	[0.33]**
1998	10,103.4	-79.61	279.37	-4,543.88	-1,576.04	1,403.22	20.29
		[1.26]	[15.76]	[46.82]**	[7.99]***	[18.45]*	[0.27]*
1999	10,010.3	-52.97	69.80	-5,282.81	-1,418.53	2,002.50	15.44
		[1.20]*	[15.75]	[54.19]***	[8.96]**	[19.89]*	[0.32]*
2000	10,134.6	-71.45	156.78	-4,922.99	-1,591.87	1,413.52	20.84
		[1.14]*	[14.60]	[46.29]***	[7.58]***	[16.83]*	[0.25]**
2001	10,334.9	-64.09	22.72	-5,276.19	-1,602.88	1,486.71	21.15
		[1.51]	[19.02]	[56.83]**	[8.96]**	[18.47]*	[0.29]*
2002	10,939.5	-70.71	126.56	-5,482.86	-1,673.52	1,796.36	21.95
		[1.17]	[14.94]	[52.14]*	[7.96]***	[19.18]**	[0.28]*
2003	11,156.8	-71.00	104.57	-5,593.13	-1,718.24	1,639.08	23.11
		[1.32]*	[16.53]	[54.56]**	[8.16]***	[18.79]**	[0.28]**
2004	11,170.6	-77.83	158.11	-5,374.63	-1,754.02	1,590.64	23.72
		[1.16]*	[15.39]	[48.90]**	[8.07]***	[18.51]*	[0.27]**
2005	11,267.3	-76.49	135.53	-5,560.51	-1,753.54	1,648.50	24.49
		[1.22]*	[16.42]	[51.63]***	[8.29]***	[18.90]**	[0.27]**
2006	11,523.1	-73.27	132.59	-5,712.53	-1,768.02	1,836.71	23.78
		[1.14]*	[15.86]	[51.60]**	[8.30]***	[19.23]**	[0.28]**
2007	11,953.2	-75.70	128.59	-6,028.40	-1,823.60	1,855.54	24.83
		[1.18]*	[16.70]	[54.71]***	[8.49]***	[19.89]**	[0.29]**
2008	11,865.4	-75.91	124.74	-5,992.22	-1,844.17	1,741.33	25.06
		[1.20]*	[17.50]	[54.03]**	[8.55]***	[19.46]**	[0.28]**
2009	11,742.0	-72.61	100.30	-5,992.98	-1,800.29	1,837.27	24.22
		[1.16]*	[17.66]	[54.39]***	[8.47]***	[19.32]*	[0.28]**

Table 1. 9 – (continued)

Year	AGDP	IDP	Casualties	Cocaine Price	Temperature	Rainfall	Output Price
2010	11,817.2	-73.58	114.94	-5,948.67	-1,793.41	1,973.31	23.24
		[1.17]*	[17.50]	[52.65]***	[8.46]***	[19.15]*	[0.29]**
2011	12,062.5	-75.23	157.71	-6,004.85	-1,834.61	2,050.38	23.35
		[1.11]*	[17.06]	[53.27]**	[8.65]***	[19.77]*	[0.29]*
2012	12,345.7	-86.87	273.46	-5,920.35	-1,948.56	1,836.85	25.65
		[1.27]**	[18.62]	[52.46]**	[9.05]***	[19.83]*	[0.30]**
2013	13,142.3	-91.87	285.11	-6,316.15	-2,074.72	2,019.80	27.03
		[1.32]*	[19.50]	[55.99]***	[9.59]***	[21.24]*	[0.31]*
2014	13,526.6	-91.60	271.85	-6,509.76	-2,114.61	2,124.06	27.16
		[1.33]*	[19.26]	[58.50]**	[9.86]***	[22.20]**	[0.33]*
2015	14,044.2	-102.56	353.07	-6,503.36	-2,207.21	2,163.57	28.65
		[1.49]*	[21.05]	[58.23]*	[10.38]***	[22.88]**	[0.34]*
2016	14,389.0	-106.21	384.17	-6,538.57	-2,268.71	2,175.03	29.36
		[1.54]*	[21.75]	[58.01]**	[10.63]***	[23.17]*	[0.35]*
2017	15,225.9	-130.05	477.16	-6,496.31	-2,453.46	1,886.66	34.11
		[1.92]*	[25.64]	[62.96]**	[11.79]***	[25.30]*	[0.38]**

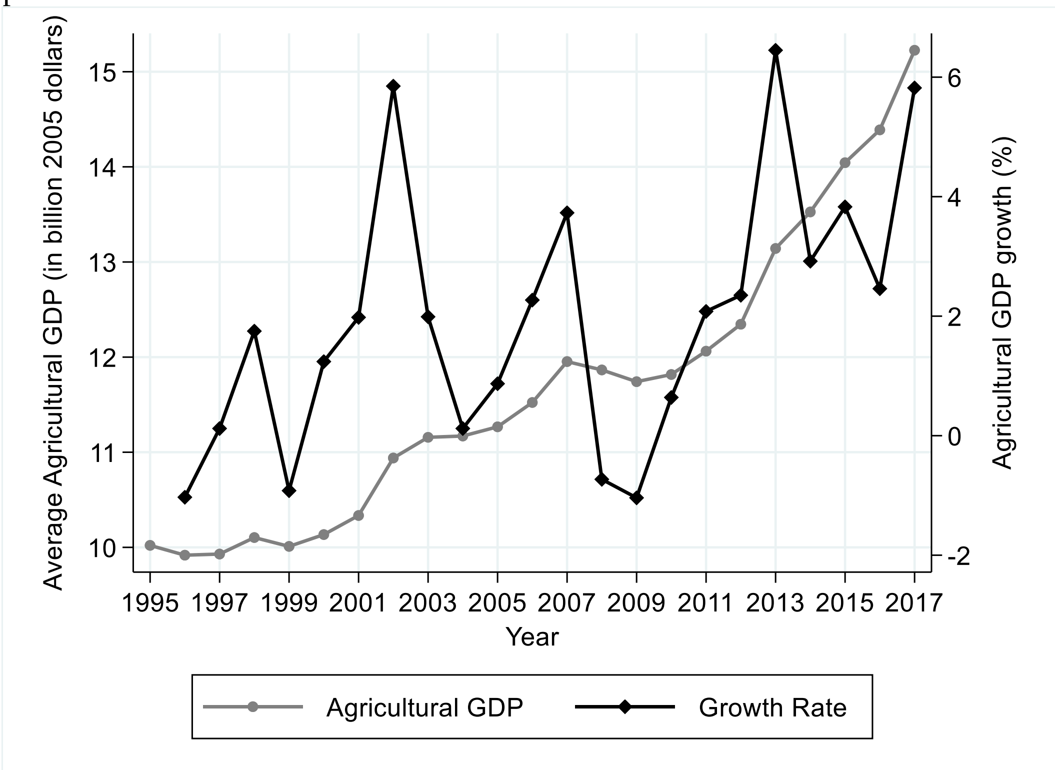
Notes The values are in 2005 US$1 million. The exchange rate in 2005 was approximately US$1 = 2,321.5 COP Colombian Peso. AGDP indicates the Total Agricultural GDP of the 26 departments. Standard errors in brackets are computed with the delta method provided by Papke and Wooldridge (2005).

Figure 1. 1 – Colombian GDP Share of Agriculture in 1995-2017



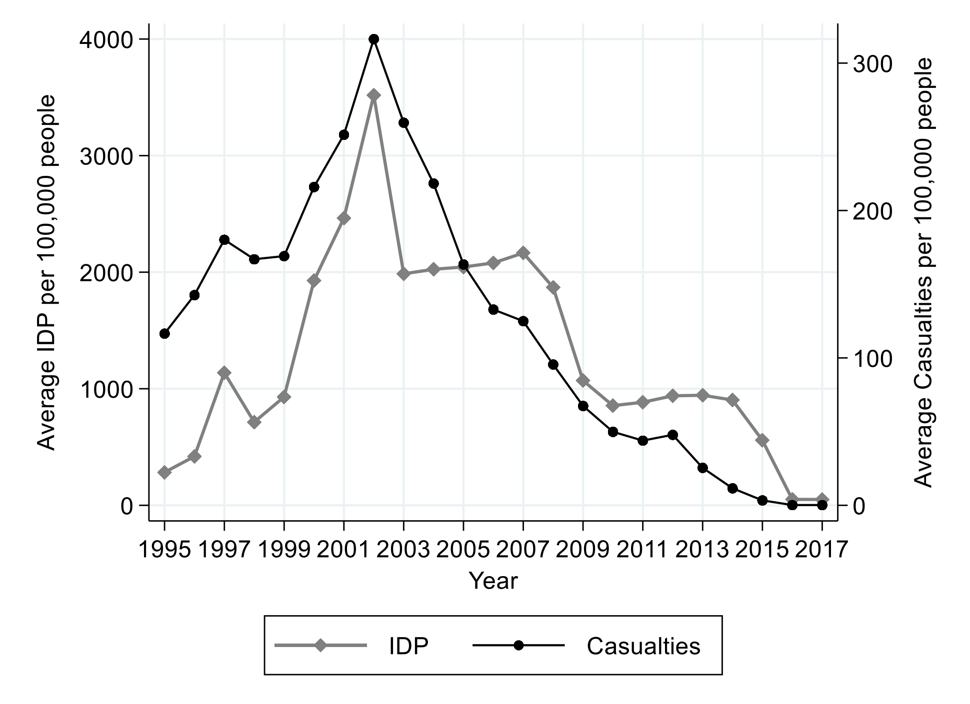
Source: Own calculations based on data from The World Bank.

Figure 1. 2– Value of Colombian Agricultural Output and its Growth Rates, 26 departments



Source: Own calculations based on data from DANE.

Figure 1. 3 – Evolution of the IDP and Conflict-Related Casualties in Colombia, 26 departments



Source: Own calculations based on data from CODHES-SISDES and UCDP.

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APPENDIX

A.1. Sensitivity Analysis of the Baseline Estimates from the Structural Model

The implementation of our model allows the inclusion of potentially relevant omitted variables. We thus control for farm size, time-invariant unobserved heterogeneity, and unobserved time-variant factors. The omission of these factors could be problematic if one believes that the structural model specification leads to biased estimates by attributing the effect of the omitted variables to the technology-changing variables included. This concern validates tests for the sensitivity of our results to other relevant-omitted sources of technological change that affect a particular region's agricultural productivity, given that the technology in Colombian agriculture could be sensitive to local environmental\institutional conditions and technological spillovers. Otherwise, all other more general time-variant factors would similarly affect all units of study through τ. Table A.1 shows our estimated productivity and production elasticities using alternative econometric specifications.

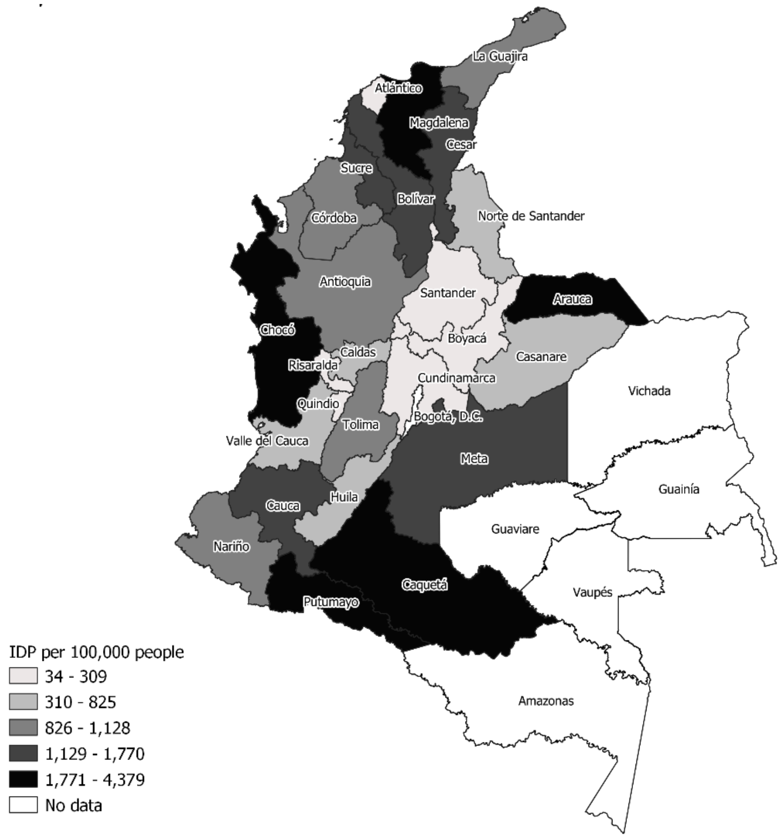
The elasticities in Table A.1 represent the mean of all the elasticities calculated for each observation. The baseline estimates from equation (4) are in column (1) of this table. Column (2) shows that including farm size as a control variable does not virtually affect the results. The standard errors in column (3) are clustered at the regional level to account for possible serial correlation across departments over time. This clusterization generates similar estimates to those in column (1). The inclusion of the linear term for department fixed effects in column (4) does not substantially affect our baseline estimates. Column (5) includes department-specific trends to the specification in column (4). Again, the estimated elasticities do not vary substantially compared to those in column (1). By including regional fixed effects in column (6), we can observe that controls for regional fixed effects reduce the statistical significance and magnitudes of all the estimated elasticities, except rainfall and labor input. Finally, column (7) (that controls for regional specific effects) shows similar results to those in column (6), with the exception that the cocaine price elasticity is less attenuated compared to the rest of the estimates.

Table A.1- Productivity and Production Elasticities with Some Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Productivity elasticity for IDP (φ_1)	-0.0408	-0.0407	-0.0408	-0.0433	-0.0437	-0.0348	-0.0338
	[0.0176]*	[0.0177]*	[0.0161]*	[0.0175]*	[0.0174]*	[0.0164]*	[0.0158]*
Casualties (φ_2)	-0.0123	-0.0123	-0.0123	-0.0157	-0.0178	0.0046	0.0051
	[0.0230]	[0.0231]	[0.0244]	[0.0224]	[0.0222]	[0.0221]	[0.0220]
Past Coca Price (φ_3)	-0.6112	-0.6114	-0.6112	-0.5524	-0.5356	-0.2685	-0.4491
	[0.1259]**	[0.1266]**	[0.1209]**	[0.1168]**	[0.1132]**	[0.1135]*	[0.1023]*
Temperature (φ_4)	-1.5784	-1.5586	-1.5784	-1.5204	-1.5338	0.5229	0.6356
	[0.2224]***	[0.2483]***	[0.1812]***	[0.2195]***	[0.2189]***	[0.3526]	[0.3412]
Rainfall (φ_5)	0.2349	0.2367	0.2349	0.2132	0.2067	0.2628	0.2828
	[0.0716]*	[0.07276]*	[0.06149]*	[0.0696]*	[0.0699]*	[0.0810]*	[0.0795]**
Past Output Price (φ_6)	0.4161	0.4153	0.4161	0.4341	0.4297	0.3841	0.3620
	[0.1272]**	[0.1280]**	[0.1101]**	[0.1265]**	[0.1256]**	[0.1312]*	[0.1290]*
Technical Change (τ)	0.0100	0.0102	0.0100	0.0104	0.0103	0.0081	0.0094
	[0.0051]	[0.0052]	[0.0049]	[0.0050]	[0.0059]	[0.0050]	[0.0070]
Production elasticity for Labor ($\ln x_1$)	0.5153	0.5118	0.5153	0.5343	0.5040	0.5343	0.5300
	[0.0556]***	[0.0598]***	[0.0506]***	[0.0564]***	[0.0567]***	[0.0676]***	[0.0731]***
Livestock ($\ln x_2$)	0.4034	0.4025	0.4034	0.4684	0.4823	0.2835	0.2546
	[0.1192]*	[0.1201]*	[0.0813]*	[0.1183]**	[0.1175]**	[0.1241]*	[0.1160]

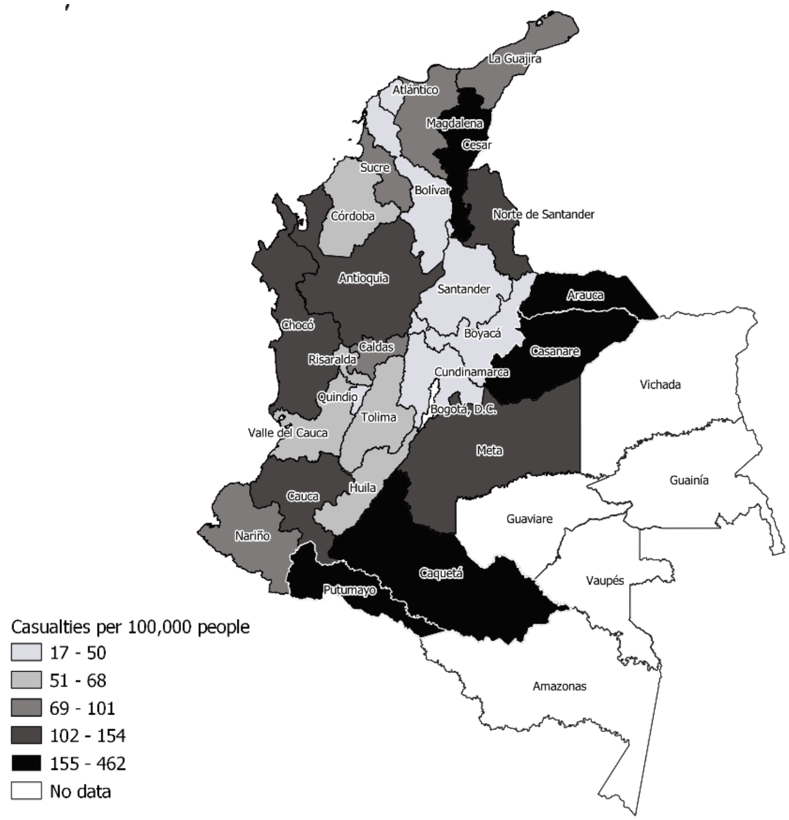
Notes: The elasticities represent the mean of all the elasticities calculated for each observation. Standard errors in brackets are computed using the delta method provided by Papke and Wooldridge (2005). Column (1) replicates our baseline estimates of Equation (4). Column (2) includes a control for farm size (or average APU size) defined here as the total number of hectares covered by the UPAs divided by the total number of UPAs. In column (3), the error term u_{0dt} of (4) is clustered at the regional level to account for possible serial correlation across departments over time. Column (4) includes a linear term for department fixed effects. Column (5) incorporates a variable identifying the departments and a linear trend for department-specific trends. Column (6) controls for regional fixed effects as time-invariant factors α_{0r}, where r indicates the region, with the Amazon Region as the omitted category. Column (7) adds time-variant omitted variables of the form $\alpha_r \times \tau$ to the estimation in column (2) to account for regional specific effects.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure A.1. 1 - Spatial Distribution of the Rate of IDP per 100,000 inhabitants



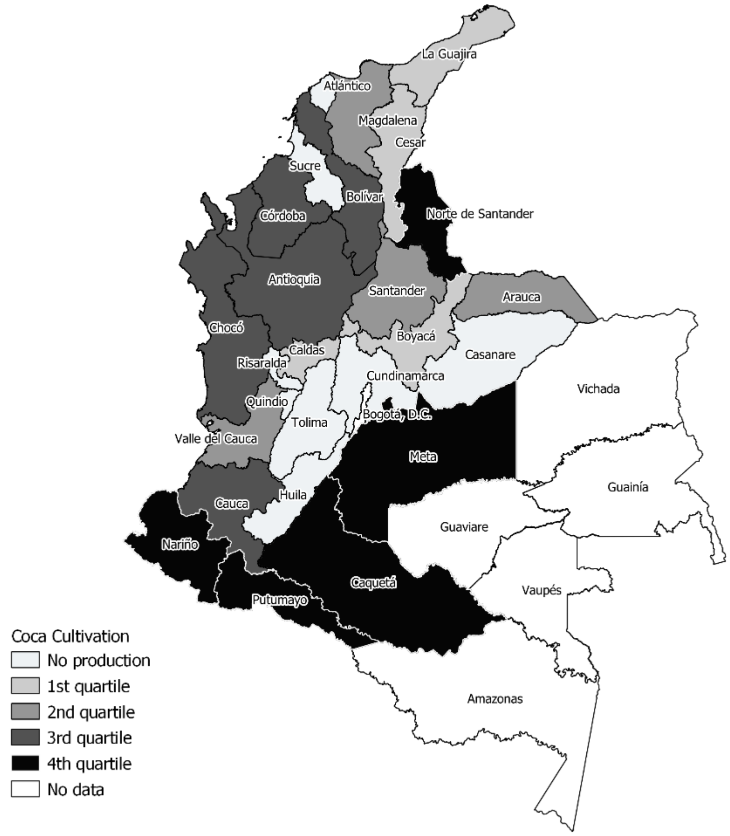
Source: Own calculations based on data from CODHES-SISDES.

Figure A.1. 2 - Spatial Distribution of Conflict-Related Casualties per 100,000 inhabitants



Source: Own calculations based on data from UCDP.

Figure A.1. 3 - Spatial Distribution of Coca Production Intensity



Source: Own calculations based on data from UNODC.

CHAPTER 2
THE EFFECT OF PLAN COLOMBIA ON THE VALUE OF LEGAL AGRICULTURAL PRODUCTION

2.1. Introduction

Colombia is among the three largest coca leaf producers and the world's leading supplier of cocaine to the US (UNODC, 2009). Because of the socio-economic costs resulting from this, both nations have aggressively pursued forced coca eradication and introduced a robust anti-drug policy named *Plan Colombia* (PC)[25] to combat cocaine production. The policy has used three primary strategies in practice for this: (i) eradication of coca cultivation by aerial spraying with pesticides over planted fields and manual coca crops destruction; (ii) alternative livelihood programs for coca-producing regions aimed at increasing the relative profit of non-coca agricultural activities by providing monetary subsidies in exchange for not cultivating coca; and (iii) interdiction of cocaine-producing laboratories and related facilities.[26]

Although the cost of the anti-drug policy was around 5.5 billion US dollars from 2000 to 2007 (ONDCP, 2006; GAO, 2008), its effectiveness in reducing coca cultivation is still controversial.[27] The literature has focused on quantifying the policy effects on the

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[25] Launched bilaterally in 2000, *Plan Colombia* (PC) was a US foreign-military aid and diplomatic initiative. The policy aimed to combat Colombian illegal drug production, organized crime, and drug trafficking organizations. In the first phase of PC (2000-2006), aid resources reached USD$4.8 billion, mainly invested in the defense industry (National Planning Department-DNP-, 2016). The second phase (2007-2009), called the "Strategy for Strengthening Democracy and Social Development," was focused on institutional strengthening in areas affected by violence and with investments of USD$2.1 billion aimed at improving the population's socio-economic conditions in municipalities with the presence of either demobilized or active illegal armed groups. The last phase of the Plan (2010-2015) implied USD$2.7 billion for supporting the socio-economic development of the most vulnerable populations to both the violent confrontations between drug trafficking organizations and the Colombian government and the adverse effects of coca crops eradication campaigns.

[26] An interdiction strategy (*interdiction policy*) is defined here as the set of Colombian government operations and direct interventions to dismantle or destroy cocaine processing facilities (or laboratories) and increase coca base, coca leaves, and cocaine seizures. The government invested in these strategies to reduce the cocaine supply by targeting its intermediate and final production stages (Cote, 2019).

[27] There is still little empirical work assessing the efficacy of drug control policies under Plan Colombia. This gap is particularly evident in the case of coca eradication, which targets the farmers that produce coca

population of areas with coca production.[28] No empirical studies have assessed their effects on the value of agricultural production in the areas growing coca. This chapter uses a 21-year panel covering almost 97% of the entire country in the 1995–2015 period to estimate these effects. More specifically, this study examines the effects of the policies controlling coca supply in Colombia on the value of legal agricultural production.

The cultivation of coca leaves in Colombia links to cocaine processing, given that coca leaf is the essential input in cocaine production. The other leading coca leaf growing countries (i.e., Bolivia and Peru) clearly distinguish coca for cocaine production and its use for culturally tied consumption such as chewing, tea, and medicine (Koops, 2009; UNODC, 2014). Although there has been a remarkable decline in the total area under coca cultivation[29] , little of this reduction has been attributed to successful eradication campaigns alone, which have been the dominant anti-drug policy in the last three decades in Colombia (Vargas, 2005; Reyes, 2014; Mejía et al., 2017). Some studies have argued that indiscriminate aerial spraying of glyphosate destroys legal agriculture proximate to coca plantations. (Bishop 2003; Ibañez and Martinsson, 2013; Camacho and Mejía, 2015; Relyea, 2005; Rozo 2014;). Other studies assert that such aerial spraying campaigns generate negative economic, social, environmental, political, and health consequences (Moreno-Sanchez et al., 2003; Vargas, 2005; Dion and Russler, 2008).

Previous literature has documented diverse responses of coca farmers to the risk of eradication. Some farmers plant coca more extensively (Moreno-Sanchez *et al.*, 2003), while others either reduce or abandon coca production such that coca supply declines and the international coca price increases. This increase in coca price may incentivize farmers to expand coca cultivation in other locations (Dion and Russler, 2008; Robledo, 2015). The Colombian government has sporadically and not consistently carried out some social

leaf, the primary input of cocaine (Reyes, 2014). Only Moreno-Sanchez *et al.* (2003), Dion and Russler (2008), and Reyes (2014) have attempted to estimate the effectiveness of coca eradication in Colombia at the national, departmental, and municipal levels, respectively. Nevertheless, there is no research relating the effectiveness of Plan Colombia to the agricultural production value of licit or conventional crops.

[28] The main alternative crops that directly compete for land allocation with coca are coffee and cocoa.

[29] The area under coca cultivation decreased by almost a half: falling from 248,189 hectares (ha) in 2007 to 98,899 ha in 2013 (UNODC Coca Cultivation Survey, 2014). More generally, Plan Colombia reduced coca cultivation from 160,000 ha in 2000 to 48,000 ha in 2013, and the estimated value of Colombia's drug-related economy shrank from US$7.5 billion in 2008 to US$4.5 billion in 2013 (Mejía, 2016).

programs to encourage farmers to abandon coca cultivation by identifying alternative legal crops that could replace coca labor and income. However, these strategies have historically received less support than eradication efforts (Vargas, 2005). Empirical evidence suggests that alternative crops to coca production are generally more effective than eradication campaigns in reducing coca supply in the short and long run (Moreno-Sanchez *et al.*, 2003; Ibañez and Carlsson, 2010; Tabares and Rosales, 2005; Ibañez and Martinsson, 2013). Also, a higher presence of governmental institutions and public forces in coca-growing regions links to a significant coca cultivation reduction (Dion and Russler, 2008). The lack of governance and the presence of insurgent groups, in turn, promote an illegal environment that induces farmers to grow and supply coca leaves to the cocaine production system (Holmes *et al.*, 2006; Angrist and Kugler, 2008; Dube and Varga, 2013; Ibañez *et al.*, 2013; UNODC, 2014). Therefore, alternative crops alone appear not to provide farmers with enough incentives to abandon coca cultivation. Suggestive evidence has shown that the threat of violence, economic risks, and the fall in the prices of legal crops increases the incentives for farmers to switch to illicit crops (Moreno-Sanchez *et al.*, 2003; Dube and Vargas, 2013; Ibañez *et al.*, 2013).

According to Robledo (2015), the eradication of coca cultivation has produced little real impact and, in some cases, the opposite effect by increasing the area under coca cultivation. Alternative crop policy and livelihood programs for coca-producing regions implemented by the Colombian government have not even been significantly more effective than the eradication policy (Robledo, 2015; Mejía, 2016). By contrast, Mejía (2016), Mejía and Restrepo (2016), Mejía *et al.* (2017), and Cote (2019) show that the interdiction of coca-and-cocaine-producing laboratories and related facilities, especially since 2007, has proven to be the most effective and even cost-effective counternarcotics strategy used by Colombia.

The US Government Accountability Office has reported that the annual US funding for the military component of PC was, on average, 540 million USD per year between 2000 and 2008. This funding added to the 812 million USD invested by the Colombian government per year in the war on illegal drug production and trafficking, representing around 1.2% of Colombia's average annual GDP during the 2000-2008 period. The results on PC effectiveness are considered mixed despite such substantial investments. Figure A.2.1 in Appendix A displays the number of hectares of coca grown, the number of hectares sprayed in aerial eradication campaigns, and the number of hectares subjected to manual eradication between 1995 and 2014. The figure shows that despite the efforts to reduce coca plantations through intensive eradication campaigns, the annual number of hectares devoted to coca cultivation did not significantly fall, especially between 2005 and 2008, when both strategies were at their peaks. Although the area under coca cultivation fell rapidly from about 140,000 hectares in 2000 to 80,000 in 2002, areas planted with coca were relatively stable at an average of about 85,000 hectares in 2003-2006.[30] However, coca cultivation decreased again from 2007 to 2013, declining to about 48,000 hectares even when coca eradication efforts were substantially reduced (see Figure A.2.1).

The remainder of the chapter is as follows. Section 1.1 provides a background of the interdiction policy under the PC since 2007. Section 2 presents the data used and describes the empirical strategy implemented in the chapter. Section 3 presents and discusses the main results. Finally, Section 4 concludes the chapter.

[30] In 1978, the Colombian government launched aerial fumigation to eradicate cannabis crops with the herbicide Paraquat (Vargas, 2002). Because of the ecological risks associated with this herbicide, the Colombian government replaced it with glyphosate, known commercially as Roundup, around the mid-1980s. Since then, aerial spraying of glyphosate-based defoliants has been the most common anti-drug policy followed by Colombian governments (Davalos, 2016). The aerial fumigation program began officially in the 1990s continuing then for 21 years until the Colombian government halted it in 2014 because of the devastating health or environmental impacts caused by glyphosate (For more details on these aspects, see the World Health Organization report, 1994; Fritschi *et al.*, 2015; and Camacho and Mejía, 2015). Manual eradication is not associated with environmental or health risks, but it is a more expensive policy because it is a labor-intensive activity. According to Davalos (2016), the Colombian government also carried out manual eradication campaigns when and where aerial spraying was restricted or in easy-access areas without armed conflict (less than 10% of total eradication actions). However, manual eradication was only an official anti-drug policy in 2004. It became a national program with a budget from the Colombian government in 2004, and Plan Colombia was allocated exclusively to this activity (DNP, 2010; Davalos. 2016).

2.1.1. Interdiction Strategies

During former President Álvaro Uribe's second term, Ex-President Juan Manuel Santos became defense minister in 2006. The emphasis of Colombia's anti-drug strategies shifted radically since Santos and his team decided to reduce eradication campaigns of coca cultivation and put more effort toward dismantling cocaine production and trafficking. Figure 2.1 shows that the number of hectares under aerial spraying declined from about 152,000 in 2006 to 80,000 in 2009 (a reduction of 48%). Figure A.2.2 illustrates that the number of laboratories destroyed increased from around 2,100 in 2006 to 3,000 in 2008 (an increase of 43%). This new anti-drug strategy reduced the net supply of cocaine by more than 50%, a supply shock that impacted the entire region and the street price of cocaine in the United States (see Figure A.2.3 in Appendix A of this chapter). Figure A.2.4 in Appendix A displays coca base and cocaine seizures series and coca crop cultivation from 1999 to 2014. These seizures derived from three policies designed for reducing the cocaine supply. (1) interdictions of the labs and facilities where cocaine is processed; (2) disruption of cocaine shipments en route to consumption markets; and (3) imposition of stricter state controls on the sales of chemicals used to turn coca leaves into coca base. We can observe that cocaine hydrochloride seizures increased from 127 kilograms in 2006 to almost 200 in 2009 (an increase of 57%).

The interdiction of coca base and cocaine-processing facilities seems to have had much higher effects—not only on cocaine trafficking but also on coca cultivation— than eradication and other policies. Empirical evidence suggests that the sharp decline in Colombia's cocaine supply from 2007 to 2009 induced by such an anti-drug strategy pushed drug trafficking organizations' bases away from Colombia while embraced by other locations such as Central America and Mexico (Castillo *et al.*, 2020). Mejía and Restrepo (2013) find that for every cocaine-laboratory interdiction (detected and destroyed by the authorities), the area under coca cultivation decreases by approximately three hectares. The systematic elimination of cocaine-processing facilities could have represented a negative shock to the demand for coca leaves, at least in the short run, and thus coca cultivation declined.

A simple demand and supply representation of the markets for cocaine and coca can illustrate the essential hypothesis of the present research. This conjecture can be associated with a Production Possibilities Frontier (PPF) relationship between coca and alternative conventional crops with and without anti-drug policies (see Figures B.2.1-B.2.3 in Appendix B of this chapter). Intuitively, the 2008 negative shock in the net cocaine supply of Colombia (displayed in Figure A.2.3) can be represented in Figure B.2.1 as a leftward (or an upward) shift of the worldwide cocaine supply curve so that the international price of cocaine will be higher. As Figure B.2.2 illustrates, this shock would imply that the demand for coca leaves in Colombia shifts to the left (or downwardly) to a lower price level when the cocaine production decreases because of the interdiction policy (making more costly the processing and sale of cocaine). Figure B.2.3 exemplifies through a PPF scheme that the shock could ultimately affect the relative prices of illicit crops (coca) to licit crops, ceteris paribus. This association perhaps implied that a significant decline in coca cultivation could increase the value of legal agricultural production to the extent that licit crops divert resources from producing coca.

This chapter uses department-level data to assess the effect of the policies implemented under PC for reducing illicit crop cultivation on the value of agricultural production in areas identified as coca-growing. This study examines the hypothesis that the production value of licit crops in Colombia is mostly negatively related to cocaine production in those areas with coca plantations. Figure 2.1 shows the intensity of coca cultivation among Colombian departments. Figure 2.3 illustrates the evolution of the agricultural GDP of coca-growing and non-coca growing departments and their difference across years. We can roughly observe that both groups follow a similar trend before PC. Their trend difference has increasingly augmented over the years during PC, notably during the official interdiction policy period.

2.2. Methodology and Data

This chapter examines a potential induced effect of interdiction anti-drug policy on the value of legal agricultural production. This link implies that the higher the relative returns from conventional crops such as coffee and cocoa, the more likely the area under coca farming to be lower. Alternatively, an effective anti-drug policy generating a systematic reduction of coca cultivation may induce many farmers to switch from coca cultivation to conventional crops. Given this reverse causality, we might need at least a plausibly exogenous source of variation in either coca cultivation or legal crops to identify any impact of the change in one on the other. This study exploits the three main strategies used by the Colombian government under PC to reduce cocaine supply as an exogenous variation in coca cultivation to the value of legal agricultural production. The two first strategies focused on illicit crop controls through forced eradication campaigns directly targeting coca farming in two different ways, i.e., aerial spraying and manual eradication. The third strategy consists of redirecting interdiction efforts to target the intermediate and final stages of cocaine production.

Total hectares with coca leaves may not be by itself a proxy for the economic relevance of coca production in most regions since it may not reflect the benefit associated with growing coca. Thus, we use the plausibly exogenous changes in coca cultivation induced by the policies for reducing the illegal drug trade, which increases the cost of drug production. The primary mechanism explaining such variation relies on the effectiveness of these interventions to increase costs associated with coca farming, limiting its profitability, discouraging farmers from growing coca, and leading them to adopt alternative production activities.

2.3. Data

2.3.1. Coca Related Variables

To measure coca cultivation, we constructed a 21-year panel of 31 Colombian departments (24 of which grew coca at some point during the 1995–2015 period). We use data from the United Nations Office on Drug and Crime (UNODC). The UNODC has conducted satellite surveys of coca crops in every municipality of the country since

1999[31]. These surveys use satellite photography to measure the number of hectares with coca plantations in a given area\municipality on December 31st of each year.

The UNODC and the Colombian government use satellite imagery and verification flights over coca-growing areas to monitor the location and spread of coca cultivation. Although the UNODC and the Colombian government achieved full national coverage in the year 2001, the information on coca leaves cultivation for the period 1995-1998 was estimated based on Angrist and Kugler (2007), "*Cuadro 1*." in Ramírez (2002), and Uribe (1997). In 2005, for example, the area within each department with active coca cultivation was between 28 and 17,305 hectares, with seven departments having no reportable levels of coca cultivation.

We identified the departments with coca-growing areas and their participation in the national total coca cultivation with the variable on coca crops. The variable captures the cross-sectional variation of coca cultivation (see Figure 2.1) and time-variation of coca crops in Colombia (see Figure 2.2). We also obtain the ratio between the area planted with coca in each department/year to the total (national) area cultivated with coca in the corresponding year to measure coca farming intensity.

Regarding the coca-eradication-interdiction policy variables, we use direct indicators for each policy that capture variations in the profitability from coca-growing for the various departments of Colombia. These indicators are the number of hectares with coca subjected to aerial spraying and manual eradication and the number of cocaine processing facilities destroyed. Alternatively, the interdiction policy is proxied as the amount (in kilograms) of coca base, coca leaves, and cocaine seized each year. Based on this information, we create a variable indicating the department level of exposition to each of the three annual indicators before 2000 (the year of PC's implementation). These indicators have been available only since 1999. Thus, we use this year's information for the pre-intervention analysis in some specifications.

[31] Although there is no data on the exact amount of coca cultivated and cocaine produced and subsequently exported, both the UNODC and the US State Department make annual estimates of the size of the illicit industry. The present study uses such estimates.

2.3.2. Agricultural Production Variables

We use the available annual data on the value added by the department and economic activity series with the base year 2005 over the 1995–2015 period from the National Administrative Department of Statistics (DANE). The departmental GDP measures the productive activity of different country departments, and it defines the behavior, development, and economic structure for analysis and regional decision-making. We also use the information at the department level available for the period of study from the statistics per department and municipality agricultural evaluations (EVA)[32] from the Ministry of Agriculture and Rural Development (MADR) related to the area planted, production, and yields of permanent and transitory crops. The final sample consists of 651 observations (31 departments × 21 years).

Information about the population in rural areas is from the DANE's departmental estimates of population projections by urban/rural area and age groups of 0-80 and more years for the 1985-2020 period. The Colombian rural working-age population was calculated here as the people aged ten years and over in rural areas of each department. The variables on legal agricultural output used in the estimation are the output variable (agricultural GDP), given by the value of agricultural production in 2005 US million dollars; agricultural land defined as thousands of hectares of arable and permanent cropland and permanent pastures; rural population and the number of participants in the working-age population in rural zones. We also calculate departmental GDP per capita and the value-added in the agricultural sector as percent of GDP (or GDP share of agriculture).

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[32] The agricultural evaluations of municipalities are investigations that have been carried out since 1970 by the Ministry of Agriculture and record the productive activity related to agriculture, livestock, forestry, and aquaculture throughout Colombia's territory.

2.3.3. Other variables

We use data also on the internal displacement of people from the Colombian government's Unique Registration System. We used consolidated statistical information from CODHES-SISDES (Information System on Human Rights and Displacement) on the number of forced internally displaced persons corresponding to each municipality (that we aggregate to the department level) from year to year. This database defines internally displaced persons as those forced to abandon their physical residences and employment activity because of armed conflict, generalized violence, massive human rights violations, or other circumstances that threaten or drastically alter public order. We specify the variable as the ratio of the annual number of displaced persons to the total population in the department of origin per 100 thousand inhabitants.

Other variables include measures of weather variables, i.e., temperature and rainfall. The construction of these variables uses data regarding the Agrometeorological Indicators produced on behalf of the Copernicus Climate Change Service. This dataset covers the world time series daily surface meteorological data from 1979 to 2020. The dataset consists of the hourly ECMWF-ERA5 data geo-localized and available at a spatial (horizontal) resolution of 0.1° x 0.1° (10km2). More specifically, we use the information on (1) *precipitation flux*, defined as the total volume of liquid water (mm3) precipitated over the period 00h-24h local time per unit of area (mm2), per day; and (2) *2m temperature* indicating the daily air temperature at 2 meters above the surface. We then aggregated the data to the monthly/municipality level. Finally, temperature and rainfall represent the annual department means of the municipality\monthly values of *2m temperature* and *precipitation flux* variables, respectively. We use these variables considering that weather shocks can lead to more prolific or lean harvests directly associated with changes in profits from rural activities, potentially affecting incentives to invest in legal agricultural activities.[33] Thus, the focus is on rural areas in Colombia.

[33] Colombia has been particularly affected by rainfall and temperature shocks. According to the Global Climate Risk Index (Harmeling, 2011), the country ranked third (after Pakistan and Guatemala) in 2010 among the countries more affected by weather-related events such as droughts, floods, and heatwaves.

Weather shocks are among the most relevant risk factors faced by rural households because of the potentially harmful effects of weather shocks on the agricultural activities on which rural populations generally rely (Giné *et al.*, 2008; Andalón *et al.*, 2016).

2.4. Empirical Implementation

Our empirical strategy follows a *difference-in-differences* (DID) estimator by assessing whether changes in the PC policies to reduce coca cultivation affect the value of agricultural production disproportionately in coca-growing departments. In this approach, time variation depends on the official year each policy started under the PC (2000-15). Aerial spraying of glyphosate is assumed to start at the beginning of the PC in 2000. As stated before, manual eradication started as a national program in 2004. Finally, as the Colombian government redefined its anti-drug strategy in 2006, emphasizing the interdiction of drug shipments and the detection and destruction of cocaine processing labs over the eradication of coca crops, the interdiction policy is thus considered official under the PC since 2007.

The variation we explore to identify the effect of these strategies on the value of agricultural production or agricultural GDP (AGDP) thus combines the timing of the policy changes and a direct measure of their implementation under the PC across different areas. With this empirical strategy, we test if the AGDP increase after each of these policies is higher in coca-growing departments and to what extent that increase results from such policies. The interventions' timing is unique for the entire country, so the effect identification comes mainly from the heterogeneous response of different areas to the policies.

We create a dummy variable equal to 1 for the interval between 2000 and 2003, capturing the first illicit coca crops control strategy used under the PC (aerial spraying of glyphosate). Then, we create a second dummy variable equal to 1 between 2004 and 2006, corresponding to the manual eradication program implemented in 2004.

Moreover, the number of disaster events registered in Colombia in the first decade of the 2000s increased by more than 60% from 1970–to 99 (Campos *et al.*, 2011; Andalón *et al.*, 2016).

Furthermore, we include a third dummy equal to 1 starting in 2007, identifying the years of increased interdiction policies from the Colombian government. Our baseline specification follows the difference-in-differences regression:

$$\begin{aligned} AGDP_{it} = \alpha + \beta_1 \cdot (D_{2000\leq t\leq 2003} \times \text{Coca}_{1i}) \\ + \beta_2 \cdot (D_{2004\leq t\leq 2006} \times \text{Coca}_{2i}) \\ + \beta_3 \cdot (D_{t\geq 2007} \times \text{Coca}_{3i}) + \mathbf{X}_{it}\phi + \alpha_i + \beta_{rt} + \varepsilon_{it}, \end{aligned} \quad (1)$$

where $AGDP_{it}$ is the (real-valued) agricultural production in millions of 2005 US dollars. for department i in the year t; $D_{2000\leq t\leq 2003}$ is a dummy variable equal to 1 for years between 2000 and 2003; $D_{2004\leq t\leq 2006}$ is a dummy variable equal to 1 between 2004 and 2006; $D_{t\geq 2007}$ is a dummy equal to 1 for 2007 and all following years; Coca_{ji} for $j = 1,2,3$ is a variable indicating the number of hectares (aerially) sprayed with glyphosate, the number of hectares manually eradicated, and the number of coca base and cocaine processing labs destroyed, respectively[34] [35]; $\mathbf{X}_{it}$ is a vector of time-varying control variables; α_i are department-fixed effects; β_{rt} is a region-specific year dummy for Colombia's five major regions (Amazon, Andean, Caribbean, Orinoco, and Pacific); ε_{it} indicates a random term; and α_0, β_1, β_2, β_3, and ϕ are parameters. OLS estimation of equation (1) would produce unbiased estimates of the βs under the usual assumptions that:

$$E[\varepsilon_{it} | D_{2000\leq t\leq 2003}, D_{2004\leq t\leq 2006}, D_{t\geq 2007}, \text{Coca}_{1i}, \text{Coca}_{2i}, \text{Coca}_{3i}, \mathbf{X}_{it}, \alpha_i, \beta_{rt}] = 0 \quad (2)$$

In some robustness exercises, we also use the information on the indicators before PC. This information is available only for 1999, so we create two sets of variables: one related to the level of each policy indicator for 1999 (before PC) and another indicating the annual variation of each policy indicator after PC. The former set provides a proxy for

[34] Each indicator is equal to zero for the departments identified as non-coca-growing in our sample (i.e., they did not grow coca from 1995 to 2015). This framework aims to identify the primary treatment and control groups. These departments are considered the primary control group consisting of the departments of Atlántico, Casanare, Huila, Quindío, Risaralda, Sucre, and Tolima (see Figure 1.2).

[35] Coca_{ji} with $j = 1,2$, and 3 are variables indicating coca and cocaine production constraints, increasing the costs associated with coca cultivation. They could also reflect the relative economic relevance (or perhaps relative profitability) of coca production for a given area. Coca_{3i} is alternatively specified in some specifications like the amount (in kilograms) of coca base, coca leaves, and cocaine seized each year at the department level.

the initial level of constraint on the coca production in the local economies before the policies under PC. The latter corresponds to a direct measure of losses to the cocaine production sector, constraining coca cultivation during the PC period. As the second set of variables differs by department, when they interact with the dummies for the timing of each policy implementation, a sort of triple differences estimator is created like in Chimeli and Soares (2007). This triple-differences estimation compares coca-growing departments to the other departments and evaluates whether the policy changes affect the outcome variable disproportionally in departments with coca cultivation.

It is noteworthy to mention some potential concerns with this difference-in-differences (DID) strategy, such as omitted variables and differential dynamic behavior of the value of agricultural production. There may be changes happening simultaneously to the implementation and effectiveness of the policies. Because a fraction of the government's budget accrues to implement the policies, such a fraction is a part of the GDP that equivalently has the agricultural GDP of each department as a component. Moreover, the policies' effectiveness may also depend on the heterogeneous institutional/geographic environment within Colombia that could have significant economic impacts that may affect the evolution of the value of legal agricultural production. Agricultural inputs endowments (quality and availability) and the prices of commodities from legal agriculture and coca-related products could also be strong predictors of $AGDP$ and the effectiveness of the policy. Another important caveat would be the incidence of violence due to the armed conflict in rural Colombia that may be highly associated with legal agricultural activities and illicit crop production. More generally, worsened environmental and socioeconomic conditions can also debilitate legal agriculture by pushing many farmers toward illegal crop production. This relationship can further constrain the intensity of each policy's execution and effectiveness. Some pervasive side effects of such policies (e.g., aerial spraying) may cause detrimental consequences to the profitability of agriculture. Farmers can also migrate to areas where they can cultivate coca. This migration would significantly change the sample composition of the treated group (and\or comparison group) by generating attrition effects. All these aspects can represent relevant driving factors changing the pattern of legal agricultural activity and illicit crops simultaneously in the production possibilities frontier of agriculture. We allow for regional-specific time dummies that immediately account for any systematic difference across regions due to the policy, environment, or socioeconomic changes to mitigate these concerns.

Some specifications also allow for flexible time trends as functions of departments' initial characteristics. Given that most of the control variables observed at the department level could be technically endogenous to the restrictions on coca cultivation, we include the interactions of the baseline values (in 1995 or 1996 according to the availability of data) of such controls with time dummies. The control variables are at the department level. These variables are agricultural land (measured as thousands of hectares of arable and permanent cropland and permanent pastures); the working-age population in rural zones; GDP per capita (in logs); the share of GDP in agriculture; the rural conflict-related number of internally displaced persons (from rural to urban zones) and casualties; the ratio between the area planted with coca of each department to the total (national) area cultivated with coca; and the average levels of temperature and precipitation. This specification also includes an interaction between the baseline value of agricultural production (in constant prices) and time dummies to allow for differential dynamics of legal agriculture.

It is also worth mentioning that, by construction, the variance of $AGDP$ is directly related to agricultural production. Thus, we weighted all regressions by the departmental total crop production in metric tons. The DID analysis may also underestimate standard errors because of autocorrelation in the residuals. Therefore, following Bertrand *et al.* (2004) and Chimeli and Soares (2017), the standard errors are clustered at the department level to account for any arbitrary structural correlation over time.

2.5. Empirical Results

2.5.1. Baseline Results

Table 2.1 presents descriptive statistics for coca and non-coca-growing departments for the sample. The table shows the average agricultural GDP ($AGDP$), GDP per capita, the fraction of GDP in agriculture, agricultural land, rural population, and annual average temperature and rainfall between 1995 and 2015. The pre-2000 period refers to the years before PC, and the post-2000 indicates the PC period in which the analyzed policies occurred. The objective of the table is to characterize the differences between departments with coca cultivation and those without coca crops.

The table shows that coca and non-coca-producing departments were not much different in their GDP per capita, agricultural land, or weather characteristics. However, non-coca departments have smaller average agricultural GDP, departmental GDP, and population, and they are also more dependent on agriculture relative to coca-producing departments. Although these differences, it is imperative to note that we are mainly interested in looking at the changes in such differences during the analyzed period.

Regarding the comparison in this way, we can infer from Table 2.1 that the differences between coca and non-coca departments in terms of agricultural GDP, departmental GDP, GDP per capita, temperature, and population increased by approximately 21%, 34%, 35%, 13.0%, and 28%, respectively. These differences do not necessarily imply a methodological issue because the DID method allows comparison groups to start at different outcome levels (DID focuses on changes rather than absolute levels). The differences between the two groups regarding the importance of agriculture in the departmental economy (GDP share of agriculture), land for agricultural activities, and mean precipitation reduced by approximately 2%, 33.4%, and 5%, respectively. To estimate any impact of the policies on curbing coca/cocaine supply under PC, we rely mainly on the three assumptions for the internal validity of the empirical strategy or DID approach. The first assumption is that comparison groups follow a parallel outcome trend before treatment (Parallel Trend Assumption). Second, the composition of groups pre/post-change is stable (Stable Unit Treatment Value Assumption). Finally, the intervention is unrelated to the outcome at baseline (allocation of the intervention was undetermined by outcome variable). We verify if these assumptions hold later in section 2.5.2.

The main results for the sample of all coca-growing departments are in Table 2.2. Column 1 does not include any control. In col-umn 2, we incorporate region-specific time dummies. Column 3 adds interactions of time dummies with baseline values for all the control variables used. These variables are the ratio of coca planted area to the national area under coca cultivation, agricultural land, GDP per capita, and share of GDP in agriculture; the working-age population in rural zones, rate of internally displaced persons (from rural to urban areas), and the rate of rural conflict-associated casualties; the average levels of temperature and precipitation; the proportions of permanent and transitory crops production relative to the total crops production plus the value of legal agricultural production.

Columns 1 to 3 reveal significant effects of the variables manual eradication ($Manual\ 2004$) and interdiction policy ($Interdiction\ 2007$) on legal agricultural production's (real) value. The estimated coefficient for the variable indicating aerial spraying ($Aerial\ 2000$) is nonsignificant in column 1 and significant but much smaller than those related to the other policies in columns 2 and 3. Overall, the estimated coefficient on the first policy change ($Aerial\ 2000$) is always smaller than those on those other policies ($Manual\ 2004$ and $Interdiction\ 2007$), considering that the three coefficients are estimated precisely, except in column 1, which does not include control variables. Therefore, coca-growing departments exhibit a relative increase in the (real) value of their legal agricultural production during the PC period. This increase was particularly significant between 2004 and 2006, and more intense after 2007.

Note that when we introduce the region-specific time dummies in column 2, the magnitude and the statistical significance of the coefficients for all the policies turn into more sizable ones. The coefficients on the first and the third policy become statistically more statistically significant when we included the set of interactions of initial conditions and the time dummies. With this same inclusion, the point estimates of the first and the second policy become somewhat bigger. However, the coefficient estimated on the third policy is still the strongest in terms of magnitude and statistical significance. Thus, it is possible to infer that the difference in the evolution of the (real) value of legal agricultural production across coca-growing and non-coca-growing departments does not seem to be driven by differential trends across regions or even departments.

These estimations are somewhat consistent with the evolution of the agricultural GDP displayed in Figure 2.3. As stated before, the figure depicts that the difference in the agricultural GDP of coca-growing departments relative to non-coca ones has increased across the years of PC, especially during the official interdiction policy period, even though they mostly follow a similar trend. Given that the difference in the AGDP across coca-growing and non-growing departments starts at a high level even before PC, we should interpret with caution the relatively large point estimate for the coefficient on the last treatment variable. To mitigate concerns about this initial difference and to analyze this pat-tern more rigorously, column 4 of Table 2.2 allows treatments to affect both the trend and the level of the outcome variable. We thus interact each treatment variable with a linear time trend that equals zero in the first year of the policy. The estimates suggest at least three relevant aspects. First, the aerial spraying policy cannot be significantly associated with a persistent increase in the agricultural GDP but with a significant increase in its trend. Second, the manual eradication program further increased the level of AGDP without significantly affecting the previous AGDP trend. Third, the interdiction policies since 2007 substantially increased the previous AGDP level. However, the interdictions can only be associated with a mild increase in the agricultural GDP trend during the following years (about USD 26 million or 2.5% in the AGDP per year afterward).

Columns 5 and 6 of Table 2.2 present the results of the triple difference esti-mates. The results in column 5 suggest that increases in AGDP were mainly due to the manual eradication, particularly in departments that had sort of eradication campaigns before PC. However, the estimates in column 6 reveal more consistently that the increases in AGDP were primarily because of the interdiction policies, especially in those departments with more coca base and cocaine processing facilities dismantled after 2007.[36]

[36] The coefficients presented in columns 5 and 6 of Table 2.2 are the cumulative effect of each policy on coca-growing departments, and they are in the measurement units of those policies. It is also important to note that the estimated coefficients from columns 5 and 6 are not directly comparable to those in other columns because the scales of the treatment variables are different.

To conclude the discussion of the baseline results, we analyze the quantitative interpretations and implications of the numbers in Table 2.2. One can directly read these estimates as changes in the (real) value of agricultural production in US million dollars after the corresponding intervention under PC. For instance, the estimates in column 3 of Table 2.2 indicate that the AGDP of coca-growing departments increased, on average, 192.9 million USD from 2000 to 2003, 224.9 between 2004 and 2006, and 384.2 after 2007 compared to non-coca-growing departments. When we compare these increases to the pre-2000 average AGDP of coca-growing departments, the estimated coefficients correspond to increases ranging from 1% to 2% or even slightly more, considering the estimates in column 2. Although these numbers could seem sizable, they are somehow consistent with and comparable to the potential total annual value of coca production estimated by the UNODC from 2002 to 2015. Figure 2.4 displays the evolution of that value in millions of USD during most of the PC years. It is worthy to note that the annual values calculated by the UNODC come from the factor of production quantities available in the market (minus seizures as product loss) and estimated farmgate prices. The UNODC also converts the values to USD based on the annual exchange market rate average, as Colombia's Central Bank reported. Thus, it is very likely that these values are very low respective to the actual ones. It is also possible to infer from Figure 2.4 that the average value of coca production during most of the years of PC was approximately US$551 million per year, which represents around 2.5% of the annual average GDP in the agricultural sector of coca-growing departments in 2002-2015.[37] Furthermore, the total value of coca was, on average, US$421, $US614, and US$496 per year in 2002-03, 2004-06, and 2007-15, respectively. These values are somewhat reasonably comparable to the estimates in columns 1 to 4 in Table 2.2.

[37] The UNODC Surveys estimate that the total coca production value from 2005 to 2015 was between 0.2% and 0.6% of Colombia's GDP and between 3% and 5% of the Colombian agricultural GDP. Moreover, the total value of coca leaves traded from 2000 to 2013 was US$200 million per year, while the expected return from coca leaves sales was around US$360 million per year, once subtracting the costs of production (mainly labor and agricultural inputs) from the total revenues (Mejía and Rico, 2011; Mejía, 2016). Using the average estimated number of households involved in coca cultivation from the UNOCD, the expected annual return from the sale of coca leaves would be about US$2,250 per household.

Figure 2.5 shows the gross average annual income per person of coca leaf production and paste/base together with the number of farms (households) involved in coca cultivation.[38] We can observe that after 2007 the gross average annual income per person of coca production decreased substantially from approximately US$2,600 in 2008 to about US$1,000 in 2013. It is also possible to see that the number of households involved in coca cultivation declined significantly.

Thus, the baseline results are consistent with the experience of the coca-growing departments during the PC period, where the overall increase in the value of agricultural production was slightly above 100% (Coefficient of Variation$-\mathrm{CV}-\approx$ 104%) compared to the non-coca-departments of about 50% ($\mathrm{CV} \approx$ 51%) percent. The cumulative percentage increase in the difference between the value of legal agricultural production of coca-growing departments to those non-coca departments reached almost 40% in 2015. Our estimated coefficients explain roughly at least 77.7% and 87.5% of the differential increase in the value of legal agricultural production across departments with and without coca cultivation when averaged over the entire period between 1999 and 2015. The interdiction policy itself contributed around 68% to this average increase. These estimates can be considered the first ones linking the value of legal agricultural products directly to the effect of PC's policies aimed at curbing coca cultivation and cocaine supply.

2.5.2. Differential Trends and Other Contemporary Variations

Although the results across the different specifications in Table 2.2 are somehow consistent, it is also reasonable to believe that treatment variables capture heterogeneous and preexisting dynamics of the AGDP in coca-growing departments. To be this the case, remarkable differences in the trends of AGDP in coca-growing versus non-coca-growing departments should be present already before implementing anti-drug policies under PC. Moreover, this would have to be the case conditional on the region-specific time

[38] The UNODC estimates the growth of households involved in coca cultivation based on: (1) a multivariate indicator (built considering the behavior of the affected area; (2) the population projection (from the DANE) of the municipalities affected by coca; and (3) the growth trend as reported in each phase of the coca productivity studies of UNODC. This information is available only starting in 2005.

dummies and interactions of initial conditions that must add the value of legal agricultural production and the time dummies already included in previous specifications.

To test such conjecture, we incorporate some relevant control variables to account for preintervention trends (or a placebo intervention) in the value of legal agricultural production. We insert a dummy for 1995–1999 interacted with a dummy variable indicating coca-growing departments. This exercise aims to identify if the value of legal agricultural production in the coca-growing departments was already differently increasing some years before the anti-drug policies under PC. The results are in column 1 of Table 2.3. We can observe that the corresponding "preintervention placebo" is relatively small and not statistically significant. Nonetheless, we can see that the estimated coefficient for the variable $Aerial\ 2000$ is not statistically significant, and its magnitude has reduced substantially.

Thus, the estimates do not provide evidence that the treatment variables $Aerial\ 2000$, $Manual\ 2004$, and $Interdiction\ 2007$ capture a differential dynamic behavior of the AGDP before the respective policies during PC. Column 2 of Table 2.2 estimates an additional specification that includes department-specific linear trends. Although this specification is rather data demanding, the results show a low impact on the estimated coefficient for $Interdiction\ 2007$. By contrast, all the point estimates increased significantly, but they turned into less significant and not statistically significant estimates for $Aerial\ 2000$ and $Manual\ 2004$).

It is important to note that the direct measures for the treatment policies used in the triple difference regressions in Table 2.2 are only consistently available since 1999. The sample is restricted to the period 1999-2015 in columns 3 and 4, presenting analogous estimations to columns 1 and 2, respectively. The results for the AGDP do not dramatically change with $Interdiction\ 2007$. Thus, the estimates for the effect of the interdiction policy are qualitatively like those obtained in columns 1 and 2.

Naturally, significant alternative driving factors arise for the relative increase in the value of agricultural production in coca-growing departments. To mitigate concerns related to these competing explanations, we analyze how economic conditions represented by the GDP per capita and the legal agricultural activity itself were evolving in these departments during the study period. This analysis could help shed light on whether the increase in the value of agricultural production was practically explained only by macroeconomic conditions and the economic growth of Colombia, creating socioeconomic opportunities for the rural population, or due to endogenous expansions of the Colombian agricultural sector. The last four columns in Table 2.2 attempt to explore these relevant driving forces. There seems to be a direct effect on coca-growing departments for GDP per capita. However, this effect loses overall statistical strength, and it concentrates mainly in the mid-2000s as we include department-specific trends in column 6. Regarding the share of legal agriculture in the total GDP, the estimates indicate a statistically insignificant difference between coca-growing and non-coca-growing departments. In general, the results suggest that it seems not likely that significant structural changes in economic conditions or trajectory in the agricultural sector itself could explain the relative increase in the value of agricultural production here observed in coca-growing departments during the period of analysis.

As final tests to the parallel trends' assumption, we conduct parametric and non-parametric tests for comparing the two types of departments. First, we run specifications that include only the initial and final periods, where the initial period is 1995, and the final varies from 1996 to 2015. This exercise allows us to detect the specific timing of the differential behavior of the value of legal agricultural production across coca and non-coca-growing departments. In Figure 2.6, the 20 coefficients estimated sequentially in this procedure, with their respective standard errors, are plotted against the final period included in each regression. The dynamics of the value of legal agricultural production across the two types of departments seem very similar up to 1999 (when there was a not statistically significant decline until 2000). The legal agricultural production value starts increasing afterward in coca-growing departments. The difference in the value of legal agricultural production across coca and non-coca-producing departments started being statistically significant in 2006 and remained so until 2015. Since 2007, the difference in the AGDP across the two groups remains relatively stable until 2010. However, it starts to rise again from 2010 until 2015, when our dataset ends.

Second, we do a more rigorous visual inspection of the pre-treatment trends or non-parametric parallel-trends tests (before PC) for the control group (non-coca departments) and treatment group (coca-growing departments). The data are initially restricted to the pre-interventions period (1995-1999) and plotted using a linear fitted trends comparison graphical form that distinguishes the coca-growing and non-coca-growing departments (See Figure A.2.5 in Appendix A). However, this test could be somewhat misleading because it forces the data into linear time trends, which might obscure differences between them. We use a subset-plot method developed by Cox (2010). This graphical display has the advantage of showing all the data (not fitted values or just averages), so if there are differences in outliers or in the variance that are inapparent in other methods, this exercise can help to identify them. Panel A of Figure A.2.6 in the Appendix shows that most of the non-coca-growing departments follow practically a parallel trend compared to most of the coca-growing departments during the period of analysis. Note that almost all the blue points corresponding to the non-coca departments in Panel A of Figure A.2.6 overlap the orange dots of the treatment group before 1999. Panel B of Figure A.2.6 displays that despite a few coca-growing departments (blue points) followed a similar trend to those in the control group (orange points) even after 2000, most coca-growing departments exhibited notable observational changes during the years of PC. Note that most blue dots there cease overlapping the orange ones indicating significant changes in their trajectory after 1999. Furthermore, the differences by construction in the composition of the treatment group validate the triple difference approach we have used to compare within the coca-growing producing departments.

Finally, a third way to analyze the parallel trend assumption is to squash the data into the annual means in each group and then plot each group's trend line separately. This exercise is similar to that fitted trends comparison we used in Figure A.2.5, except that this third approach does not impose a linear model on the changes in the value of legal agricultural production over time. Figure A.2.7 shows that the parallel trend assumption reasonably fits in the context of the present study, which is perhaps the most critical assumption to ensure the internal validity of DID models. Therefore, this study provides some statistical evidence that, in the absence of the anti-drug policies under PC, the difference in the legal agricultural production value between coca-growing departments and non-coca-growing departments would have been relatively constant over time.

2.6. Conclusions

This paper presents evidence of the increase in the value of agricultural production in Colombian areas with coca cultivation following the introduction of a series of anti-drug and anti-illicit crop production policies under Plan Colombia. The popular press and academic literature have investigated the relationship between coca crop eradication and anti-drug governmental strategies to reduce Colombian coca cultivation and cocaine supply. Still, there is practically no empirical or direct quantitative evi-dence on the link between such policies and their impact on the value of legal agricultural production in the coca-growing areas. This research presents unique evidence of the increase in the legal agricultural GDP mainly because of the interdiction of coca base/paste and cocaine-processing facilities policy in Colombia (circa 2007). The increase in the value of legal agricultural production documented here is undriven by notable changes in the economic, geographical, or environmental conditions, nor preexisting trends in the GDP from agriculture or the agricultural sector itself. Instead, the interdiction policy of coca paste and cocaine-processing facilities in Colombia (circa 2007) has driven such an increase. More specifically, this study points out that the interdiction policy since 2007 in Colombia has boosted the value of producing conventional licit crops in the coca-producing departments. Previous studies have documented the counternarcotics policy of 2007 as the most effective strategy for reducing cocaine production and coca cultivation, which mitigates concerns about reverse causality. Coca-growing areas saw substantial drops in coca cultivation consistently from 2007 until 2013. The licit crop production or, more generally, legal agriculture of departments with areas under coca cultivation seems to have benefited from such policy, while legal agriculture in departments without coca cultivation was not. The estimates suggest that the agricultural GDP grew approximately 2.5% more per year in coca-growing departments since 2007 due to the interdiction policy. The results also indicate that the value of agricultural production in the coca-growing departments gained a monetary benefit from that policy of about US$284.2 million. Overall, our estimates roughly explain between 77% and 87% of the averaged differential increase in the value of legal agricultural production across coca and non-coca-growing departments over the 1999-2015 period. Most of this increase is driven by the interdiction policy, which explains about 68% of the total average differential increase among the two types of departments. These estimates can be considered the first ones linking the value of legal agricultural products directly to the effect of Plan Colombia's policies aimed at curbing coca cultivation and cocaine supply. Based on the findings, efforts to reduce coca cultivation should emphasize anti-drug strategies in the stages of production and trafficking that generate the highest value-added. This assertion is particularly relevant for strengthening legal agriculture, at least in terms of its production value.

Table 2.1–Descriptive Statistics for Selected Variables in the 1995–1999 and 2000–2015 Periods

	Agricultural GDP	Real GDP	GDP per capita	% GDP in agriculture	Agricultural land	Rural Pop.	Mean Temp.	Mean Rainfall
Non-Coca-Growing Departments (*N*= 7)								
Pre-2000	901.2	5,809.6	6,321.7	15.9	128.2	919.0	292.9	10.5
	(112.9)	(437.2)	(6,049)	(0.91)	(20.90)	(72.3)	(0.45)	(1.21)
Post-2000	952.8	7,012.4	7,209.5	14.0	138.2	972.7	293.8	9.1
	(52.3)	(257.7)	(5,969)	(0.40)	(9.86)	(43.2)	(0.26)	(0.54)
Coca-Growing Departments (*N*= 24)								
Pre-2000	1,678.1	21,747	7,825.2	10.7	192.9	2,779.1	291.7	16.0
	(107.9)	(2,475)	(10,050)	(1.10)	(12.9)	(246.3)	(0.23)	(1.43)
Post-2000	1,891.3	28,390	9,236.1	8.9	181.2	3,073.8	292.2	14.3
	(76.4)	(2,011)	(12,546)	(0.48)	(5.75)	(160.3)	(0.13)	(0.75)

Notes: Averages are weighted by department total crop production in metric tons (standard errors are in parentheses). Variables are agricultural GDP in million 2005 USD, real GDP in million 2005 USD, GDP per capita in 2005 USD (in thousands), percentage of GDP in agriculture, agricultural land in thousand hectares, rural population thousand inhabitants, and the annual mean temperature and rainfall. Pre-2000 is the average between 1995 and 1999 for each variable; post-2000 is the average from 2000 to 2015 for each variable.

Table 2.2–PC's Policies and Value of Agricultural Production, 1995-2015, DID Benchmark Results

	Departments with coca cultivation					
					Triple-difference	
				Treatments interacted with linear trends	Indicators (Before PC) 1999	Indicators (During PC) 2000-15
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Aerial 2000	-0.0872	127.3*	192.9**	64.11	0.0423	0.00337
	[84.53]	[75.01]	[74.38]	[84.60]	[0.0269]	[0.00243]
Aerial 2000 × *trend*				42.14**		
				[19.89]		
Manual 2004	123.3*	219.0*	224.9*	189.1*	0.901***	0.0102
	[68.08]	[117.6]	[115.1]	[99.20]	[0.302]	[0.0104]
Manual 2004 × *trend*				29.87		
				[29.50]		
Interdiction 2007	295.3***	428.1**	384.2***	323.8**	0.149***	0.0132***
	[98.90]	[180.0]	[138.5]	[149.2]	[0.0219]	[0.00352]
Interdic. 2007 × *trend*				26.08**		
				[12.61]		
Region FE × year FE		✓	✓	✓	✓	✓
Baseline charact. × year FE			✓			
Observations	651	651	651	651	651	651
R-squared	0.874	0.882	0.896	0.882	0.889	0.883

Notes: Robust standard errors are in brackets (clustering at the department). The dependent variable is the real value of agricultural production (in 2005 USD). All regressions include a constant, department, and year dummies, and are weighted by total crop production (in metric tons). Treatment variables are dummies = 1 between 2000–2003, between 2004–2006, and after 2007 interacted with: dummy = 1 for coca-growing departments and = 0 otherwise (columns 1– 4); level of the corresponding indicator pre-PC (1999) × dummy = 1 for coca-growing departments and = 0 otherwise (column 5); annual level of the corresponding indicator × dummy = 1 for coca-growing departments and = 0 otherwise (column 6). Columns 2 to 6 control for region-specific time dummies. Column 3 controls for interactions of year dummies with baseline (1995) values of the following department characteristics: agricultural land, working-age population in rural zones, rate of internally displaced persons, rate of casualties, ratio of coca planted area to the national area under coca cultivation, per capita GDP (ln), the fraction of GDP in agriculture, the average level of temperature, the average level of precipitation, the proportion of permanent crops, the proportion of transitory crops, and the value of agricultural production.

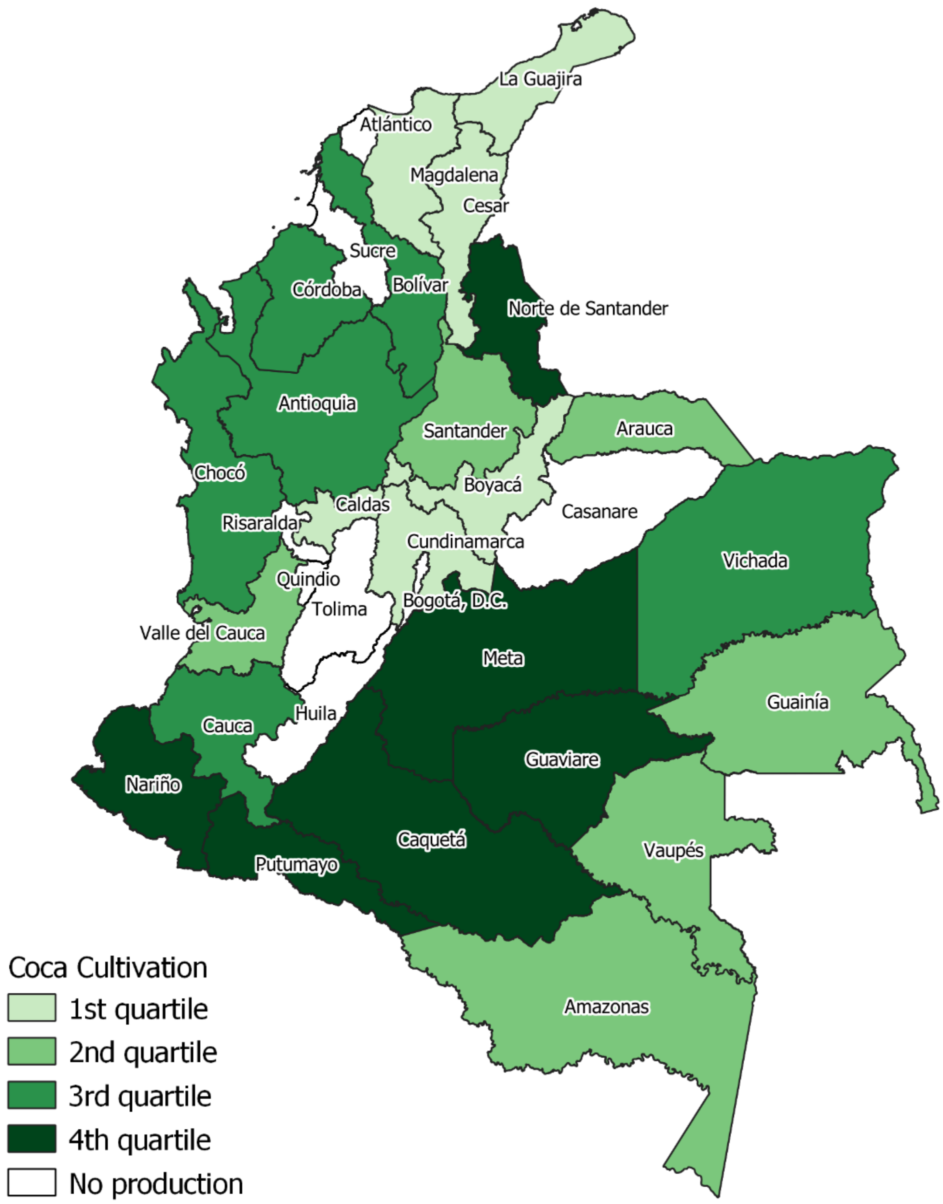
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 2.3—PC's Policies and AGDP, Testing Parametrically for Parallel Trends and Some Other Effects

	Effects on AGDP and parallel trends, 1995-2015				Other economic changes explaining the results, 1995-2015			
	Testing for pre-trend	Department linear trend	Dependent variable: AGDP		Dependent variable: GDP per capita		Dependent variable: Percent GDP in agriculture	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Aerial$ 2000	8.159	33.67	-4.775	7.778	0.0551*	0.0557**	-0.00146	0.000551
	[75.46]	[108.3]	[96.22]	[110.2]	[0.0309]	[0.0259]	[0.00784]	[0.00974]
$Manual$ 2004	131.5**	183.3	118.6	148.7	0.115*	0.116*	-0.00597	-0.00240
	[61.60]	[117.8]	[82.83]	[119.6]	[0.0567]	[0.0663]	[0.00752]	[0.00946]
$Interdiction$ 2007	303.5***	400.3**	290.6**	350.8*	0.167*	0.169	-0.00414	0.00211
	[90.19]	[168.4]	[125.0]	[176.4]	[0.0894]	[0.118]	[0.0161]	[0.0190]
Placebo	20.62							
	[50.09]							
Department specific trend		✓		✓		✓		✓
Observations	651	651	527	527	651	651	651	651
R-squared	0.974	0.978	0.978	0.982	0.959	0.988	0.914	0.971

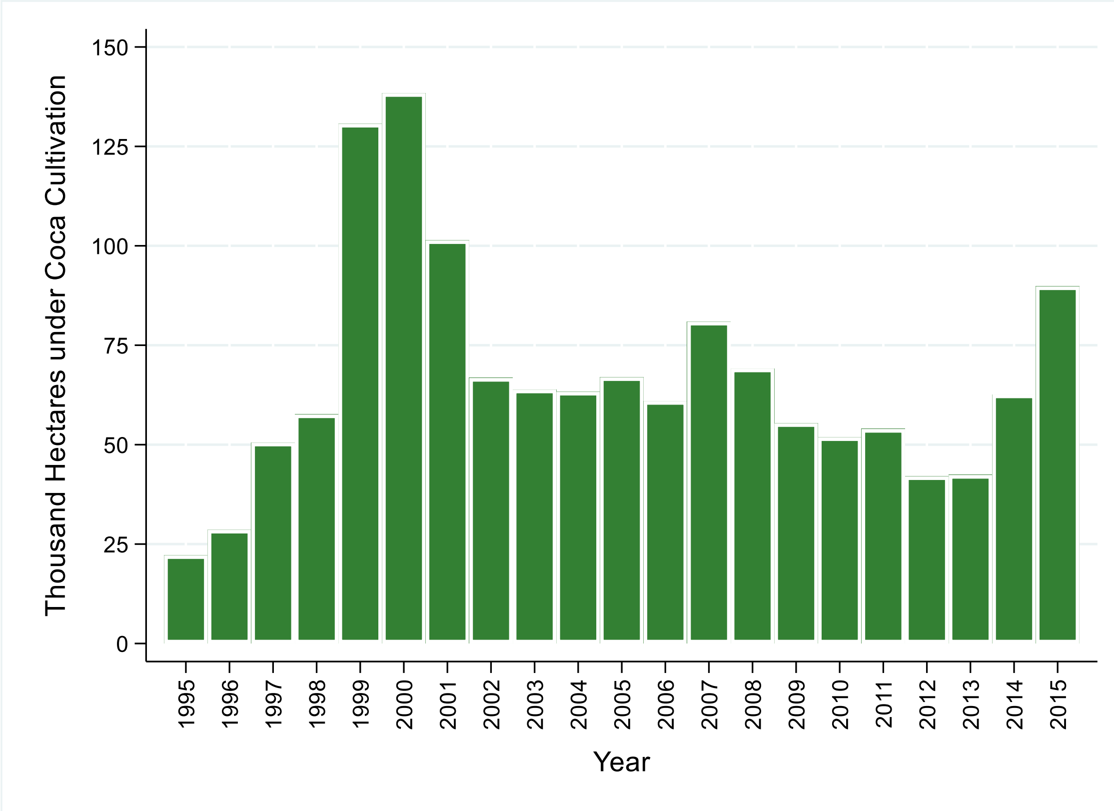
Notes: Robust standard errors are in brackets (clustering at the department). The dependent variable is the value of agricultural production (in million 2005 USD) in columns 1– 4, the log of GDP per capita in columns 5–6, and the share of GDP in agriculture in columns 7–8. All regressions include a constant, department, and year dummies, and are weighted by total crop output in metric tons. Treatment variables are dummies = 1 between 2000–2003, between 2004–2006, and after 2007 interacted with the dummy of the coca-growing department. Pre-2000 placebo is a dummy for 1995–1999 interacted with the coca-growing department dummy. Columns 2, 4, 6, and 8 include, as additional controls, interactions of department dummies with a linear time trend.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure 2.1–Coca Plantation Intensity in Colombian Coca-Growing Departments



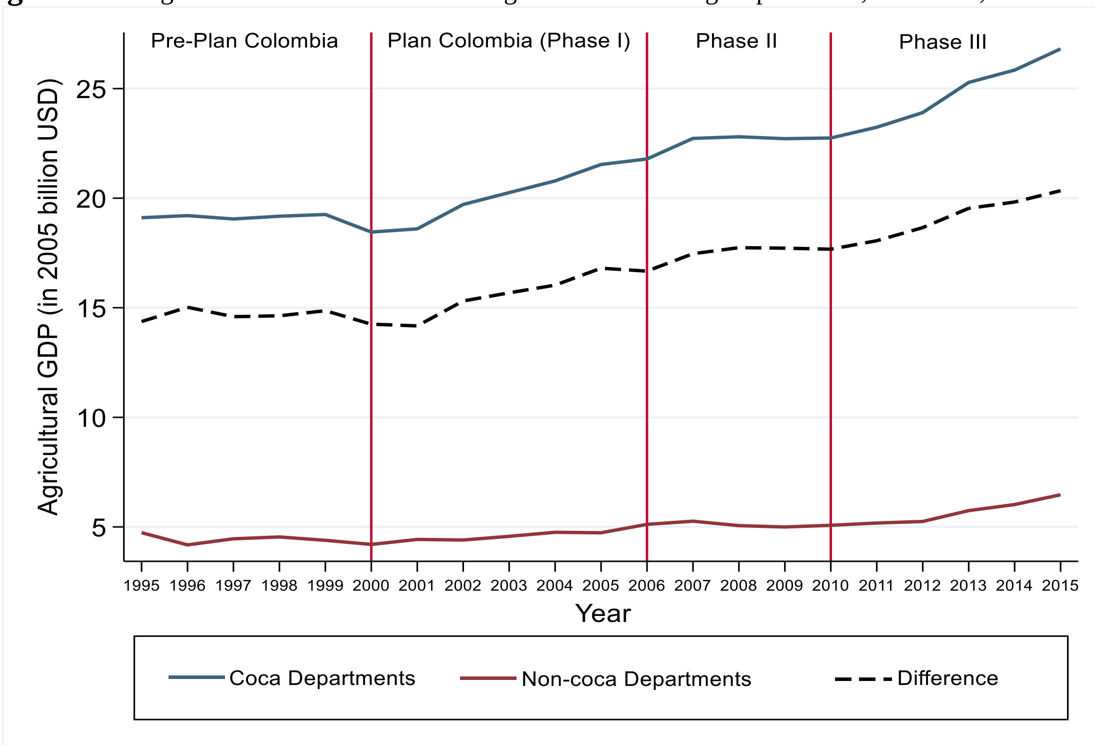
Source: Own calculations based on data from UNODC.

Figure 2.2−Annual Coca Crops in Coca-Growing Departments of Colombia, 1995-2015



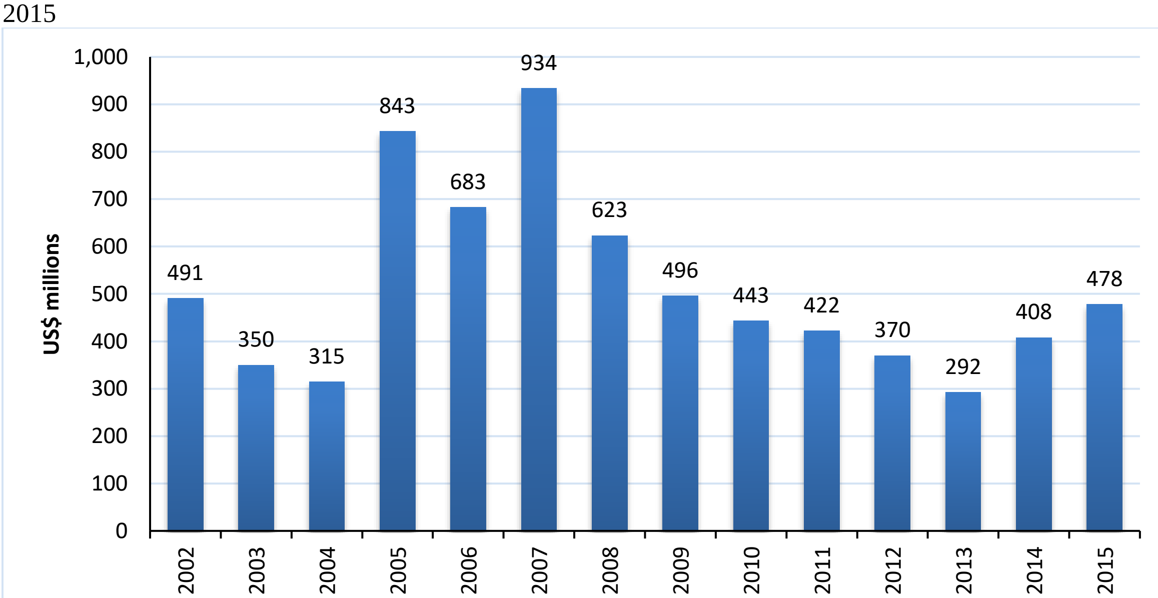
Source: Own calculations based on data from UNODC.

Figure 2.3—Agriculture GDP in Coca-Growing and Non-Growing Departments, Colombia, 1995-2015



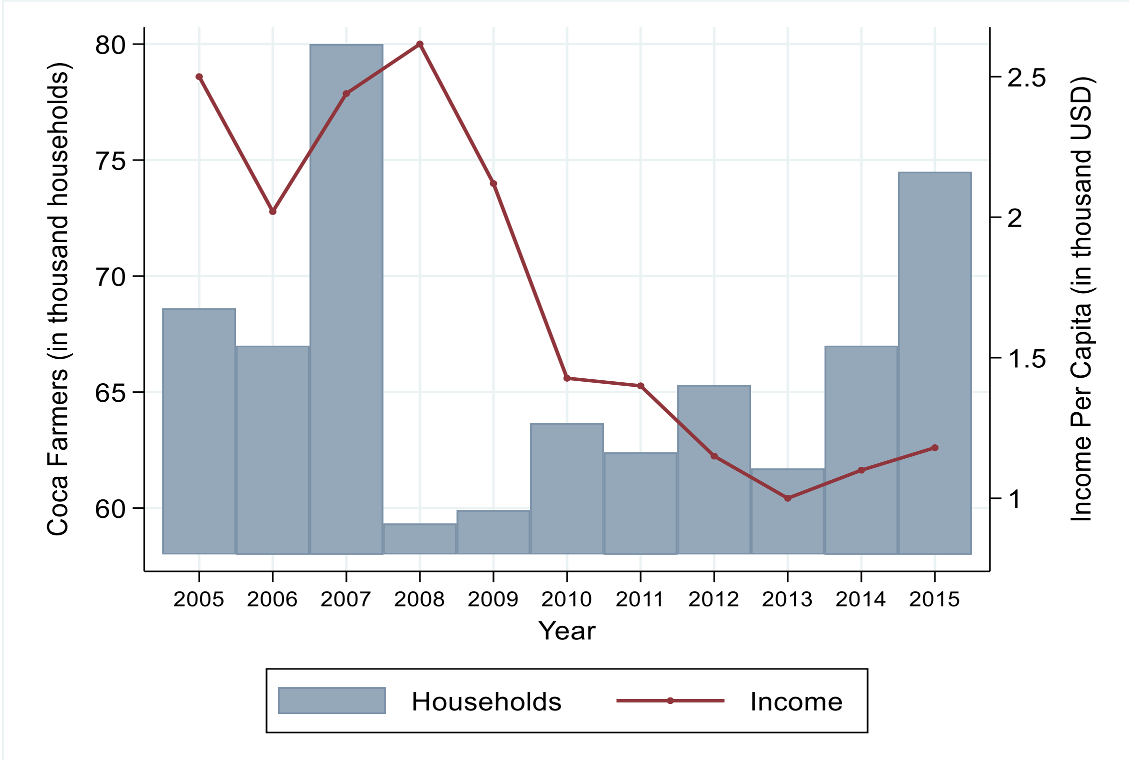
Source: Own calculations based on data from DANE.

Figure 2.4—Total Estimated Value of Coca Leaf Production and Coca Derived Farm Products, 2002-2015



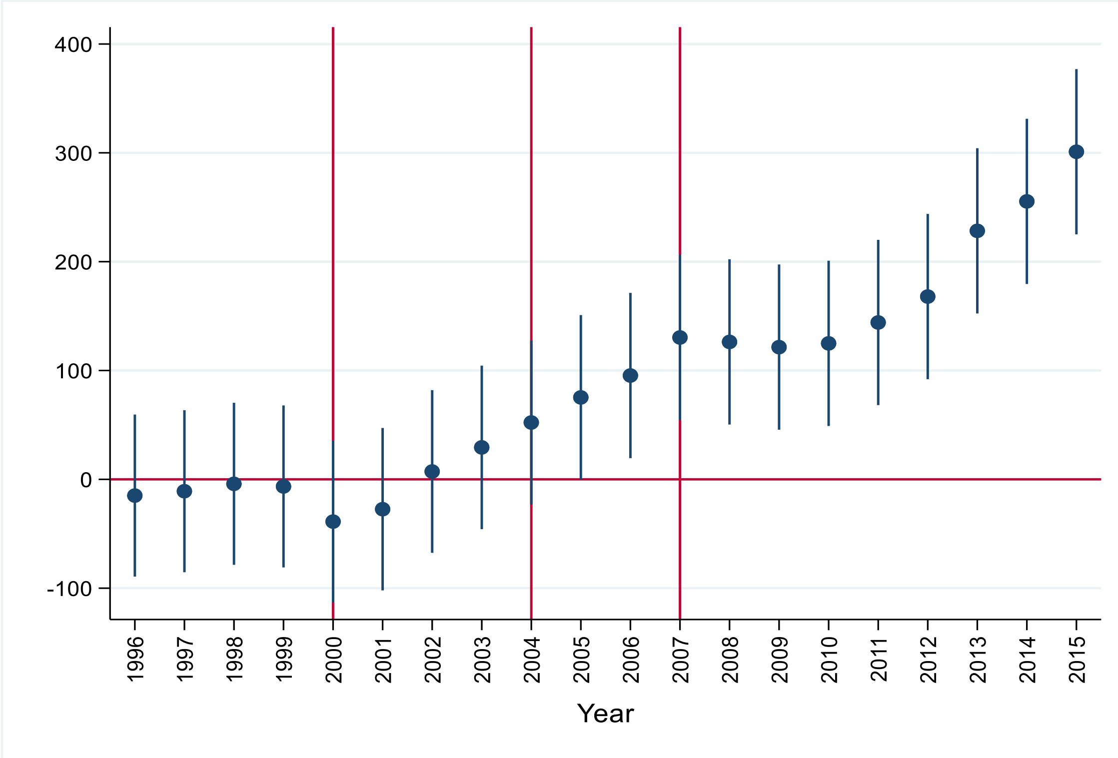
Source: Own elaboration based on data from UNODC.

Figure 2.5—Per Capita Gross Income from Coca Production and Farmers Involved in Coca Cultivation



Source: Own calculations based on data from UNODC.

Figure 2.6—Timing of the Effects under Plan Colombia, All Coca-growing Departments, 1996-2015



Source: Own calculations based on data from EVA.

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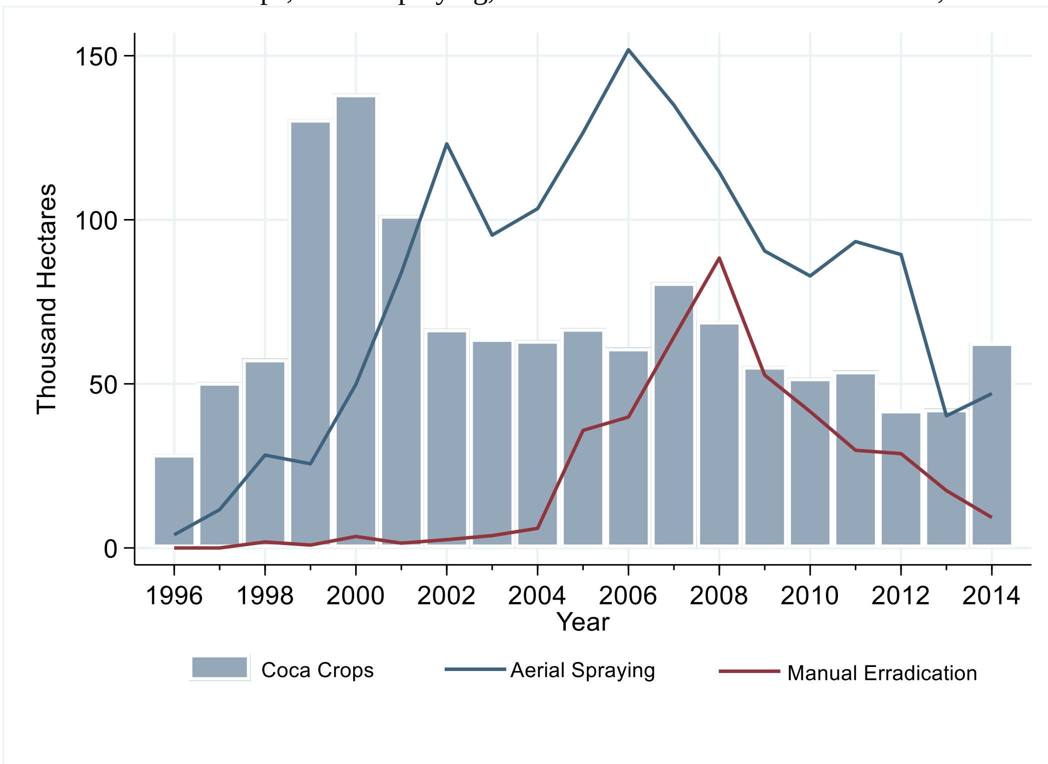
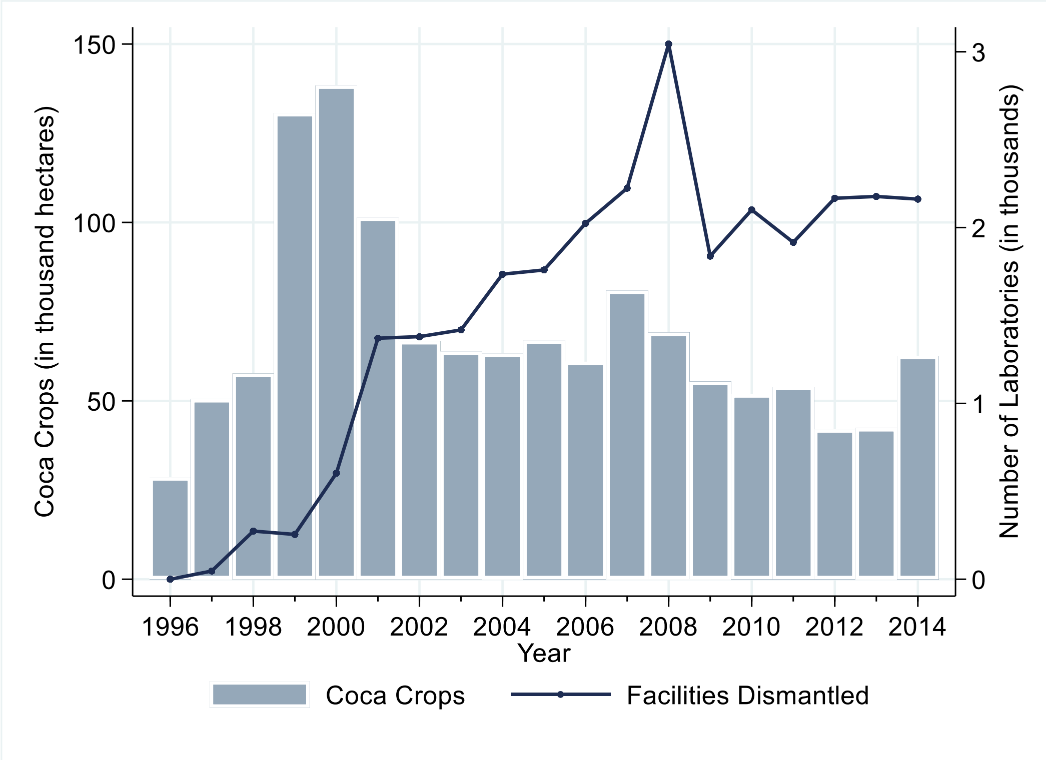
APPENDIX A

Figure A.2.1−Coca Crops, Aerial Spraying, and Manual Eradication in Colombia, 1996-2014



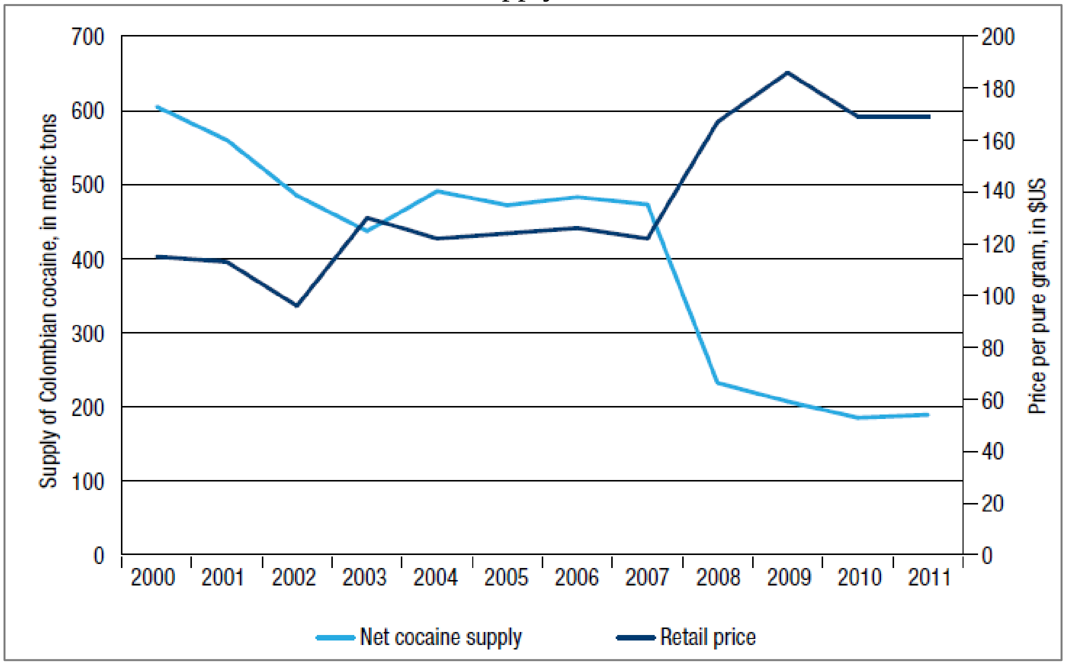
Source: Own calculations, based on data from UNODC and ODC.

Figure A.2.2−Number of Cocaine Processing Facilities Destroyed in Colombia, 1996-2014



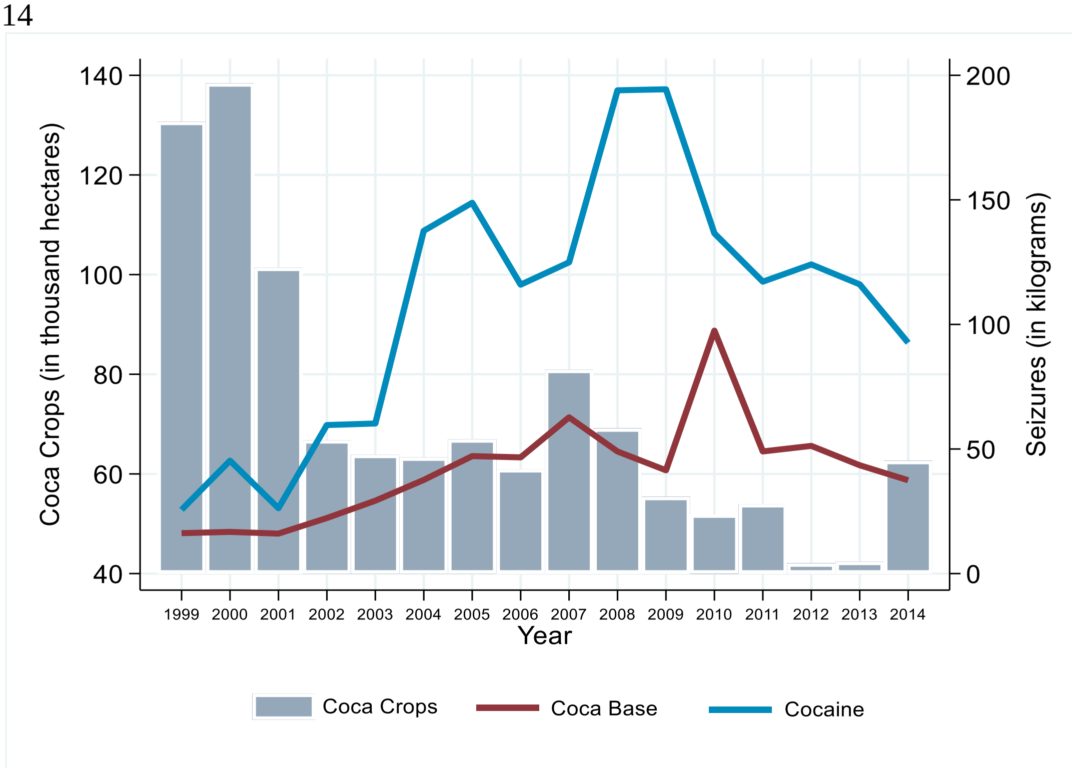
Source: Own calculations, based on data from UNODC censuses and surveys and ODC.

Figure A.2.3−Colombian Net Cocaine Supply and Cocaine Street Prices in the U.S.



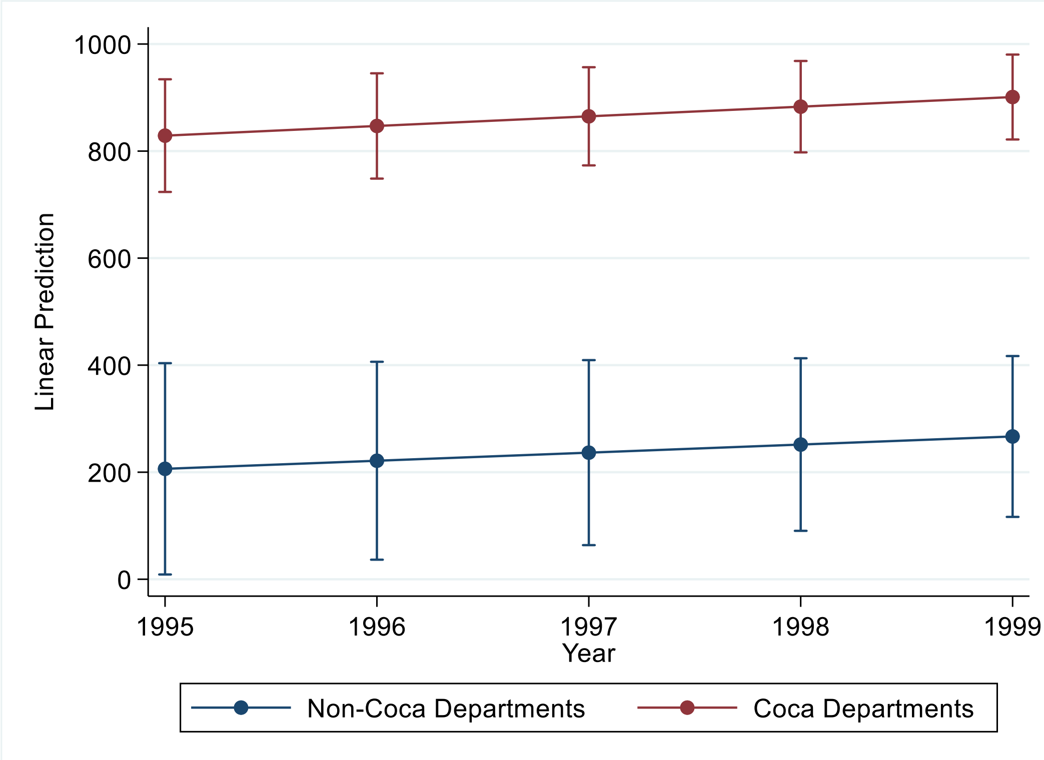
Source: Mejía (2015)'s calculations, based on data from UNODC and the government of Colombia.

Figure A.2.4−Coca Crops, and Coca Base and Cocaine Seizures in Colombia, 1999-2014



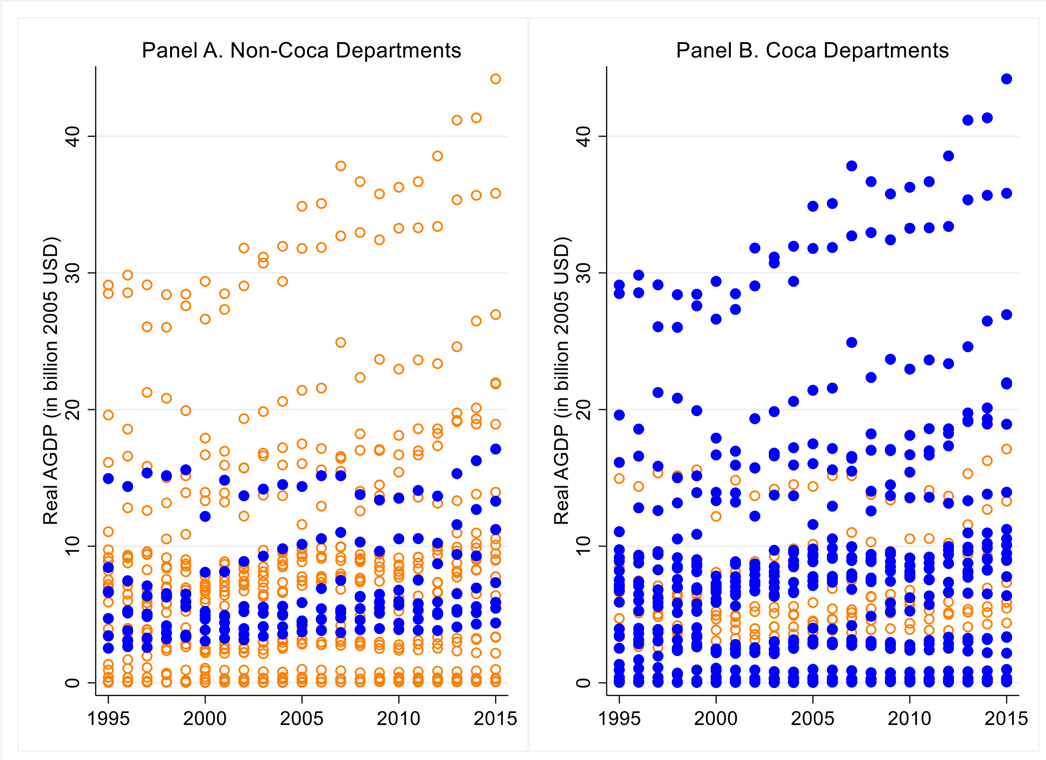
Source: Own calculations, based on data from UNODC and ODC.

Figure A.2.5—Predict Margins of Coca and Non-Coca Departments with 95% CIs, 1995-1999



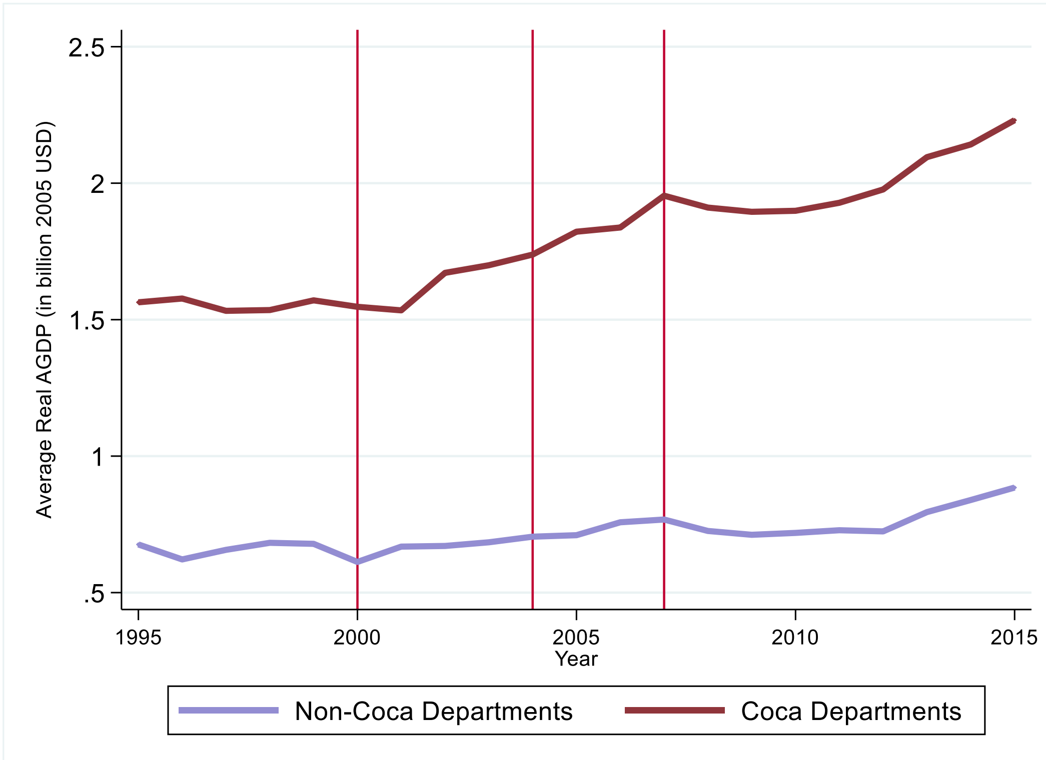
Source: Own calculations based on data from EVA.

Figure A.2.6– Real AGDP Comparison of Coca and Non-Coca Departments, 1995-2015



Source: Own calculations based on data from EVA.

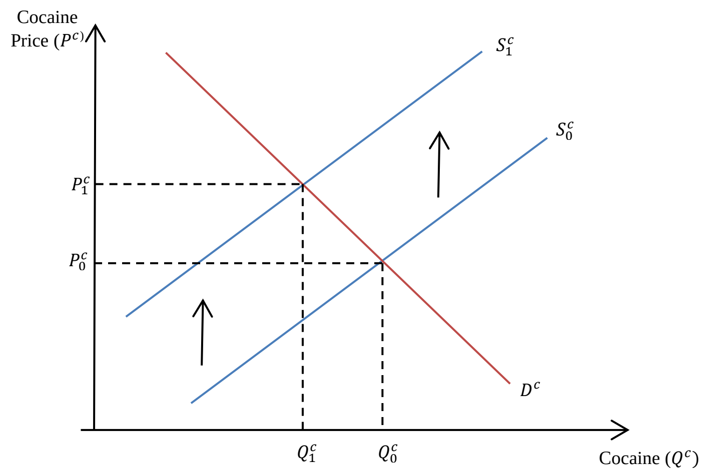
Figure A.2.7−Plot of Real AGDP of Coca and Non-Coca Departments, 1995-2015



Source: Own calculations based on data from EVA.

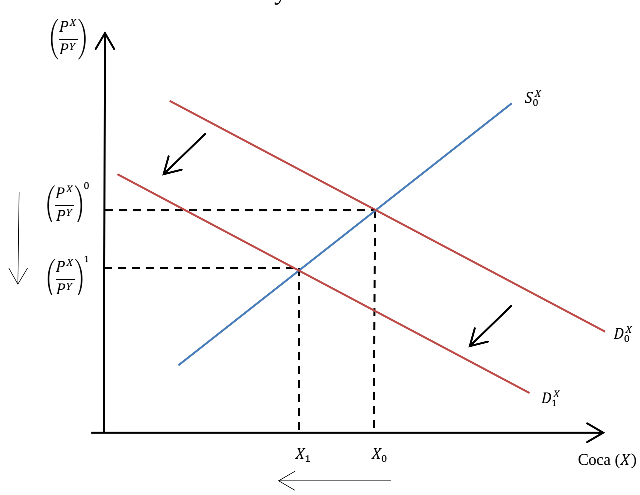
APPENDIX B

Figure B.2.1–Effect of Cocaine-Laboratory Interdiction-Supply-Reduction Policy on Market for Cocaine



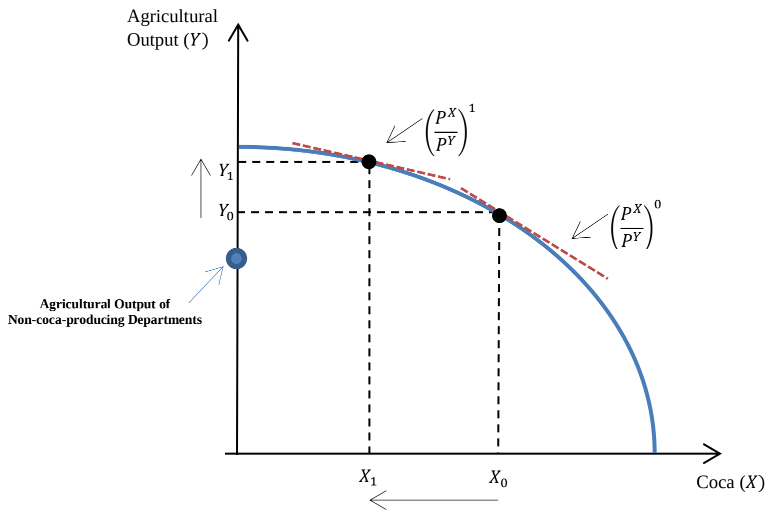
Source: Own elaboration.

Figure B.2.2–Effect of Cocaine-Laboratory Interdiction on Market for Coca Leaves in Colombia



Source: Own elaboration.

Figure B.2.3–Effects of Interdiction on Coca and Agricultural Production in Coca-Growing Departments



Source: Own elaboration.

CHAPTER 3

THE IMPACT OF THE RENEWABLE ENERGY STANDARD ON THE LAND USE AND CROP YIELDS IN THE US GREAT PLAINS

3.1. Introduction

The side effects of energy and environmental policies constitute one of the central concerns of economists and policymakers. The design of these regulations can hinge on whether the production standards in the energy markets can affect interrelated sectors at extensive or intensive margins.[39] The US government has enacted biofuel blending targets (mandates) to tackle greenhouse gas (GHG) emissions, reinforce the security of energy supply, and enhance rural economic development to some extent (Xiaoguang and Madhu, 2013; Clancy and Moschini, 2017). Biomass[40] to produce fuels and energy has rapidly grown, perhaps mainly because of such policies. Farmers and biomass producers thus could have faced significant variations in their land opportunity costs, production possibilities, profitability, and operational environments.[41]

The Renewable Fuel Standard (RFS) was introduced in the 2005 Energy Policy Act (EPA) and then significantly expanded in the Energy Independence and Security Act

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[39] The term extensive margin refers to the number of land units used to produce a determined crop output. Intensive margin (or yield) refers to the crop output amount per land unit. An increase in land use for agricultural production raises the extensive margin, and a land productivity increase represents an increase in yields or the intensive margin.

[40] Biomass is a renewable energy source obtained from plants and animals mainly used in energy production, such as biofuels. In 2016, 48% of the US biomass consumption for biofuel production came from agricultural residues, 41% wood, and 11% municipal waste (Energy Information Administration, 2017). The present study uses a measure of the individual crop quantity consistent with *net primary agricultural production* (Trindade et al., 2015; Prince et al., 2001). This notion implies that the crop biomass calculated for each county and year here includes the harvested crop and the residual above-ground biomass left in the field. This calculation implies a biomass quantity entirely harvested as forage crops or twice the amount harvested in most grain crops. For instance, biomass from corn includes the amounts of corn grain and corn stover potentially harvested for biofuel energy, where corn stover is primarily a by-product or residual from corn grain production. This corn stover consists of stalk, leaves, sheaths, husks, shanks, cobs, tassels, lower ears, and silks.

[41] Carter *et al*. (2017) estimate that about 37% of the US corn crop went to the ethanol industry to blend with gasoline in 2015, while in 2005, it was up to 14%. The federal government incentivized this rapid growth in corn use by requiring a minimum annual quantity of renewable biofuel or ethanol content in motor fuel. Since then, corn plantations have covered more agricultural land than any other crop in the United States.

(EISA) of 2007. This policy determines mandates for specified quantities of biofuels.[42] The expanded 2007 RFS nearly doubled the previous ethanol mandate and turned corn ethanol into 10% of finished motor gasoline in the United States in 2017, up from 3% in 2005. This study estimates the effects of the 2007 RFS biofuel mandates on the supply of corn biomass and alternative crops evaluated at the intensive and extensive margins. We use data on agricultural biomass produced in counties along the 41st north latitude parallel in the US from 1960–to 2018.

Biomass accounts in the United States for about 39% of the total renewable energy and almost one-quarter of the total primary non-fossil energy produced (US EIA, 2021). The prime input to produce ethanol in the United States is corn (US Grains Council, 2021). Biofuels (biodiesel and ethanol) production from different crops has offered the main alternative to fossil fuels regarding GHG reduction from a political viewpoint. These biofuel regulations aim to support farm incomes, reduce dependency on fossil fuels, and mitigate global warming effects (Carter *et al.*, 2017). However, biofuels compete with products conventionally used for human and animal consumption, which has raised concerns about food security mainly because of the increase in food and feed prices (Steer and Hanson, 2015). Regarding the last objective, biofuel production may involve significant land-use changes leading to additional GHG emissions (Gohin, 2014).

The regulated expansion of biofuels could have triggered structural changes in the US agriculture sector. The changes may occur mainly through an induced rise in crop quantity supplied and cropland demands for producing biofuels to the extent that the policy increases the prices of these crops. The percentage of corn used in the ethanol industry grew to 40% around 2013 in the US, where corn is the feedstock used for 94% of the US ethanol production (US Department of Energy Ethanol Fuel Basics, 2020). The increase in corn prices since the 2007 RFS has been attributed mainly to the rise in ethanol production (see, e.g., Condon *et al.*, 2015, and Carter *et al.*, 2017). However, economics literature offers not enough empirical evidence that the federal ethanol

[42] According to Anderson and Elzinga (2014), the original RFS had little effect on the corn quantity used for ethanol. The reason is that the 2005 RFS set mandates at the levels required to meet just air quality regulations for reformulated gasoline under the 1990 Clean Air Act (Anderson and Elzinga, 2014).

mandates are structurally related to this phenomenon. Runge and Senauer (2007) found that the expansion of ethanol production is closely associated with increasing corn demand, prices, and producer profit. As far as we know, there are no studies structurally and simultaneously quantifying the effects of such ethanol supply expansion on biomass supply and land productivity. This study estimates the impact of ethanol mandates on the corn biomass supply and the simultaneous response of land planted with corn in the US.

The remainder of this chapter is structured as follows. Section 3.1.1 provides a background of biofuel policies and the RFS in recent decades in the US and discusses the relationship between ethanol market changes and crop-related prices and supply. In section 3.2, we present the economic and econometric models of production used in this paper. The data used in the analysis are described and illustrated in Section 3.3. Section 3.4 presents the estimation results. Section 3.5 concludes.

3.1.1. Mandates in the Ethanol Market

The 2005 EPA is the policy with the most significant role in the US biofuel industry recently. The main reason for this is that mandates on minimum quantities of biofuels consumption\production initiated with such legislation. Although the Act focused on biofuel energy production in the US between 2005 and 2007, the EISA of 2007 expanded mandated targets (Renewable Fuel Standards, or RFS) progressively since 2007 from 9 million gallons to 36 million gallons by 2022.

The analysis of biomass supply response to the RFS in this paper can provide insights into the discussion on energy crops competing with food crops for land. Responding to the potential increase in the price of corn relative to other crops due to the RFS, for instance, can lead producers of this crop to expand such crop area (at the cost of other crops) or increase yields. Carter *et al*. (2017) estimate the effects of the 2007 RFS on the corn market and find that the mandates raised corn prices by about 30%. Smith (2018) finds that the RFS that became law in 2007 increased soybean and wheat prices by about 20%. The 2007 RFS impact estimation on corn biomass supply could provide crucial insights into the farmers’ willingness to expand the crop supply or crop area in response to potential increased profitability attributed to the RFS-ethanol mandates.[43] Evaluating how much the biofuel mandates contributed to higher crop prices would require estimates of the underlying crop supply and demand elasticities (Roberts and Schlenker, 2013). However, examining the effects on crop supply could benefit from the assumption of price-taking crop producers as the perfect competition archetype. The RFS-induced crop price increases (due to the rise in the demand for crops to produce biofuels) may allow identifying econometrically the crop supply price elasticity. The crop producers' response to such price variations could translate into yield changes (i.e., effects at the intensive margin) or changes in the area planted (i.e., impacts at the extensive margin). The identification strategy thus relies on exogenous price changes affecting the crop demand to produce the corresponding biofuels.

Previous literature has investigated agricultural crop supply elasticities and crop acreage responses consistent with a dual theoretical framework (see, for example, Morzuch *et al.*, 1980, Ball, 1988, Chambers and Just, 1989, Coyle, 1993a,b; Arnade and Kelch, 2007). According to Coyle (1993a), because output and acreage decisions are not separable in crop production, it may be unrealistic to assume that crop output decisions and inputs allocations are modeled independently in agriculture. In his seminal papers, Coyle (1993a,b) derived a system of equations for modeling crop acreage responses by incorporating allocation decisions for fixed inputs such as land into a two-stage aggregation model of multioutput production decisions. At least there are four advantages of Coyle's approach over alternative theoretical frameworks. The separability conditions are consistent with a two-stage aggregation approach, more plausible, and less restrictive than standard models, such as those following Nerlove (1979) or based on a single output supply or acreage response equation. The dual approach permits the inclusion of

[43] There was a rapid ascent of commodity prices between late 2005 and 2008 that led to renewed debate about what drives the supply of food commodities. According to Roberts and Schlenker (2013), corn prices nearly quadrupled (from 2 to almost 8 USD per bushel), followed by a brief drop in 2009–2010 due to the recession, but the corn bushel broke 8 USD in 2011. These authors estimate supply elasticities of storable commodities (corn, rice, soybeans, and wheat) to evaluate the impact of the 2009 RFS on commodity prices, quantities, and food consumers' surplus. They found that prices increase 20% percent if one-third of commodities used to produce ethanol (shift in demand stemming from the US ethanol policy) went recycled as feedstock. However, the US price received by farmers for corn has been between USD 3.1 and USD 4.2 from 2013 to 2019 (USDA, 2020).

contemporaneous co-variance of disturbances across equations. The hypothesis of competitive profit maximization implies symmetry/reciprocity restrictions on coefficients across equations. Finally, the production decision scheme represents a two-stage decision-making process for producers that is more empirically reliable and feasible to recover the underlying technology.

3.2. Methodology

3.2.1. Theoretical Framework

This study follows a dual model based on Chambers and Just (1989), Coyle (1993a,b), and Arnade and Kelch (2007) as an attempt to assess the simultaneous effects of RFS on corn biomass supply and acreage demand. The empirical approach analyzes the technology for producing biomass within a set of counties across the central US Great Plains. A relevant assumption is that production decisions are consistent with the profit-maximization behavior of farmers operating under perfect competition in both outputs and inputs markets. Given the vectors of output and input prices and exogenous factors, farmers choose an optimal vector of outputs and inputs. The exogenous factors include environmental conditions or a county's physical characteristics (e.g., the topography, climate, water field, soil organic matter, and time).

3.2.1.1. Two-stage Profit Maximization Approach with Land Fixed and Allocatable

The decision-making unit (DMU) produces a vector of $M + 1$ annual crop outputs $\boldsymbol{Y} = (Y_0, \dots, Y_M)$ using a vector of N allocatable variable inputs $\boldsymbol{X} = (X_1, \dots, X_N)$ and a fixed total amount of agricultural land (L) allocated among the individual crops. The producer follows a two-stage decision-making process, given non-allocatable fixed inputs, exogenous factors (e.g., environmental or institutional variables), and time as a proxy for exogenous technical change included in the vector $\boldsymbol{Z} = (Z^1, \dots, Z^K)$. In the first stage, the DMU maximizes profits from each output given the land allocated to each crop. In the second stage of profit maximization, the DMU distributes the available agricultural land optimally across crops. The profit function for each crop i is represented by

$$\Pi^i(P_i, \boldsymbol{W}, l_i, \boldsymbol{Z}) = \max_{(Y_i, \boldsymbol{X^i})} \left\{ P_i Y_i - \sum_{n=1}^{N} W_j X_j^i : Y_i \in F^i(\boldsymbol{X^i}; l_i, \boldsymbol{Z}) \right\} \qquad \forall\, i = 0, \dots, M \quad (1)$$

where P_i is the price of the crop i; Y_i is the produced quantity of crop i; $\boldsymbol{W} = (W_1, \dots, W_N)$ is the vector of the variable inputs' prices; $\boldsymbol{X^i}$ is the vector of variable inputs quantity used in producing crop i; l_i is the amount of land allocated to the crop i production. The producer's dual profit function is assumed to be continuous and twice differentiable with respect to all its arguments; linearly homogenous and convex in prices; and non-decreasing in output prices P_i, while non-increasing in variable inputs prices $\boldsymbol{W}$.

The second stage implies that DMUs allocate available agricultural land to optimally managed crops. The producers thus solve the constrained optimization problem yielding:

$$\Pi(\boldsymbol{P}, \boldsymbol{W}, L, \boldsymbol{Z}) = \max_{l_0, \dots, l_M, \lambda} \left\{ \sum_{i=0}^{M} \Pi^i(P_i, \boldsymbol{W}, l_i, \boldsymbol{Z}) + \lambda(L - \sum_{i=0}^{M} l_i) \right\} \qquad (2)$$

where $\boldsymbol{P} = (P_0, \dots, P_M)$ represents a vector of the $M+1$ crop prices; L is the total amount of land allocatable to the $M+1$ crops, λ is the shadow price of agricultural land, and the other variables are defined as above. Using Hotelling's lemma, we obtain the output supply and variable input demand equations conditional on L and $\boldsymbol{Z}$, and acreage demands are implicit in the first-order conditions (FOC) from equation (2). The (negative of the) partial derivative of the profit function [equations $(1) - (2)$] with respect to the variable input price W_n yields the optimal variable-input demand:

$$-\frac{\partial \Pi}{\partial W_n} = -\sum_{i=0}^{M} \frac{\partial \Pi^i}{\partial W_n} = \sum_{i=0}^{M} X_n^{i*} = X_n^*(\boldsymbol{P}, \boldsymbol{W}, L, \boldsymbol{Z}) \qquad \forall\, n = 1, \dots, N \qquad (3)$$

where X_n^{i*} represents the optimal allocatable nth variable input used in producing crop i and X_n^* is the total level of the nth variable input employed over the $M+1$ crops.

Similarly, by differentiating equation (2) with respect to the output price of the crop i, we obtain the output supply function of that crop (Y_i):

$$\frac{\partial \Pi}{\partial P_i} = Y_i(\boldsymbol{P}, \boldsymbol{W}, L, \boldsymbol{Z}) = \frac{\partial \Pi^i}{\partial P_i} = Y_i^*(P_i, \boldsymbol{W}, l_i, \boldsymbol{Z}) \qquad \forall\, i = 0, \dots, M \qquad (4)$$

where Y_i^* represents the optimal output quantity of crop i. We can also derive the optimal allocation of the quasi-fixed factor land to crop i from the restricted profit function as the negative of the derivative with respect to land price, λ_i. Following Arnade and Kelch (2007), the first-order condition of the (constrained) profit function in equation (2) with respect to the quasi-fixed factor (l_i) results in the shadow price equation for land used in the production of the output of crop i:

$$\frac{\partial \Pi}{\partial l_i} = \frac{\partial \Pi^i}{\partial l_i} - \lambda = \lambda_i(P_i, \boldsymbol{W}, l_i, \boldsymbol{Z}) - \lambda = 0 \qquad \forall\, i = 0, \dots, M \qquad (5)$$

where λ_i is the shadow price of the additional unit of land allocated to the production of crop i. We can infer from equation (5) that the shadow prices of land across alternative crop equations are equal at the optimum[44]:

$$\frac{\partial \Pi^j\left(P_j, \boldsymbol{W}, \bar{l}_j, \boldsymbol{Z}\right)}{\partial l_j} = \frac{\partial \Pi^0\left(P_0, \boldsymbol{W}, \bar{l}_0, \boldsymbol{Z}\right)}{\partial l_0} \qquad \forall\, j = 1, \dots, M \qquad (6)$$

We can further infer from (5) that the shadow price of land allocated to each crop (i.e., λ_i) equates to the overall shadow value of the marginal land unit:

$$\frac{\partial \Pi}{\partial L} = \lambda = \lambda_i(P_i, \boldsymbol{W}, l_i, \boldsymbol{Z}) = \frac{\partial \Pi^i}{\partial l_i} \qquad \forall\, i = 0, \dots, M \qquad (7)$$

Because the term l_i represents the area allocated to the ith crop and is represented in each shadow price equation in (7), jointly solving the shadow price equations and the constraint: $\sum_{i=0}^{M} l_i = L$ for the allocation terms (l_i) obtains a function for the area devoted to crop i. This result applies for every crop by considering that equations (6) and (7) together suggest that: $\frac{\partial \Pi^j}{\partial l_j} = \frac{\partial \Pi^i}{\partial l_i} = \lambda$, with $i, j = 0, \dots, M$. Moreover, the inverse of each

[44] Previous studies have shown how to explicitly recover the land allocation vector from the multioutput profit function (see, for instance, Chambers and Just, 1988; Paris, 1989; and More and Negri, 1992).

cropland shadow price equation in (7) is equivalent to an acreage demand equation (l_i) that is a function of all product prices, all variable input prices, and the total amount of cropland:

$$l_i = l_i(\boldsymbol{P}, \boldsymbol{W}, L, \boldsymbol{Z}) \qquad i = 0, \dots, M \qquad (8)$$

The main feature of interest from each of these crop area functions is that they include output prices as arguments, which is the key to calculating the response of area to a price change (Coyle 1993a,b; Arnade and Kelch, 2007).

3.2.2. Empirical Implementation

To implement the model empirically, we specify a normalized quadratic profit function, a member of the class of flexible, functional forms. This normalized quadratic profit function satisfies homogeneity properties by construction, and it eases in imposing symmetry, monotonicity, and convexity properties (Chambers, 1988; Arnade and Kelch, 2007). We normalize the input and output prices with one of the prices of the output (e.g.,P_0) and impose symmetry. The profit function for the normalized quadratic is:

$$\begin{aligned}\pi = \alpha_0 + \sum_i \alpha_{i0} p_i + \sum_j \delta_j l_j + \sum_k \varepsilon_k Z^k + \frac{1}{2}\sum_i \sum_h \alpha_{ih} p_i p_h + \sum_i \sum_k \beta_{ik} p_i Z^k \\ + \sum_i \sum_j \gamma_{ij} p_i l_j + \frac{1}{2}\sum_j \delta_{jj} l_j^2 \\ + \sum_j \sum_k \varepsilon_{jk} l_j Z^k \qquad (9)\end{aligned}$$

where $\pi = \Pi/P_0$ and p_i represents both output and input prices normalized on P_0. By using Hotelling's Lemma, the optimal output supply function of the ith crop and optimal variable input demand equations are respectively expressed as:

$$\frac{\partial \pi}{\partial p_i} = Y_i^* = \alpha_{i0} + \sum_h \alpha_{ih} p_h + \sum_k \beta_{ik} Z^k + \sum_j \gamma_{ij} l_j \qquad \forall\, i = 1, \dots, M \qquad (10)$$

$$\frac{\partial \pi}{\partial p_n} = -X_n^* = \alpha_{n0} + \sum_h \alpha_{nh} p_h + \sum_k \beta_{nk} Z^k + \sum_j \gamma_{nj} l_j \quad \forall\, n = M+1, \dots, N \quad (11)$$

where Y_i^* represents the profit-maximizing supply of the ith crop output of a county, and X_n^* denotes the profit-maximizing demand for the nth variable input. We also differentiate equation (9) with respect to the acreage term (l_j) to obtain the shadow price of land used in producing crop i:

$$\frac{\partial \pi}{\partial l_j} = \lambda_j^* = \delta_j + \sum_i \gamma_{ij} p_i + \delta_{jj} l_j + \sum_k \varepsilon_{jk} Z^k \qquad \forall\, j = 0, \dots, M \qquad (12)$$

where λ_j^* denotes the shadow price of the parcel of land optimally allocated to produce the jth crop. To obtain the jth acreage response equation, we manipulate the system of $M + 1$ equations derived from (12) using equations (6) and (7) and including the land constraint $l_0 = L - \sum_{j=1}^{M} l_j$. Replacing this constraint into the expression (12) for the crop $i = 0$ and then subtracting the resulting equation from each of the other equations in the system of equations in (12) to reduce the system to M equations, we obtain:

$$0 = \left(\delta_j - \delta_0\right) + \sum_i \left(\gamma_{ij} - \gamma_{0i}\right) p_i + \delta_{jj} l_j - \delta_{00}\left(L - \sum_{j=1}^{M} l_j\right) + \sum_k \left(\varepsilon_{jk} - \varepsilon_{0k}\right) Z^k \qquad \forall\, j = 1, \dots, M \qquad (13)$$

Solving this expression for l_j other than $j = 0$ gives estimable equations for the optimal allocations of land as a function of crop output prices, variable input prices, total available land (L), and other exogenous factors:

$$l_j = \theta_{j0} + \sum_i \theta_{ji} p_i + \upsilon_{j0} L + \sum_k \upsilon_{jk} Z^k \qquad \forall\, j = 1, \dots, M \qquad (14)$$

where $\theta_{j0} \cong \frac{1}{\delta_{jj}}(\delta_0 - \delta_j - \delta_{00} \sum_{j=1}^{M} l_j)$; $\theta_{ji} = \frac{1}{\delta_{jj}}(\gamma_{0i} - \gamma_{ji})$; $\upsilon_{j0} \cong \frac{\delta_{00}}{\delta_{jj}}$; and $\upsilon_{jk} = \frac{1}{\delta_{jj}}(\varepsilon_{0k} - \varepsilon_{jk})$ are all reduced form parameters to be estimated. The production of agricultural outputs (corn, soybeans, and other crops) arises from a profit-maximizing allocation of (finite) cropland across the three alternatives.

To evaluate the effect of the policy at the extensive and intensive margins and consistent with recent work addressing agricultural supply response to price changes induced by the biofuel expansion (e.g., Carter *et al.*, 2017; Moschini *et al.*, 2017: Hendricks *et al.*, 2014, Berry 2011), we postulate both a land allocation response and a yield response. For this, we can rearrange the equations (10) and (12) using the constraint $\sum_{j=0}^{M} l_j = L$ or $l_0 = L - \sum_{j=1}^{M} l_r$ such that we have the estimable equations:

$$Y_i^* = \varphi_{i0} + \sum_h \alpha_{ih} p_h + \rho_i L + \sum_k \beta_{ik} Z^k \qquad \forall\, i = 1, \dots, M \qquad (15)$$

$$-X_n^* = \psi_{n0} + \sum_h \alpha_{nh} p_h + \omega_n L + \sum_k \beta_{nk} Z^k \qquad \forall\, n = M+1, \dots, N \qquad (16)$$

where $\varphi_{i0} = \alpha_{i0} - \rho_i \sum_{j=1}^{M} l_j$; $\rho_i = \sum_j \gamma_{ij}$; $\psi_{n0} = \alpha_{n0} - \omega_n \sum_{j=1}^{M} l_r$; and $\omega_n = \sum_j \gamma_{nj}$ are all parameters to be estimated. we can obtain the price elasticity of supply and infer the extensive and intensive margins. Furthermore, from the acreage response equations (14) and the supply function for biomass from corn in equation (15), we can obtain the price elasticity of supply and infer the extensive and intensive margins. First, denote $\boldsymbol{p} = (p_1 = \frac{P_1}{P_0}, \dots, p_M = \frac{P_M}{P_0})$ as a vector of normalized crop output prices and $\boldsymbol{w} = (w_1 = \frac{P_{M+1}}{P_0}, \dots, w_N = \frac{P_N}{P_0})$ as a vector of normalized variable input prices. Second, considering that agricultural land (L) is the only quasi-fixed input such that a crop yield is a ratio between its output and cropland (land productivity), we have:

$$\frac{\partial y_i(\boldsymbol{p}, \boldsymbol{w}, L, \boldsymbol{Z})}{\partial p_i} \times \frac{p_i}{y_i} = \frac{\partial Y_i(\boldsymbol{p}, \boldsymbol{w}, L, \boldsymbol{Z})}{\partial p_i} \frac{p_i}{Y_i} - \frac{\partial l_i(\boldsymbol{p}, \boldsymbol{w}, L, \boldsymbol{Z})}{\partial p_i} \frac{p_i}{l_i} \qquad (17)$$ [45]

where y_i represents the crop yield per acre resulting from dividing Y_i by the optimal quantity of land planted (l_i). Equation (17) in elasticity form is:

$$\epsilon_{ii}^{yp} = \epsilon_{ii}^{Yp} + \epsilon_{ii}^{lp} \qquad (18)$$

[45] Following Babcock (2011), agricultural sectoral models define agricultural supply (Y) as the product of area (L) and yield (y). A change in output results from dY =dA×Y + dY×A, where the first term measures the change in output at the extensive margin and the second term measures the change at the intensive margin. Define the supply response to higher output prices as $\frac{dY}{dP} = Y \times \frac{dA}{dP} + A \times \frac{dy}{dP}$ or, in elasticity form, $\varepsilon_Y = \varepsilon_A + \varepsilon_y$, where ε_Y, ε_A, and ε_y are price elasticities of total supply, area, and yield, respectively. A crop yield response in logs is $lny_i = lnY_i - lnl_i$. From this way of thinking about agricultural (crop) supply, we obtain equation (17).

where the left-hand side is the price yield elasticity as the intensive margin, the first right-hand side term the price crop-output supply elasticity, and the last expression represents the price elasticity of planted land as the extensive margin.

3.2.3. *Estimation*

This paper studies the impact of RFS mandates on the intensive and extensive margins of biomass produced in 101 counties in Colorado, Nebraska, Iowa, and Wyoming from 1969 to 2018. For this, we estimate a system of equations (i.e., output supplies, derived demand for variable factors of production, and crop acreage demands) obtained from $(14) - (16)$:

$$\boldsymbol{Y} = \boldsymbol{\varphi}_0 + \boldsymbol{\varphi}_1 \boldsymbol{p} + \boldsymbol{A_Y} \boldsymbol{w} + \boldsymbol{\varphi}_2 L + \boldsymbol{B_Y} \boldsymbol{Z} + \boldsymbol{\varepsilon_Y} \tag{19}$$

$$\boldsymbol{X} = \boldsymbol{\omega}_0 + \boldsymbol{\omega}_1 \boldsymbol{p} + \boldsymbol{A_j} \boldsymbol{w} + \boldsymbol{\omega}_2 L + \boldsymbol{B_j} \boldsymbol{Z} + \boldsymbol{\varepsilon_X} \tag{20}$$

$$\boldsymbol{l} = \boldsymbol{v}_0 + \boldsymbol{v}_1 \boldsymbol{p} + \boldsymbol{A_l} \boldsymbol{w} + \boldsymbol{v}_2 L + \boldsymbol{B_l} \boldsymbol{Z} + \boldsymbol{\varepsilon_l} \tag{21}$$

where $\boldsymbol{Y}$ is a vector of crop biomass quantities (tons harvested including stalks and leaves) of corn, soybeans and other crops; $\boldsymbol{X}$ is a vector of variables inputs including fertilizer and chemicals (measured in implicit quantity indexes), labor, and capital; $\boldsymbol{l}$ is a vector of the acreage planted with corn, soybeans, and other crops; L is the total cultivated area in the county; $\boldsymbol{p}$ is a vector of corn and soybeans prices relative to an index of the biomass price for all other crops; $\boldsymbol{w}$ is a vector including the prices of fertilizer, chemicals, labor (wages), and capital relative to the price index of biomass from all other crops; $\boldsymbol{Z} = (irrigation, r, \boldsymbol{DD}, time)$ with $irrigation$ as the fraction of planted land in the county that is irrigated, r as annual precipitation in centimeters, $\boldsymbol{DD}$ as a vector of temperature degree-day interval variables (the total length of time, in days, that the crops were exposed to temperatures in a specific range during the growing season), and $time$ = 1,…,49 as a proxy for exogenous technical change; $\boldsymbol{v}$'s, $\boldsymbol{\varphi}$'s, $\boldsymbol{\omega}$'s, $\boldsymbol{A}'s$, and $\boldsymbol{B}'s$ are set of parameters to be estimated; and the $\boldsymbol{\varepsilon}$'s denote sets of stochastic error terms in the system of equations. We assume correlated error terms ($\boldsymbol{\varepsilon}$'s) across the equations above.

The critical assumption here is the significant dirent effects of the policy in the ethanol market on the crop (or input) markets related to such biofuel production. As stated before, corn is the main crop used in producing ethanol in the United States. Thus, the mandates on ethanol production would significantly and exogenously affect the prices (mainly through the demand) of the staple crops used to produce such biofuel, i.e., essentially corn.

3.2.4. Endogenizing Corn Price to the RFS

We use the RFS policy in the ethanol (gasoline) market as a potential source of exogenous variation in the price of corn. To implement the model empirically and identify the extensive and intensive margins in corn production due to the policy, we thus specify an additional equation for corn price as a function of a variable proxy for the effects of the RFS mandates since 2007. We use this proxy as an instrument for the corn price equation. This variable is used to identify the impact of corn price variation due to the 2007 RFS on the output supplies, input demands, and crop-acreage demand equations.

We approximate the policy by the variable ζ. To specify this variable, first, consider a dummy variable ($Post = 1$ if the year $\geq 2007; = 0$ otherwise) indicating years of exposure to RFS mandates expansion starting 2007. We also use a variable denoted RFS as a direct measure of the 2007 RFS effect on the corn markets. More specifically, RFS is equal to the state-level fuel ethanol production in barrels capturing potential shocks to the demand for biomass from corn. To create a county-level variation and to further specify ζ for capturing the intensity of the policy effect or exposure, the terms $Post$ and RFS are also interacted with (or multiplied by) the inverse of the distance of each county's centroid to the closest biorefinery producing ethanol ($distance^{-1}$). Therefore, the instrument for corn price is given by:

$$\zeta = Post \times distance^{-1} \times RFS \tag{22}$$

where ζ is assumed to be a proxy for the 2007 RFS mandates shock to corn demand, and more concretely, corn prices. This variable is our instrument for corn prices. It indicates the years when the counties were exposed ($Post$) to some extent or intensity ($distance^{-1}$) to potential corn demand shocks, increasing corn prices induced by the mandated quantities reflected in the ethanol production (RFS). The first-stage equation is thus estimated as:

$$p_{corn} = \psi_0 + \psi_1 \zeta + \boldsymbol{\Omega V} + \nu \quad (23)$$

where $p_{corn} = P_{corn}/\hat{P}_{others}$ is the price of corn relative to an index of the biomass price from all other crops except soybeans ($\hat{P}_{others}$); $\boldsymbol{V}$ represents all other exogenous variables in the model including $\boldsymbol{Z}$ defined as before and $\boldsymbol{C}$ representing a vector of county dummies; ψ_0, ψ_1, and $\boldsymbol{\Omega}$ are parameters to be estimated; the ν denotes the corresponding stochastic error terms of the equation. It is worth noting that even though corn prices (and soybeans prices) are determined at the national level, we end up having these prices at the county level because we divide those national prices by an index of the biomass price from all other crops, which varies by county.

3.3. Data

We obtain data for 101 counties along the 41st parallel north in part of the Midwestern US over 1969-2017. Figure 1 shows the area of analysis that stretches from the Rocky Mountains to the Mississippi River across Nebraska (47 counties), Iowa (47 counties), Colorado (4 counties) Wyoming (3 counties). The region is not just a significant cereal production area in the US but may also have worldwide implications for similar agroecosystems. This area includes both a vast gradient of weather and soil and underground water characteristics that are highly representative of agriculture production in other temperate regions of the world (Trindade, 2011).

The construction of the variables used is based on information from the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA), the United States Historical Climatology Network (USHCN), and the USS Energy Information Administration (EIA) State Energy Data System (SEDS). The information about state-level ethanol production was retrieved from the Primary Energy

Consumption Estimates by Source, 1960-2017 of the USS EIA. To compute the distance of each county to the closest ethanol biorefinery, we also use data on the georeferenced locations of these biorefineries in the US retrieved for the year 2010 from the Renewable Fuels Association (RFA).[46]

Data on annual crop outputs and total acreages planted per crop in the county are from the surveys conducted by the NASS-USDA. The vector of crop outputs $\boldsymbol{Y}$ indicates total biomass production in metric tons[47] of dry matter. To simplify the econometric model, we aggregate crops into three groups: corn, soybeans, and all other crops produced in the county, including wheat, barley, sorghum, rye, oats, hay, and sugar beets. Thus, vector $\boldsymbol{Y}$ consists of the aggregate of all above-ground biomass produced by corn, soybeans, and all other crops in the county. The total amount of biomass produced from $corn$, $soybeans$ and all other crops $(others)$ for county c in year t is calculated as: $Y_{crop,c,t} = \frac{Q_{crop,c,t}}{HI_{crop}} \times (DM_{crop})$ and $Y_{others,c,t} = \sum_c \frac{Q_{o,c,t}}{HI_o} \times (DM_o)$, where $crop = corn, soybeans$ and o indexes all other crops produced in the county each year. The county-wide harvest for crop $i = corn, soybeans, o$ expressed in metric tons is denoted by Q_i. The term HI denoting harvest index is the fraction of the above-ground biomass of crop $i = corn, soybeans, o$ that is harvested (Hay, 1995; Unkovich *et al.*., 2010)[48]. The term DM indicates the dry matter proportion of the harvest for crop $i = corn, o$.[49] We also

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[46] The RFA provides the location of U.S. fuel ethanol plants by county. These production facilities are classified as installed ethanol biorefineries, operational ethanol biorefineries and biorefineries under construction/expansion. We use the location of the installed and operating ethanol biorefineries on September 1, 2010 retrieved from http://www.ethanolrfa.org/bio-refinery-locations/ to construct the weighting variable $distance^{-1}$. In 2010, the U.S. ethanol industry was made up of 200 nameplate refineries with a total capacity of 13.544 million gallons per year (MGY): 192 of which were operating with an annual capacity of 12.9 MGY, while 12 plants were under construction or expansion. See Urbanchuk (2010) for a detailed description of ethanol plants location in 2010. In general, the ethanol biorefineries concentrated in the Midwest corn-belt states, mainly in Iowa and Nebraska. See the current location in https://ethanolrfa.org/biorefinery-locations/ at a county level, and https://ethanolrfa.org/where-is-ethanol-made/ at a state level.

[47] For instance, coefficients to convert to metric tons (i.e., tonnes) from bushels were 0.0254 for corn, sorghum, and rye and 0.0272 for wheat and soybeans.

[48] The harvest indexes used were 0.5 for corn and sorghum for grain; 1 for corn and sorghum for silage and hay; 0.4 for soybeans, rye, and barley; and 0.35-0.85 for other minor crops.

[49] The dry matter fraction for a crop is equivalent to one minus the respective moisture index of that crop. Following Loomis and Connors (1992), the moisture indexes used were 0.145 for corn and sorghum for grain, barley, and rye; 0.55 for corn and sorghum for silage; 0.135 for wheat; 0.13 for soybeans and beans; and 0.10-0.78 for all other minor crops.

compute the comparable prices of corn and soybeans by dividing each crop price by a biomass weighted average value of all other crops, excluding corn and soybeans. This value is calculated by dividing the value of total production (price×quantity) of each crop by the total biomass produced. This value was then calculated as $\hat{p}_{others,c,t} = \frac{\sum_o (P_{o,c,t}) \times \frac{Q_{o,c,t}}{HI_o} \times (DM_o)}{Y_{others,c,t}}$ where $P_{o,c,t}$ is the reported price for crop o (other than corn and soybeans) in county c at year t and $\hat{p}_{o,c,t}$ represents the "average price" of all other crops except corn and soybeans.

The variable inputs considered are fertilizer, chemicals, labor, and capital. The fertilizer and chemicals inputs represent implicit quantity indexes. These indexes were estimated using county-level expenditures on these inputs reported approximately every five years by the Census of Agriculture published by the USDA–NASS. We divided the reported input expenditure by a national level input price index obtained from USDA–Economic Research Service for fertilizers and USDA–NASS for chemicals (base 1990-1992=100) for each census year. We apply inter-census interpolation to these county-level quantity indexes by using annual state fertilizer indexes. All these values were finally divided by the index in Adams County, Nebraska, for 1969. We also measure the variable labor following a similar approach to fertilizer and chemicals. Data on the number of total hired farm workers and total expense with hired farm labor (US$1,000 payroll) was obtained from the USDA Census of Agriculture Historical Archive for the census years from 1964 to 1992 and USDA–NASS for the census years from 1997 to 2017. We use that total county-level number of hired farmworkers as a proxy for labor and create the nominal wages for each census year/county resulting from dividing the total payroll by the number of these hired workers. Linear interpolation was used for both series to fill the information gaps between the census years. We deflated all these wages using the corresponding 1969 value for Adams County, Nebraska.

We also created a capital input variable using data on the inventory of tractors, trucks, and agricultural equipment on the farm place at the county level, also retrieved from the NASS-USDA censuses. The time series for the cost of capital derives from the information about the US expenditures on each of these items from ERS/USDA considering the Producer Price Index for Farm Machinery and Equipment Manufacturing

(Index Dec 1982=100, Annual, Not Seasonally Adjusted) from the Federal Reserve Economic Data (FRED), and the depreciation rates from the Bureau of Economic Analysis (BEA). To calculate the "quantity of capital" for each county, we calculate the county share of each of three equipment types (tractors, trucks, and machinery) to the national level, based on the values of each census year. Linear interpolations were used between census years to obtain equipment shares for the non-census years. We then multiply these shares by the national annual capital stock using corresponding depreciation rates, service life (in years), and declining-balance rates. Finally, we aggregate all the resulting annual values to obtain county-level annual capital stock. [50]

The independent variables consist of the prices of variable inputs and outputs (all normalized or divided by the $\hat{p}_{o,c,t}$), the share of irrigated cropland, weather variables and time as a proxy for exogenous technical change. The irrigation variable is the ratio of irrigated cropland to total planted cropland by county and year. Weather variables included are yearly precipitation and annual temperature intervals. We use weather station data collected from the High Plains Regional Climate Center. Using this information, we estimate degree-days (DD)[51] and precipitation as the distance-weighted average (of the five closest weather stations to the county center) of daily (minimum and maximum) temperature and daily precipitation level in centimeters, respectively (see Trindade, 2011, for more details). The annual precipitation variable was bounded to the "growing season"[52] by summing up values obtained from March through August each year. The number of hours each day was added for March through August and then divided by 24 to compute the DD variables. We further use a set of three aggregated DD variables, i.e., the number of days in a year with temperatures between 0 and 29ºC

[50] The data on the national capital stock is from the NASS-USDA censuses. The data on depreciation rates, services lives, and declining-balance is from:
https://apps.bea.gov/scb/account_articles/national/wlth2594/tableC.htm

[51] An adaptation of the agronomic measure "growing degree days" is used to measure the effect of temperature. According to the agronomic literature, a "growing degree day" is the amount of time (in days) when the level of temperature is above a certain threshold; hence when the temperature exceeds by one degree a given threshold for a period of 24 hours, one accumulated degree day occurs (Ritchie *et al.*, 1991; Trindade, 2011).

[52] In this study, we define the "growing season" as the period from March to August as in Schlenker and Roberts (2009), Trindade (2011), Miao *et al.* (2015), and García *et al.* (2019) because planting and harvesting of corn, for example, in most growing states starts in March (NASS 2010).

($DD0029$); 30 and 35ºC ($DD3035$); and higher than 35ºC ($DD35plus$). Table 3.1 presents summary statistics of all previously described variables.

3.4. Empirical Results

The purpose of this study is to determine quantitatively the effects of the Renewable Fuel Standards on the corn supply and acreage using a county-level panel data framework of an area in the US Great Plains for the period from 1969 to 2017. I estimate the entire system of equations given by $(19) - (21)$ through a Seemly Unrelated Regression Estimation (SURE). The estimates are more efficient by estimating all equations together because the SURE takes account of the very likely potential correlation between the error terms in the vectors $\boldsymbol{\varepsilon_Y}$, $\boldsymbol{\varepsilon_X}$, and $\boldsymbol{\varepsilon_l}$. Furthermore, simultaneous estimation allows me to impose cross-equation "symmetry" restrictions, particularly the corresponding cross-price effects in the equations. This implies that, for instance, the cross-price slope effect (slope) of demand for fertilizer with respect to the price of chemicals equals the slope of demand for chemicals with respect to fertilizer price.

A three-stage least squares (3SLS) estimation is used to endogenize relative corn prices to the demand shocks caused by the RFS mandates for identifying corn supply and corn acreages demand equations. This identification strategy is conducted to retrieve the effects of such policy on the extensive (acreage) and intensive (yield) margins of corn biomass supply. At the same time, instrumenting corn prices, efficiency gains by accounting for correlation of errors $\boldsymbol{\varepsilon}$'s, and the possibility of imposing cross-equation coefficient restrictions are still a feature allowed by the 3SLS estimation.

Table 3.2 and Table 3.3 present the 3SLS estimation of the system of equations in $(19) - (21)$. Table 3.2 shows the estimates of the crop output supply equations in (18) and the variable input demand equations in (19). These equations were restricted to satisfy symmetry between the cross-price parameters in the crop supplies, variable inputs demands, and crop acreage demands. The table contains a total of ninety-one parameters, sixty-two of which are significant at the 1% level, five at the 5% level, and five at the 10% level. Columns (1)-(3) present the estimates for the three crop output supply equations considered here, whereas columns (4)-(7) correspond to those of the variable inputs derived demand equations. The estimated coefficient for the own-price coefficient of corn is positive and statistically significant at the 1% level. The coefficient for soybeans is insignificant though it is positive as expected. These coefficients imply that if corn price (relative to other crops) increases by 1 dollar a year, the quantity supplied of corn biomass increases by around 1.8 million metric tons. The cross-price coefficients indicate that, in production, corn and soybeans are complements, but corn and all other crops are substitutes, while soybeans and all other crops are complements. Regarding the increase in the total available cropland, it seems to affect corn quantity supplied more than all other crops. On the other hand, the coefficients estimated for the variable time across the columns (1)-(3) suggest that the trend of the output supplies reflects a biased technological change mainly towards corn and apparently against all other crops together, excluding soybeans.

The input demands in columns (4) to (7) of Table 3.2 show that all the computed own-price effects are statistically significant and have a negative sign as expected. Moreover, the cross-price coefficients between fertilizer and chemicals indicate that these inputs are complements in production, while labor and capital inputs appear as substitutes for fertilizer. We can also observe that the cross-price elasticities for capital and labor suggest that these factors of production can be considered substitutes. All inputs are affected positively by increasing the total amount of land allocated to crop production, especially capital. If the price of corn (or soybeans) increases, the demands for fertilizer, chemicals, and capital input also increase, while the demand for labor decreases (though this last effect is not statistically significant). The coefficient in the variable time indicates that the exogenous presence of a technical change in crop production is biased towards fertilizer and chemical usage and against capital and labor. An increase in the ratio of irrigated land increases the supply of corn and the demand for fertilizer, chemicals, and labor input. However, the soybeans supply and the supply of all other crops and capital demand decrease when the ratio of irrigated land increases.

Table 3.3 presents the 3SLS estimates of crop acreage demand equations (21) for corn, soybeans, and other crops. The table contains thirty-nine parameters, thirty-one of which are significant at the 1% level and only one at the 5% level. All own-price effects (corn and soybeans) have a positive sign and are statistically significant at the 1% level. The crop output cross-price effects have positive signs between corn and soybeans acreage demands but negative between corn and other crops acreage demand. The cross-output-price effects are positive between soybeans and other crop demand areas. These estimated coefficients imply that the demand for crop areas increases with their output prices. Also, those coefficients reveal that corn and soybeans are complements (also other crops with soybeans) in cultivation, whereas corn and other crops are substitutes. The coefficients of total crop acreage in response to own crop price are significant at the 1% level for all three crop categories. The coefficient for the time trend is positive for corn and soybeans and negative for other crops. These results imply that technology changes have led to increased land allocated to corn and soybeans and a decline in the land allotted to all other crops across the years.

Table 3.4 presents the first-stage regression estimates following the specification in (23). We can observe that *P*-Corn (corn price relative to *P*-Ocrops in 1969) responds significantly to variations in the variable RFS-Shock (ζ). This latter variable is in thousands of barrels of fuel ethanol. The results are robust to other specifications in columns (2) and (3) of table 3.4. We used the first-stage specification of equation (23) in column (1) of Table 3.4 to estimate the results in Tables 3.2 and 3.3. The simple average national price for corn from 1969 to 2017 was approximately 107 nominal US dollars per metric ton (mt). The estimated average price for other crops (excluding corn and soybeans) was 95 nominal US dollars per mt during the 1969-2017 period. The average ratio is ($107/$95 ≈ 1.13=) 113: 100. This ratio eases putting our estimates from the first-stage regression in context. The estimated coefficient of 0.0014 for the RFS Shock (ζ) in the price equation displayed in Column 1 of Table 3.4 means that a unit increase in the ratio (1.13) when assuming a 1,000 barrels of fuel ethanol increase after 2007 for the fixed or constant counties' distance to the closest biorefinery. Therefore, the average ratio changed to 2.36 (236: 100), about 2: 1, implying that the 2007 RFS almost doubled the price of corn relative to all other crops price (excluding soybeans price) in the 41st Parallel Region within the 1969-2017 period. We use this exogenous variation in corn price because of the 2007 RFS mandates to identify the parameters estimated in Tables 3.2 and 3.3.

Table 3.5 reports own-price and cross-price elasticities calculated from the parameter estimates in tables 3.2 and 3.3, evaluated at the mean of all the observations. We have three sets of price elasticities: output supply, variable input demand, and crop area. All own-price elasticities have the correct sign, i.e., both corn and soybean supply elasticities are positive, and all variables input demand elasticities are negative. The crop acreage demand elasticities have a positive sign for their own-output price. Overall, the coefficients reflect the patterns of those in tables 3.2 and 3.3. The estimated elasticities could be considered somewhat small (or mostly inelastic) but indicate crop supply responses to prices that are not unreasonable given the RFS mandates. The own-price elasticity of corn supply implies that if the corn price were to double due to the RFS mandates, corn output would rise by about 87%. Own price elasticities of inputs and for crop area are generally inelastic. Due to the RFS mandates, a doubling of corn prices would raise the land devoted to corn production by approximately 59%.[53] With these price elasticities, specifically for corn supply ($\epsilon_{corn}^{Yp} \approx 0.87$) and corn land $\epsilon_{corn}^{lp} \approx 0.59$, we approximate the corn yield price elasticity using equation (18) as $\epsilon_{corn}^{yp} = \epsilon_{corn}^{Yp} - \epsilon_{corn}^{lp} \approx 0.87 - 0.59$. The estimated corn yield price elasticity so calculated is approximately 0.28.

We find positive and statistically significant estimates for the corn price effects on corn biomass supply and acreage demand. Our findings show that the corn biomass supply response to increases in relative corn price (RFS-induced or otherwise) reflects changes at the extensive margin, increasing the demand for cropland producing corn, and the intensive margin that increases yields (output per acre). Moreover, the results indicate that the corn supply and area planted are price inelastic, which means that quantity supplied and corn acreage both increase by smaller percentages than relative corn price increases. Column (1) of Table 3.2 shows that the average biomass supply of corn would have increased by more than 1.8 million metric tons per county and year in response to the observed corn price increases caused by the RFS requirements reported in Table 3.4. The annual acreage demand for corn response to the corn price increases since the 2007's RFS mandates (see

[53] However, note that the relatively small own-price elasticities for crop acreages may be so since a large area is already devoted to corn (and soybeans) production. A doubling of corn prices would still significantly reduce the land devoted to other crops in the region by more than 100%.

Table 3.4 for this price increase) is approximately 32 thousand acreages per county. Finally, using the results in Table 3.5, we break down the total corn biomass supply increase caused by the mandates-induced corn price rise (reported in the first-stage regression in Table 3.4) as 30% due to yield increase (intensive margin) and 70% to acreage expansion (extensive margin). Thus, corn yields are less responsive to corn price changes than the area planted with corn in the analyzed region.

These results are consistent with some previous studies estimating agricultural supply response to price changes induced by the RFS. (see, e.g., Hendricks *et al*., 2014; Mochini *et al*., 2017; Kim and Mochini, 2018). Berry (2011) provides an extensive review of existing empirical evidence on yield elasticities that shows that previous work reveals that virtually all of the crop supply response comes from acreage response, not from a yield response. Our results imply that corn supply translates into both land allocation and yield responses. Corn acres are more elastic than corn yields to the exogenous price variations associated with the implementation of the RFS after 2007.

3.5. Conclusions

We investigated the effect of crop and variable inputs prices and environmental and policy variables on corn, soybeans, and other crop yields and acreage in the US Midwest using a panel dataset for the 1969–2017 period. More specifically, this paper explores the extent to which the corn price effects induced by a policy in the energy market also affected corn biomass supply and crop acreage demands. These effects translate into elasticities at the intensive and extensive margins of agricultural land use of crops produced at the county level. A profit function model is specified to represent agricultural decision-making units in the region. We use a two-stage profit maximization approach with land assumed fixed but allocatable for crop production. Crop acreage demands are estimated jointly with output supply and variable input demand equations using a normalized quadratic functional form and county-level panel data from the region over 49 years. Simultaneous equations panel model is adopted to analyze land use and crop yield responses to exogenous output prices changes using the 2007's Renewable

Fuel Standard. Through this policy, the US federal government mandates specific quantities of total biofuels and ethanol from starchy crops, i.e., essentially corn. The corn price effects of these mandates are assumed to create exogenous market shocks to the supply of corn in several counties along the US Great Plains. Our results show that the corn biomass supply and the demand for land to produce corn have grown because of the price increases induced by such mandates. For each 1% increase in corn price due to the RFS, the corn biomass quantity supplied increases by about 0.87%. This change occurs because the counties in the region allocated more land to corn production and partly because they produced more corn per land unit. Of the increase in corn biomass supply caused by the mandates, 62% is due to policy-induced price-yield increase, and 38% is because of policy-induced price-acreage expansion. Response to the RFS thus occurs primarily at the intensive margin. These findings have important implications for future policies on promoting renewable energies combined with economic policies. The results of this analysis might have a crucial external validity because the climatic and hydrologic ranges observed in the analyzed area may be representative of other important temperate regions of the world. The main contribution of this paper is to provide some insights into the current discussion on the implications of the US RFS for the agricultural commodity markets, productivity analysis of agricultural production, and to a certain extent, the environmental consequences of this type of policy.

Table 3. 1 – Summary Statistics, 101 41st Parallel Counties, 1969-2017

Variables	Units	Mean	Min	Max	Std. Dev.
Corn Biomass (Q-Corn)	Metric tons	652,207.1	0.00	2,293,663	410,756.17
Soybeans Biomass (Q-Soy)	Metric tons	146,977.3	0.00	670,914	130,053.89
Other Crops Biomass (Q-Ocrops)	Metric tons	116,485.9	0.00	1,309,579	145,127.64
Corn Planted Area (A-Corn)	Acres	112,142.4	0.00	279,700	56,089.62
Soybean Planted Area (A-Soy)	Acres	56,933.4	0.00	232,000	45,249.15
Other Crops Planted Area (Q-Ocrops)	Acres	99,126.8	0.00	1,356,010	161,140.21
Total Cropland (Land)	Acres	268,202.7	1,250	1,008,710	95,148.89
Fertilizer	Index	3.17	0.08	10.83	1.61
Chemicals	Index	9.61	0.12	39.32	6.57
Labor	Workers	1,084	0.20	11,662	1,019.28
Capital	Machines	34,578.1	8,251	147,584	8,446.43
Price of Corn (P-Corn)	1969 dollars per metric ton	1.13	0.40	2.43	0.28
Price of Soybeans (P-Soy)	1969 dollars per metric ton	2.48	0.00	5.76	0.92
Price of Other Crops (P-Ocrops)	Numeraire	−	−	−	−
Price of Fertilizer (P-Fertilizer)	Index	0.03	0.01	0.08	0.01
Price of Chemicals (P-Chemicals)	Index	0.02	0.01	0.06	0.01
Wages	1969 dollars per worker	47,005.3	107.34	47,8045	44,650.44
Price of Capital (P-Capital)	Index	0.05	0.01	0.13	0.02
Irrigated acres fraction	Fraction	0.20	0.00	0.91	0.27
$DD(0\ to\ 30)$	24 hour days	165.37	132.23	178.83	5.84
$DD(31\ to\ 34)$	25 hour days	4.03	0.14	12.78	2.32
$DD(35+)$	26 hour days	0.16	0.00	3.55	0.29
Precipitation	Centimeters	52.09	9.48	125.21	16.62

Table 3. 2– 3SLS estimation of the output supplies and derived input demands from the system of equations in (19) and (20)

	Dependent Variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Q-Corn	Q-Soy	Q-Ocrops	Q-Fertilizer	Q-Chemicals	Labor	Q-Capital
P-Corn	1904.029	533.4238	-968.937	639.286	3729.535	-0.0535	3.8395
	[130.6268]***	[103.9753]***	[211.9889]***	[97.1311]***	[208.7567]***	[0.0862]	[1.8365]**
P-Soy	533.4238	222.1666	105.7722	464.2425	1960.337	-0.1145	6.9825
	[103.9753]***	[302.7588]	[548.9199]	[149.9761]***	[168.3306]***	[0.0326]***	[3.6258]*
P-Fertilizer	639.286	464.2425	485.6729	-1036.06	-152.505	0.129	42.099
	[97.1311]***	[149.9761]***	[333.4057]	[234.0583]***	[207.1736]	[0.0435]***	[4.4396]***
P-Chemicals	3729.535	1960.337	-1292.76	-152.505	-9012.08	-0.0232	1.9971
	[208.7567]***	[168.3306]***	[607.3453]**	[207.1736]	[646.7977]***	[0.1452]	[10.1346]
Wages	-0.0535	-0.1145	0.0256	0.129	-0.0232	-0.0004	0.0023
	[0.0862]	[0.0326]***	[0.0394]	[0.0435]***	[0.1452]	[0.0002]*	[0.0005]***
P-Capital	3.8395	6.9825	6623.252	42.099	1.9971	0.0023	-3372.57
	[1.8365]**	[3.6258]*	[27688.0043]	[4.4396]***	[10.1346]	[0.0005]***	[459.5165]***
Land	0.0024	0.0006	0.0006	0.0012	0.0037	0.0035	0.051
	[0.0000]***	[0.0000]***	[0.0000]***	[0.000047]***	[0.0001]***	[0.0001]***	[0.015]***
Irrigation	726.4833	-54.9756	-37.2622	189.879	280.2434	0.8495	-0.6408
	[15.9702]***	[5.6589]***	[7.0382]***	[9.4052]***	[31.0073]***	[0.0670]***	[0.1187]***
$DD(0\ to\ 30)$	-12.577	0.7842	0.0255	0.9504	2.6894	-0.0003	0.0018
	[2.1340]***	[0.2121]***	[0.2610]	[0.2879]***	[0.9584]***	[0.0012]	[0.0035]
$DD(31\ to\ 35)$	-0.0036	6.9765	-4.9472	-1.2675	-14.8255	-0.0048	0.0353
	[0.0003]***	[0.7782]***	[0.9661]***	[1.0755]	[3.5537]***	[0.0047]	[0.0131]***
$DD(35+)$	-5.5445	-46.4187	15.7536	19.1999	115.5497	0.0412	-0.1748
	[16.6184]	[6.1645]***	[7.5070]**	[8.4135]**	[27.9137]***	[0.0341]	[0.1015]*
Precipitation	1.4722	0.9096	-0.8544	0.222	1.2629	-0.0007	0.0026
	[0.2442]***	[0.0911]***	[0.1175]***	[0.1227]*	[0.4047]***	[0.0005]	[0.0015]*
Time	9.2699	4.3102	-2.1193	2.5832	27.8136	-0.0257	-0.0328
	[0.2884]***	[0.1404]***	[0.2487]***	[0.2044]***	[0.4829]***	[0.0006]***	[0.0036]***

Standard errors are in brackets.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 3. 3 – 3SLS estimation of the crop area equations from the system in (21)

	Dependent Variable:	
	(1)	(2)
	A-Corn	A-Soy
P-Corn	32.7319	3.9688
	[2.9610]***	[2.5782]
P-Soy	3.9688	24.3586
	[2.5782]	[5.8932]***
P-Fertilizer	-78.357	-45.6191
	[7.9224]***	[6.7360]***
P-Chemicals	119.7935	6.2592
	[17.7440]***	[14.5540]
Wages	-0.0011	-0.0041
	[0.0013]	[0.0011]***
P-Capital	-2815.18	3812.579
	[792.1089]***	[633.6176]***
Land	0.00004	0.00002
	[0.0000004]***	[0.0000003]***
Irrigation	9.424	-1.9928
	[0.2626]***	[0.2041]***
$DD(0\ to\ 30)$	-0.0039	0.1538
	[0.0086]	[0.0255]***
$DD(31\ to\ 35)$	-0.1788	-1.0427
	[0.0318]***	[0.2003]***
$DD(35+)$	1.2075	-1.0438
	[0.2473]***	[0.2003]***
Precipitation	0.0188	0.0218
	[0.0036]***	[0.0029]***
Time	0.0872	0.1277
	[0.0070]***	[0.0057]***

Notes: Both output prices (P-Corn and P-Soy) and variable input prices (P-Fertilizer, P-Chemicals, Wages, and P-Capital) are real values relative to P-Ocrops in 1969. Standard errors are in brackets. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 3. 4 – First-stage estimation results of equation (23)

	Dependent Variable: P-Corn		
	(1)	(2)	(3)
RFS-Shock (ζ)	0.0014 [0.0001]***	0.001 [0.0001]***	0.0008 [0.0001]***
Time	-0.0002 [0.000024]***	-0.0002 [0.000025]***	-0.0003 [0.000029]***
Irrigation		-0.025 [0.0032]***	0.0245 [0.0015]***
$DD(0\ to\ 30)$		0.0008 [0.0001]***	0.0007 [0.0001]***
$DD(31\ to\ 35)$		0.002 [0.0002]***	0.002 [0.0003]***
$DD(35+)$		0.003 [0.0016]*	-0.0045 [0.0020]**
Precipitation		0.0005 [0.000024]***	0.0005 [0.000026]***
Constant	0.1039059 [0. 0030342]***	-0.0441 [0.0100]***	-0.0362 [0.0115]***
County Dummies	✓	✓	
Observations	4,824	4,824	4,824
R^2	0.717	0.719	0.717

Notes: P-Corn is in real values of corn price relative to P-Ocrops in 1969. The variable RFS-Shock (ζ) is in thousands of barrels of fuel ethanol. Standard errors are in brackets.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 3. 5– Output Supply and Variable Input Demand Elasticities, and Cropland Response Elasticities

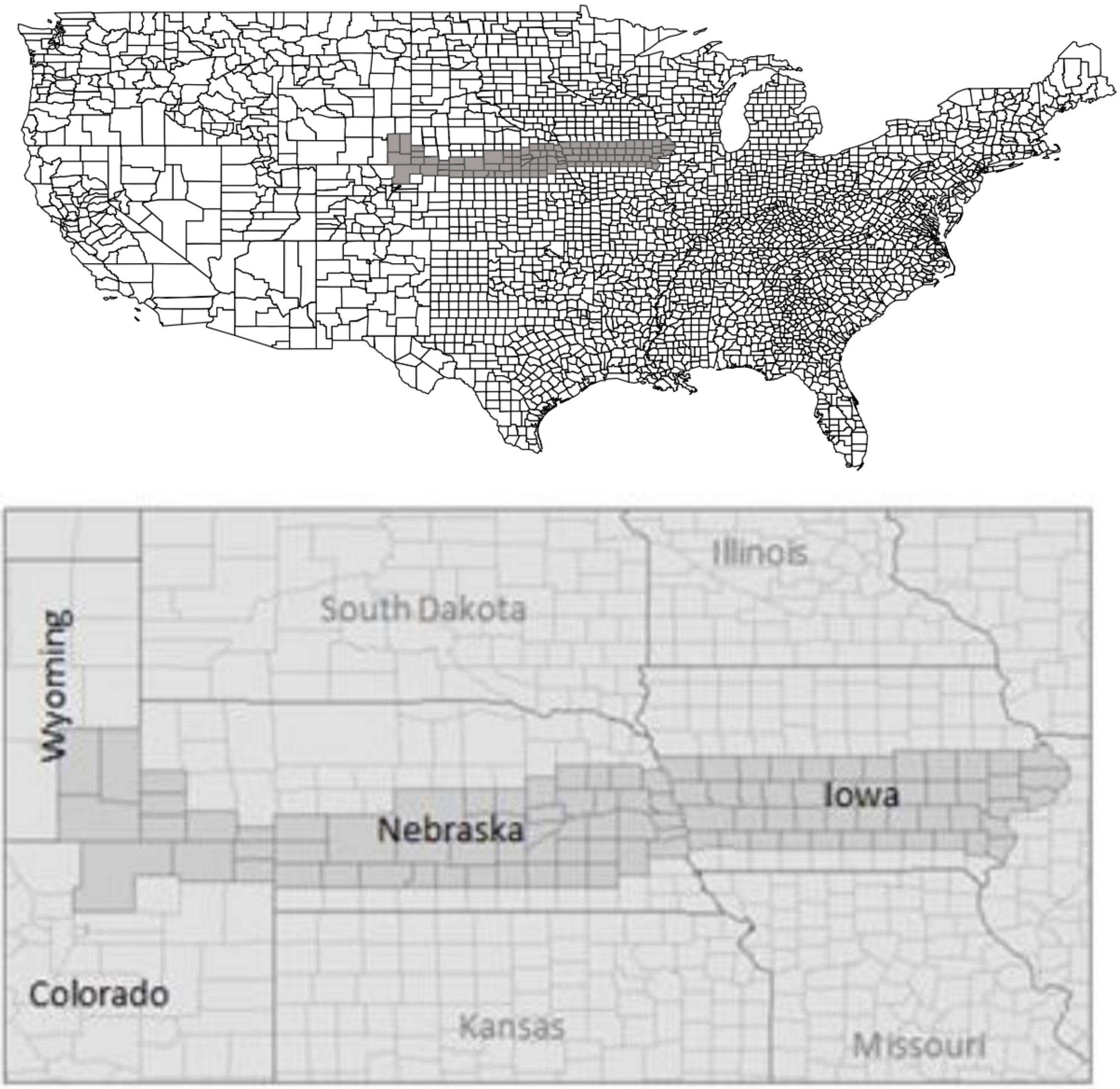
	P-Corn	*P*-Soy	*P*-Fertilizer	*P*-Chemicals	Wages	*P*-Capital	Land
Q-Corn	0.8737972	0.0386937	0.0705223	0.3335907	-0.0082814	6.3E-06	2.050
	[0.0599472]***	[0.008]***	[0.011]***	[0.019]***	[0.013]	[3.1E-06]**	[0.029]***
Q-Soy	0.8411733	0.035	0.151	0.561	-0.040	0.0003	1.704
	[0.0075422]***	[0.113]	[0.049]***	[0.048]***	[0.012]***	[0.0002]**	[0.037]***
Q-Ocrops	-1.536	0.431	0.302	-0.204	0.017	-0.633	1.065
	[0.186]***	[0.106]***	[0.082]***	[0.116]*	[0.105]	[0.951]	[0.026]***
Fertilizer	0.338	0.050	-0.153	-0.015	0.026	9.3E-05	1.072
	[0.051]***	[0.016]***	[0.034]***	[0.022]	[0.009]***	[9.7E-06]***	[0.015]***
Chemicals	0.869	0.092	-0.008	-0.418	-0.003	2.1E-06	1.552
	[0.049]***	[0.008]***	[0.012]	[0.030]***	[0.011]	[8.9E-06]	[0.023]***
Labor	-0.021	-0.010	0.020	-0.003	-0.114	4.5E-06	-0.667
	[0.035]	[0.003]***	[0.007]***	[0.012]	[0.066]*	[1.0E-06]***	[0.116]***
Capital	0.130	0.055	0.438	0.018	0.035	-0.539	0.045
	[0.063]**	[0.028]**	[0.046]***	[0.077]	[0.008]***	[0.073]***	[0.014]***
A-Corn	0.5866567	0.013697	-0.3822133	0.4406773	-0.0078322	-0.2072531	1.328326
	[0.053]***	[0.009]	[0.039]***	[0.065]***	[0.009]	[0.058]***	[0.017]***
A-Soy	0.101	0.158	-0.263	0.032	-0.028	0.326	1.007
	[0.071]	[0.038]***	[0.039]***	[0.073]	[0.007]***	[0.054]***	[0.020]***
A-Other Crops	-1.900	0.195	1.130	-0.840	0.045	-0.006	1.689
	[0.101]***	[0.034]***	[0.077]***	[0.140]***	[0.013]***	[0.112]	[0.027]***

Source: Own computations.

Notes: Elasticities are computed at the sample mean values of the variables from Table 3.1 and using coefficient estimates taken from Tables 2 and 3; numbers in brackets are standard errors calculated with the delta method provided by Papke and Wooldridge (2005). Output prices (*P*-Corn and *P*-Soy) and variable input prices (*P*-Fertilizer, *P*-Chemicals, Wages, and *P*-Capital) are real values relative to *P*-Ocrops in 1969.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure 3. 1– Selected Counties along the 41st Parallel



Source: Elaborated based on Trindade *et al.* (2011).

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