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THERE WILL BE BLOOD: THE IMPACT OF DRUG TRAFFICKING ON VIOLENCE AND ECONOMIC WELL-BEING

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THERE WILL BE BLOOD:
–The Impact of Drug trafficking on Violence and Economic Well-being– *

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Abstract

This paper examines the impact of illicit drug markets on violence and economic well-being, focusing on the case of the cocaine trade in Colombia between 2011 and 2021. We construct a network of cocaine trafficking routes from coca-growing areas to exit points and identify the municipalities located in the proximity of these routes. By leveraging temporal changes in coca cultivation, we induce variation in exposure to cocaine trafficking along the routes. Our identification strategy exploits the quasi-experimental setting provided by the unanticipated announcement in 2014 of a governmental crop-substitution program (PNIS), which led to a sizable increase in coca production. We find a significant positive effect of the amount of cocaine trafficked on the homicide rate along the routes, while we find no significant impact on economic well-being, proxied by nighttime light intensity. The effect on violence is strongest in municipalities with multiple competing criminal organizations and in areas closer to a route's origin or endpoint, as well as in departmental capitals. These results highlight the importance of considering trafficking routes and export nodes when evaluating drug policy. Accordingly, cocaine supply-reduction policies might help achieve a substantial reduction in drug-related violence while imposing no net economic cost on the general population.

Keywords: Colombia, Drug trafficking, Violence.
JEL Codes: H50, P35, O13.

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1 Introduction

The threat and use of violence stand out as prominent features of illicit markets, with drug markets serving as prime examples. Indeed, as often portrayed in popular fiction, criminal actors engage in conflicts to secure dominance both within the production hubs and throughout the downstream distribution networks of illegal substances.

Supply shifts, such as those generated by governmental policies aimed at curbing production, can result in substantial changes in the availability of drugs for illicit trade, thereby impacting profitability and the incentives that drive criminal organizations to use violence. Nevertheless, the direction of the causal link between the volume of drug trade and violence remains a subject of debate. On the one hand, a larger amount of traded drugs increases the total market size to be shared among contenders, therefore reducing the incentive to exert violence against opponents. On the other hand, a larger amount of traded drugs might imply higher returns from exerting violence to defeat competitors and gain control over the market.

Additionally, while the quantity of illegal substances undoubtedly influences the degree of profitability associated with the trade business for criminal organizations, it is still unclear whether there are broader economic impacts. In particular, do the huge profits from the drug trade have any cascade effect on the economic conditions of the rest of the population?

Understanding both the dynamics of violence and the economic impacts in the context of the illegal drug trade is hence of crucial importance, in particular to inform the ongoing global debate on the effectiveness of public policies to combat crime. If the availability of drugs for trade were to increase violence while also having positive economic spillovers, policies intended to curb the volume of trafficking might pose a critical trade-off between violence reduction and the improvement of the economic conditions of the population.

This paper studies the effect of exposure to drug trafficking on both violence and economic well-being by focusing on the case of the cocaine trade in Colombia. Colombia represents an ideal setting because of its long-standing role as a hub for the cultivation of coca, the primary input in cocaine production, and for the export of the refined product to international markets. While small farmers in rural areas primarily sustain coca cultivation, narcotraffickers are responsible for the refinement and export of cocaine, with the latter activities constituting up to 75% of the market's added value (Mejía and Rico, 2010).

We employ highly granular data provided by the United Nations Office on Drugs and Crime (UNODC) on coca cultivation and construct a network of trafficking routes connecting coca-growing areas to the nearest major exit point via roads or waterways. We then identify the municipalities located in the vicinity of the trafficking routes. Because the quantity of cocaine passing through the routes cannot be directly measured, we rely on a predicted measure of a municipality's exposure to drug trafficking. This is derived by aggregating the hectares of coca cultivated at the origin points of the routes. Leveraging the variability in the production of coca in the growing areas, we induce variation at the intensive margin in the exposure to drug trafficking for municipalities along the routes and assess its impact on homicide rate and nighttime light intensity (Zhao et al., 2022), which we adopt as a proxy for economic activity (Henderson et al., 2012; Pérez-Sindín et al., 2021).

We consider the period between 2011 and 2021, during which a series of governmental interventions significantly altered the amount of coca grown over time, causing an unprecedented surge in the supply of the main input in cocaine production and, consequently, in the profitability of narcotraffickers' core business. Specifically, we leverage the quasi-experimental setting provided by the unanticipated announcement of PNIS, a governmental program designed to encourage coca farmers to transition to alternative legal crops. As documented by Prem et al. (2023), the announcement of this policy led to a significant increase in coca production, starting from 2014, particularly in areas with higher suitability for cultivation. Our identification strategy hinges on this policy shock to construct an instrumental variable for the quantity of cocaine produced in cultivation areas and subsequently trafficked along the routes. This approach mitigates the potential endogeneity stemming from unobserved time-varying local factors that may simultaneously influence both coca production in cultivation areas and outcomes along trafficking routes. Furthermore, to specifically assess the influence of cocaine trade rather than coca cultivation, we focus solely on municipalities that have never had a history of coca cultivation at any point during the period under investigation. Therefore, our estimation samples include non-coca-growing municipalities that are located at any point in time along our network of predicted trafficking routes.

Our results consistently reveal a positive and significant effect of exposure to cocaine trafficking on violence, measured by homicide rate per 100,000 inhabitants. These results remain robust even after controlling for a wide range of municipality-level variables at the baseline. Two-stage least squares (2SLS) estimates indicate that a 1% increase in trafficked cocaine raises the homicide rate by 0.066 per 100,000 inhabitants. Given the 42.1% average annual growth in trafficked cocaine since 2014, this effect translates to approximately 2.3 additional homicides per 100,000 inhabitants annually or 10.22% of the sample mean homicide rate.

The violent response to cocaine trafficking is highly heterogeneous across municipalities, highlighting the importance of local criminal market structures and geographic factors. The effect is strongest in municipalities with multiple competing criminal organizations, consistent with the idea that greater competition or fractionalization within the criminal ecosystem may generate stronger incentives to use violence. In contrast, municipalities where a single dominant criminal organization operated before the policy shock exhibit a much weaker effect, suggesting that monopolized trafficking routes reduce the need for violent enforcement. Proximity to strategic nodes along trafficking routes amplifies the intensity of violence: municipalities located nearer to a route's origin or endpoint, and to departmental capitals experience substantially greater impacts. This pattern reflects the heightened strategic value of these areas for controlling trafficking corridors. In addition, departmental capitals tend to be more populous and constitute sizable markets for domestic consumption.

To account for the possibility that narcotraffickers opt for alternative routes rather than the network of shortest routes identified in our analysis, we examine whether alternative sets of trafficking routes yield similar results to our baseline findings. We do so by performing a sequence of 10,000 iterations of placebo estimates where our predicted measure of trafficked cocaine is randomly reshuffled across municipalities within the same year and department. The placebo estimates never replicate our baseline findings based on the network of shortest routes.

Conversely, cocaine trafficking has no significant impact on average municipality nighttime light intensity. This suggests that cocaine trafficking may have a negligible net effect on economic prosperity in the areas along the routes. According to these results, policies intended to limit the supply of cocaine might help achieve a substantial reduction in incentives for drug-related violence while imposing no net economic cost on the general population.

Our study contributes to the literature analyzing the role of criminal organizations within illicit markets, and in particular drug markets, and the implications in terms of violence and spillover effects on the rest of the economy. Building upon the framework established by Becker (1968) in his seminal work on crime, scholars have developed a solid theoretical foundation for understanding the behavior of individuals involved in criminal networks. In line with this framework, scholars agree that drug trafficking organizations (DTOs) employ violence to gain a larger market share or deter the entry of new gangs (Fiorentini and Peltzman, 1997; Donohue and Levitt, 1998; Kugler et al., 2005; Ballester et al., 2006, 2010; Castillo and Kronick, 2020). Additionally, drug dealers compete through violent means to control trafficking routes in regional oligopolies (Echandía, 2013; Mejia and Restrepo, 2016).

Empirical studies provide valuable insights into the link between illegal markets and violence. For instance, Angrist and Kugler (2008) find that the expansion of coca paste production in Colombia, after the interdiction of air-bridges from Peru and Bolivia in the 1990s, resulted in modest economic gains but a significant increase in violence in rural regions. The authors highlight that natural and agricultural resources with substantial black market value, such as coca, opium, and diamonds, are particularly prone to exploitation during civil conflicts. This pattern extends beyond drug markets, as evidenced by Chimeli and Soares (2017), who study the use of violence in Brazil following the declaration of illegal status for the mahogany trade. Similarly, Rigterink (2020) show how variations in the price of labor-intensive, lootable natural resources like diamonds can lead to heightened violence in resource-abundant areas. Berman et al. (2017) document a positive association between mining activities and local-level conflict in Africa, with the historical rise in mineral prices accounting for a significant portion of the average violence levels across African countries.

Nonetheless, the focus has primarily been on studying producing areas and assessing how resource abundance and profitability impact conflict and the well-being of populations in those regions. Due to data limitations on trafficking, limited empirical evidence has been provided on the violent dynamics and economic impact of criminal networks within the context of trafficking routes. Neglecting to consider the spillover effects in regions where illicit resources are trafficked might lead to an underestimation of the broader effects and toll of illicit markets. Dell (2015) is the first paper to analyze the dynamics of violence along trafficking routes within the context of the war on drugs during the 2000s in Mexico, where narcos transport either drugs produced locally (heroin and marijuana) or South American cocaine to the US. The study shows that close municipal victories of President Calderón's PAN party, strongly committed to dismantling the drug trade, led to crackdowns that weakened incumbent organizations and spurred violence between competing narcos. Furthermore, in an approach that strongly inspires our analysis, the paper considers a network of optimal trafficking routes that connect drug production areas and US entry points while avoiding municipalities administered by PAN mayors, where the higher likelihood of crackdowns could impose a fatal cost for the drug trade. The panel results reveal that municipalities suddenly crossed by the predicted trafficking routes, because of a PAN mayor victory in surrounding areas, experienced higher drug confiscations and homicides, thus suggesting a substantial geographical diversion of the drug trade due to crackdowns.

More recently, Millán-Quijano (2020) investigates the relationship between fluctuations in international cocaine prices and violence in municipalities located on trafficking routes in Colombia between 1994 and 2009. More in detail, the author exploits changes over time in cocaine prices between the US and Europe and internal variation in the comparative geographical advantage of serving the two distinct international markets. The study finds a positive association between cocaine prices in geographically connected international markets and the local homicide rate.

We make a novel contribution to this strand of literature by jointly analyzing the impact of exposure to drug trade on violence and well-being along the trafficking routes in Colombia during a crucial period, the years from 2011 to 2021, marked by an unprecedented surge in coca cultivation. While the identification strategy in Millán-Quijano relies on changes in international cocaine prices, which might be endogenously influenced by the local illicit market structure, we exploit the quasi-experimental setting generated by the announcement of the PNIS substitution program (Prem et al., 2023) that resulted in a plausibly exogenous variation in the supply of coca and the profitability of the cocaine trade. Finally, our analysis intends to provide meaningful policy implications regarding the control of a local market factor – the supply of coca – which is allegedly under the more direct influence of Colombian policymakers.

This paper is structured as follows. In Section 2, we offer a historical overview of coca production and cocaine trafficking in Colombia, as well as of the public policies implemented by the Colombian government to combat crime. Section 3 describes the various data sources utilized in this study and the construction process of the network of predicted cocaine trafficking routes. Section 4 outlines our empirical strategy and addresses the econometric challenges associated with assessing the impact of drug trafficking. Section 5 reports our main empirical findings on the impact of drug trafficking on violence and well-being. Finally, Section 6 concludes the paper by summarizing the key findings and discussing their potential implications.

2 Background

Colombia emerged during the 1980s as the worldwide leading producer of coca, with small farmers predominantly responsible for its cultivation and processing into coca paste.[1]

[1]Until the beginning of 1990s, Peru and Bolivia were the main production hubs for both coca leaves and paste, which were subsequently ferried, mostly by small planes, to Colombia where cocaine used to be refined and exported abroad. The considerable shift of coca cultivation to Colombia occurred after 1992, when military efforts by Peruvian and Bolivian authorities, in collaboration with US forces, disrupted these cross-border air bridges. For a more thorough description of the events that led to the displacement of the

This period witnessed the rise of the notorious Colombian drug cartels - first Medellín, followed by Cali and Norte del Valle - which played pivotal roles in cocaine refining and export. The dismantling of these organizations, which operated in the drug trade on a large scale both within and outside Colombia, led to the fragmentation of power among numerous small criminal gangs, often referred to as BACRIM, which became mostly involved in the domestic drug trafficking up to export points. In contrast, foreign criminal organizations took over the operations targeting international destination markets (Echandía, 2013). Furthermore, beginning in the late 1990s, the Colombian government, with the support of the United States of America, implemented a variety of policies aimed at reducing coca cultivation and drug trafficking. Aerial eradication of coca crops through fumigation with glyphosate, an herbicide, had been one of the pillars of the war on drugs carried out by the National Police with the support of the US Drug Enforcement Administration (DEA). These operations were extensively carried out throughout the first decade of the century and potentially contributed to the sizable drop in coca cultivation between 2000 and 2013 (Figure 1).

However, coca cultivation again surged from 2014 onward, leading to an all-time production record in 2018, with an estimated 171,000 hectares planted, accounting for more than 85% of the total cultivation in the South American region. The remaining coca cultivation was concentrated in Peru and Bolivia and remained stable over the same period.[2] Two major changes in the policy and operational framework of Colombia's war on drugs are the main suspects behind such an unprecedented surge. First, national and local governments implemented a series of policies aimed at favoring the transition from coca to alternative and legal crops. The most relevant was the Comprehensive National Program for the Substitution of Crops for Illicit Use (PNIS). This program involved the provision of economic incentives to coca farmers to transition from growing coca to cultivating alternative legal crops. Notably, this policy garnered considerable attention due to its unanticipated announcement in May 2014, coinciding with the peace negotiation process between the Colombian government and the Revolutionary Armed Forces of Colombia (FARC). Second, a decision in 2015 by the Colombian Constitutional Court imposed a ban on aerial fumigation with glyphosate because of concerns about its environmental impact.

According to Prem et al. (2023), the unexpected announcement of the PNIS in 2014 significantly fueled the surge in coca cultivation. The expectation of higher financial gains and impunity offered farmers the incentives to grow more or switch to growing coca, thus

bulk of coca cultivation to Colombia during the 1990s (see Angrist and Kugler (2008)).

[2]Neither Peru nor Bolivia experienced a comparable surge in coca cultivation to that of Colombia during the same period, suggesting that there was no concurrent increase in international demand for cocaine.

contributing to the boom.[3] The authors rule out the overlapping 2015 ban on fumigation as a confounding factor, as the impact of the PNIS announcement remains significant even after considering exposure to aerial fumigations prior to 2014 as a control variable.[4] In essence, the PNIS announcement acted as a catalyst for increased coca cultivation, driven by the expectation of financial incentives for farmers.

3 Data

The analysis relies on very granular information on coca cultivation, which is obtained from satellite imagery and estimated annually by the Integrated Monitoring System of Illicit Crops (SIMCI). The program is operated by the UN Office on Drugs and Crime (UNODC). We use the data from SIMCI covering the period from 2011 to 2020, which provides the number of hectares of coca cultivated per 1 km^2 grid-cell.[5] Panel A of Table 1 shows that around 10 percent (slightly less than 115,000 out of approximately 1.150 million) of all grid cells in Colombia had coca cultivation at some point in the period under consideration. The geographical distribution of coca crops is displayed in Figure 2. Among the grids where coca cultivation occurred at least once between 2010 and 2021, the average cultivated area was approximately 0.96 per 100 hectares.

We employ a municipality measure of coca suitability developed by Mejia and Restrepo (2016). This is based on information gathered from various rounds of a nationally representative household survey of coca farmers conducted by SIMCI/UNODC between 2005 and 2010. The survey sample consists of 1,678 farmers from 64 municipalities throughout the country, randomly selected using satellite estimates to identify where coca crops were located. The survey provides self-reported data on coca crop yields, integrated with exogenous geographic and climatic variables at the municipal level to estimate an index of each municipality's suitability for coca growing. Altitude, soil erosion, and aptitude indexes, minerals, geography, and average rainfall levels are among these features. The

[3] Although the PNIS was announced in 2014, its actual implementation did not take place until 2017. Cash transfers from the Colombian government, a key component of the program, began in 2017, offering financial support to participating farmers.

[4] More in detail, Prem et al. demonstrate that exposure to the PNIS announcement significantly influenced coca cultivation, even when accounting for the hectares of coca eradicated by aerial fumigation before 2014. This suggests that the PNIS announcement had a distinct impact on coca cultivation beyond any effects of fumigation exposure prior to 2014. However, these findings do not conclusively rule out the possibility of an independent or concurrent role of the 2015 ban on fumigations in the surge of coca cultivation, which warrants further investigation.

[5] It should be noted that the estimation of coca hectares is conducted on an annual basis, specifically on December 31 of each year. For the purposes of this analysis, we treat the observation on coca produced in year $t-1$ as the contemporaneous situation in year t.

suitability index is normalized to zero and ranges from -1.57 to 3.01 (see Table 1). For the purpose of our analysis, we follow the procedure in Prem et al. (2023) and derive a 1 km^2 grid-cell level measure of coca suitability.[6]

To evaluate the effect of the increase in illegal drug cultivation in the municipalities along the predicted drug trafficking routes, we use publicly available data on crime statistics from 2012 to 2021 provided by the Colombian Ministry of Defence. These include information on crimes such as homicide, lesions, theft, terrorism, and domestic violence. The nature, date, and municipality of each crime are provided. To assess the impact of drug trafficking on violence, we will exclusively focus on the number of homicides per municipality.[7] As indicated in Panel B of Table 1, municipalities situated along drug trafficking routes exhibit a higher average level of violence. Across all municipalities in Colombia, the homicide rate is 25.5 per 100,000 inhabitants. However, when focusing on the subset of municipalities located along drug trafficking routes, the average homicide rate slightly increases to 31.08 per 100,000 inhabitants.

Moreover, we employ the municipality average of the nighttime light intensity, captured through remote sensing, as a proxy of economic well-being (as suggested by Pérez-Sindín et al. (2021)). In particular, we utilize the nighttime light (NTL) dataset compiled by Zhao et al. (2022), which combines and standardizes data from NOAA's Visible Infrared Imaging Radiometer Suite (VIIRS) and Defense Meteorological Satellite Program (DMSP) (Elvidge et al., 2021). These data are represented as Digital Numbers, ranging from zero (representing the darkest value) to 63 (representing the brightest value) (see Table 1), and they do not possess an inherent interpretation in terms of radiance values.

Lastly, we gather several municipality-level variables that we add as controls to test the robustness of our results. This group includes economic indicators in the baseline period, such as population, the Multidimensional Poverty Index, the share of employment in agriculture, and the distance from the departmental capital, all sourced from DANE. Moreover, we employ the Data on Violent Presence of Armed Actors (VIIPA, Osorio et al., 2019), which reports violent activities by municipality, year, and type of armed actor involved (criminal organizations; paramilitary; insurgents; government). We use this information to define the number of criminal gangs involved in violent activities between

[6]We first consider 19 bioclimate variables at the 1 km^2 grid-cell level from wordclim.org and take their average between 1984 and 2013. We then train a random forest algorithm with the municipality-level measure of suitability as outcome and the 19 bioclimate variables as predictors. We performed 100,000 simulations, and for each predictor, we consider the average of the estimates across all iterations. Finally, we use these results to assign to each grid cell a predicted measure of coca suitability based on the corresponding values of the 19 bioclimate variables.

[7]Estimates with other types of crime as outcome yield no significant impact of drug trafficking. These results are available on request.

2000 and 2010, before the period under observation.

Table 2 reports descriptive statistics for these municipality-level control variables for all municipalities intersecting the predicted trafficking routes and excluding coca-growing areas. The table also includes the distances to the closest origin and endpoint of the predicted trafficking routes, computed along the optimal network described in Section 3.1.

3.1 A network of optimal routes for cocaine traffic

To examine the effects of trafficked cocaine along the drug routes, we build a network of optimal routes for cocaine trafficking by connecting coca-growing areas to the nearest country's main exit point and we identify the municipalities located in the vicinity of trafficking routes. We then leverage the variability of coca production in the growing areas to induce variation in the exposure to drug trafficking for municipalities along the routes.

More in detail, we first resort to UNODC data on coca cultivation at 1 km^2 cell level and pick all those cells where at least once between 2011 and 2020 a positive amount of coca was grown (1.3 million cells) (see Figure 2). Because of computational limitations, we group the coca-growing cells into $J = 1000$ clusters, with the largest one having a 15 km^2 area (see Figure 3). Secondly, we consider a group of sixteen Colombian main exit points and the entire network of roads and rivers from the most updated version of OpenStreetMap (2023) (see Figure 4). The latter is used to draw 1000 optimal routes that represent the shortest connections, either by road or by river, between each coca-growing cluster j and one of the sixteen exit points (see Figure 5). The lengths of the routes range from 8.7 km to 1,406 km. The average length of the routes is 449 km (see the descriptive statistics in Panel C of Table 1). Since coca bushes are principally located in rural areas lacking infrastructure, drug routes mainly start from small rivers or secondary roads.

Next, we identify all the municipalities located within 1 km buffer from every trafficking route (see Figure 6). We determine for each origin cluster j the set $\tilde{\boldsymbol{j}}$ including all the municipalities lying on the corresponding trafficking route. Finally, we predict the amount of cocaine trafficked through municipality m as follows:

$$\widehat{Cocaine}_{mdt} = ihs(\sum_{j=1}^{J=1000} Coca_{jt} \times \mathbb{1}\{m \in \tilde{\boldsymbol{j}}\}) \quad (1)$$

where $Coca_{jt}$ is the number of hectares of coca grown in year t and cluster j, and it is computed by collapsing UNODC 1 km^2 cell-level data by cluster. $\mathbb{1}\{m \in \tilde{j}\}$ is an indicator variable equal to 1 if the municipality m lies on the trafficking route originating from cluster j, and imputes the hectares of coca produced in a particular cluster j only to municipalities belonging to the set $\tilde{j}$. The underlying assumption is that the cocaine produced and then trafficked until the closest exit point is strongly correlated to the number of cultivated hectares of coca.[8] Thus, we argue that the amount of coca grown in origin clusters represents a fair proxy of the volume of cocaine subsequently trafficked along the drug routes.

4 Empirical Strategy

With the aim of studying the impact of local exposure to illicit drug trafficking on violence and economic well-being, we employ the following two-way fixed effects model:

$$Y_{mdt} = \alpha + \beta \widehat{Cocaine}_{mdt-1} + \mu_m + \phi_{dt} + \varepsilon_{mdt} \tag{2}$$

where the outcome variable, Y_{mdt}, is either the homicide rate per 100 thousand inhabitants or the average nighttime light intensity. The main explanatory variable, $\widehat{Cocaine}_{mdt-1}$, is the inverse hyperbolic sine transformation (IHS henceforth) of our predicted cocaine trafficked during year $t-1$ through municipality m, located in department d. As extensively described in section 3.1, it is computed by collapsing UNODC 1 km^2 cell-level data by cluster of origin, and then assigned to each municipality m lying on the shortest route to the closest exit point. Municipality fixed effects, denoted as μ_m, account for time-invariant cross-sectional differences, including historical and geographical factors that may affect the level of violence and criminal organizations' activity. Department-by-year fixed effects, denoted as ϕ_{dt}, control for common shocks to all municipalities within the same department, while ε_{mdt} represents an idiosyncratic local component. Standard errors are clustered at the municipality level.

We also estimate an augmented specification featuring a set of control variables at the

[8]The coca leaf is not the final trafficked illicit product, as it must be transformed into coca paste and ultimately cocaine base. This conversion process involves the use of several ingredients, such as water, sodium carbonate, kerosene, sulfuric or hydrochloric acid, potassium permanganate, and ammonia, and typically takes place in a structure located near the harvesting site, or at a point further along the trafficking route where a water source is accessible (U.S. Department of Justice - Drug Enforcement Administration Report).

baseline interacted with year dummies. This allows us to control for differential changes in the outcomes due to the baseline local conditions. The group of baseline characteristics first includes a series of economic indicators - 2010 population (IHS), 2005 poverty index; share of employment in agriculture in 2005; distance from department capital (IHS). The set of controls also comprises the homicide rate and average nighttime light intensity in 2011, immediately prior to the period under investigation. Because the past presence of violent actors, such as criminal gangs or paramilitaries, might also influence the subsequent dynamics of the outcomes and drug trafficking along the routes, the set of controls is also complemented by an indicator for the presence of FARC and by the number of criminal gangs involved in violent events in the same department between 2000 and 2010. FARC had indeed gained substantial participation in the illicit market of cocaine, in particular in coca-growing areas. After the peace agreement with the Colombian government in 2016, the void of power left by FARC might have raised the incentives for new competitors to exert violence for a higher share of earnings from cocaine production and trade. The information on the number of criminal gangs involved in violent events, which we derive from ViPAA data (Osorio et al., 2019), described in section 3, aims at controlling for the degree of competition among criminal actors in the period before the years under investigation. Finally, since the origin and endpoint of a trafficking route often represent the most strategically salient locations - where refinement activities may take place in the former case, or where shipments are organized, consolidated, or transferred in the latter — we include the municipality's distance (IHS) to the closest of these points in any associated route to capture their heightened importance for the cocaine trade.

We estimate model (1) using the sample of non-coca-growing municipalities that, at any given time, are situated along our predicted network of trafficking routes. This selection is motivated by the need to exclude municipalities located far from major roads and rivers, as their inclusion could introduce bias in our estimates of β. Remote areas may exhibit distinct levels of economic development and are disconnected from transportation routes, which could affect the accuracy of our results. Focusing on municipalities along the trafficking routes enables us to capture variation on the intensive margin in predicted volume of cocaine trafficking.

4.1 Identification strategy

The OLS estimation of model (1) may yield a biased estimate of the average causal effect of exposure to drug trafficking if unobserved time-varying local factors influence both the production of coca in growing areas and the homicide rate along the routes. This may particularly apply to municipalities located in proximity to coca-growing areas. For instance, a political shock, such as the election of an administrator who is lenient toward criminal gangs, could increase incentives for producing a significant volume of cocaine while simultaneously reducing the utility derived from exerting violence, resulting in a lower homicide rate.

To address these concerns, we leverage the quasi-experimental setting provided by the unanticipated announcement, by the Colombian government in May 2014, of a crop substitution program that involved financial aid for those farmers who would have replaced coca cultivation with alternative and legal crops (PNIS). The announcement contributed to a sizable and persistent increase in coca production, especially in areas with higher suitability for coca production (Prem et al., 2023). We exploit the PNIS announcement to induce plausibly exogenous temporal and spatial variation in coca production and in the exposure to drug trafficking for municipalities along the routes.

We first resort to 1 km^2 grid-cell and follow Prem et al. (2023) by specifying the following econometric model:

$$Coca_{cmdt} = \lambda + \delta S_c \times Post\text{-}ann._t + \theta_c + \chi_{mt} + v_{cmdt}, \tag{3}$$

where the outcome variable, $Coca_{cmdt}$, is the number of hectares of coca grown in a grid-cell c, located in municipality m, at time t. $Post\text{-}ann._t$ is an indicator for post-PNIS announcement years, i.e., from 2014 onward. S_c is the coca suitability index at the grid-cell level, described in section 3, which quantifies the cross-sectional exposure to the announcement. The rationale is that areas with higher suitability for coca cultivation were more responsive to the economic incentive generated by the announcement. The model includes cell and municipality-by-year fixed effects, which are denoted by the parameters θ_c and χ_{mt}, respectively. This specification, therefore, captures time-invariant characteristics at the most granular level (grid-cell) and time-varying shocks, including changes in political, economic, and climatic factors at a very detailed level (municipality). Moreover, we estimate Conley's standard errors (Conley, 1999) to account for spatial dependence, up to 100 km, and serial correlation until $t-2$.

Table 3 shows the estimated impact of the crop-substitution program announcement on coca production. The model estimated in column 1 features department-by-year fixed effects, while column 2 displays the result from the specification with municipality-by-year fixed effects as in equation (3). In line with the findings in Prem et al. (2023), Table 3 reports positive and significant point estimates. The result from the more demanding specification in column 2 indicates that a one-standard-deviation increase in the coca suitability index in post-announcement years is associated with a 0.036 increase in the hectares of coca per cell, which amounts to more than 100% of the sample mean before 2014.

We further test for diverging pre-trends in coca cultivation across grid-cells with different suitability by employing a dynamic version of model (3), using 2013 as the baseline year, one year before PNIS announcement. Figure 7 reveals that, in comparison to the baseline, there are no significant differences in coca production across grid-cells with different coca-suitability in the years leading up to the PNIS announcement. However, consistently with the findings in Prem et al. (2023), we observe significantly diverging trends from 2014 onward.

We use the point estimates from the estimation of model (3) to construct an instrumental variable for the municipality-level measure of predicted exposure to cocaine trafficking along the routes that we defined in equation (2).

We first consider the level of coca cultivated in cell c in 2011, the baseline year, and add the predicted PNIS-induced difference in cultivation by imputing the estimated coefficient $\hat{\delta}$ from model (3) to each coca-growing cell for post-PNIS years according to its level of coca suitability S_c, as follows:

$$Coca_{ct}^{PNIS.} = Coca_{c,2011} + \hat{\delta} \times S_c \times Post\text{-}ann._t \tag{4}$$

We then add up these cell-level predicted values for each of the 1000 coca-growing clusters to obtain:

$$Coca_{jt}^{PNIS} = \sum_{c \in \tilde{j}} Coca_{ct}^{PNIS} \tag{5}$$

Finally, analogously to equation (2), we define the instrumental variable for the cocaine trafficked through municipality m as follows:

$$Cocaine_{mdt}^{PNIS} = ihs(\sum_{j=1}^{J=1000} Coca_{jt}^{PNIS} \times \mathbb{1}\{m \in \tilde{\boldsymbol{j}}\}) \tag{6}$$

Table 4 collects the first stage estimates. The estimation sample in column 1 includes department-by-year fixed effects and municipality fixed effect, while column 2 adds a set of municipality controls at the baseline. Both estimates exhibit a significant and positive correlation between the predicted measure of cocaine trafficked through a municipality and the instrumental variable. Specifically, a 1% increase in the instrument is associated with a 1.28% increase in the predicted amount of cocaine trafficked through a municipality. The F-statistic for weak instrument test equals 62.51 and 76.68 in Columns 1 and 2, respectively, well above 10 which is the conventional rule-of-thumb threshold for a robust first stage (Stock and Yogo, 2002).

5 Results

Panel A of Table 5 presents the estimated effects of exposure to cocaine trafficking on the homicide rate according to the specification of model (1). Columns 1 and 2 show the OLS estimates, while Columns 3 and 4 the 2SLS estimates with the PNIS announcement IV. In columns 2 and 4, we estimate the augmented model featuring the set of baseline municipality characteristics interacted with year dummies. We present in square brackets the p-values from the Conley's standard errors (Conley, 1999), which account for spatial dependence and serial correlation until $t-2$.[9]

The results point to a positive impact of the predicted volume of cocaine trafficking on homicides across all the specifications. The statistical significance is stable, at 5% significance level, across all specifications. Point estimates range from 1.11 in column 2 (OLS, controlling for municipality characteristics) to 6.47 in column 4 (2SLS, controlling for municipality characteristics). More in detail, the latter indicates that a 1% increase in the amount of cocaine trafficked through a municipality is associated with a 0.065 increase in the homicide rate. Considering that the average yearly growth in our measure of predicted trafficked cocaine corresponds to 42.1%, this impact amounts to about 2.27 additional homicides per 100,000 inhabitants every year.[10] This corresponds to about 10.06% of the sample mean in the homicide rate ($2.307/22.57 = 10.22\%$).

It is worth noting that point estimates from OLS are substantially lower than the 2SLS counterparts. As we discuss in the identification section 4.1, the downward bias is possibly due to time-varying factors, such as the election of local administrators who are lenient toward criminal organizations, which might simultaneously affect in different directions the incentive to produce coca in growing areas and the utility from exerting violence.

[9] We allow spatial correlation to extend to up to 275 km from each municipality's centroid to ensure that each municipality has at least one neighbor.

[10] This value is obtained by multiplying the 2SLS coefficient (6.466) by $\ln(1.421)$, which corresponds to a 42.1% increase in predicted cocaine trafficking.

Lastly, Panel B shows the estimated effects of exposure to cocaine trafficking on the nighttime light intensity, which we employ as a proxy for economic well-being. None of the estimated coefficients are statistically significant across the different specifications. These estimates indicate that cocaine trafficking does not significantly affect nighttime light intensity, suggesting that the impact on average economic well-being in these areas is negligible, at least in the short term.

5.1 Placebo tests

Our empirical strategy assumes that narcotraffickers transport cocaine along the shortest available routes via roads or rivers, as detailed in Section 3.1. However, traffickers may opt for alternative routes to the nearest or even further exit points to avoid detection by authorities.

To resemble the potential choice of alternative trafficking routes, we implement a battery of placebo tests to assess whether our baseline findings on the impact of cocaine trafficking on violence hold under simulated routes. Specifically, we run 10,000 simulations for both OLS and 2SLS estimates, applying two distinct reshuffling strategies for predicted trafficked cocaine: one that reassigns values within the same year, and another within the same year and department. The latter strategy attempts to mimic plausible permutations of trafficked cocaine to nearby areas.

Table 6 collects the descriptive statistics from the placebo estimates. Regardless of estimation type and reshuffling strategy, the mean of the estimated coefficients across all simulations is equal to zero, and the rejection rate, i.e., the percentage of simulations with a p-value below 5%, never exceeds 5%. Moreover, the maximum of the placebo estimated coefficient is far below the corresponding baseline point estimates. Figure 8 displays the distribution of placebo-estimated effects for each type of estimation and reshuffling strategy, with the indication of the corresponding baseline estimate coefficient.

5.2 Conditional Average Treatment Effects (CATE)

To analyze heterogeneity in the violent response to cocaine trafficking exposure across a variety of local baseline factors, we estimate conditional average treatment effects (CATE) using causal forest estimators (Athey and Imbens, 2016; Athey and Wager, 2019; Athey et al., 2019).

Causal forest is a supervised machine learning method designed to identify which subgroups are most impacted and their socio-economic and geographic characteristics. It hence unveils which variable explains most of the heterogeneity while allowing for non-linear effects and high-order interactions among the variables in the chosen set of covariates.

The algorithm grows, across several simulations, multiple "trees" on randomly selected subsamples and a set of covariates. Each tree recursively partitions the data by choosing split points that maximize differences in treatment effects across groups. The splitting point at each node is the value of one of the covariates that maximizes treatment effect heterogeneity. This process allows the algorithm to identify subpopulations where the impact of cocaine trafficking varies the most, until the observations are grouped into "leaves" with similar treatment effects. CATE are then estimated within each terminal node and averaged across trees.[11]

We feed the algorithm the following specification:

$$\widetilde{HR}_{mdt} = \beta(\boldsymbol{X_m})\widehat{Cocaine}_{mdt}^{PNIS} + \epsilon_{mdt} \tag{7}$$

where $\widetilde{HR}_{mdt}$ is the homicide rate after partialling out municipality and department-by-year fixed effects. The term $\beta(\boldsymbol{X_m})$ denotes the treatment effect, which varies with the municipality-specific values of the covariates contained in the vector $\boldsymbol{X}$. $\widehat{Cocaine}_{mdt}^{PNIS}$ is the PNIS-predicted value of the proxy for trafficked cocaine.[12]

The vector of covariates $\boldsymbol{X_m}$ includes a set of: 2010 population (IHS), 2005 poverty index; share of employment in agriculture in 2005; distance from department capital (IHS); distance (IHS) from the closest origin and endpoint of any associated route (IHS); an indicator for the presence of FARC; the number of criminal gangs involved in violent events at the department level between 2000 and 2010.

Figure 9 plots the distribution of $\beta(\boldsymbol{X_m})$ by percentile, showing that cocaine trafficking

[11]To avoid over-fitting, we adopt the "honest" approach which entails dividing each training sample into two parts: half of the observations are used to grow the tree, i.e., performing the sample splits, while the other half is used to estimate the treatment effects. We train the causal forest algorithm to build 100,000 trees and we set to 50 the minimum number of observations in a leaf. The causal forest function of the R package grf (generalized random forest) has a default value for the minimum leaf size equal to 5 observations. However, because our treatment variable is continuous, we decide to use a substantially higher value of this parameter to improve the precision of our estimates.

[12]It is computed as the product $\hat{\beta}^{FS} \times \widetilde{Cocaine}_{mdt}^{PNIS}$, where $\hat{\beta}^{FS}$ is the coefficient from the first stage estimates reported in column 2 of Table 4, while $\widetilde{Cocaine}_{mdt}^{PNIS}$ is the PNIS instrumental variable defined in eq. (6), purged of municipality and department-by-year fixed effects. Estimates where we directly plug in $\widetilde{Cocaine}_{mdt}^{PNIS}$ in eq. (7) yield similar results and are available upon request.

exposure increases homicide rate in all municipalities, with an average estimate of around 5 p.p.. However, there is substantial heterogeneity in responses, with estimates ranging from 0.2 p.p. to more than 10 p.p.

To further explore treatment heterogeneity, we compare the average baseline characteristics of municipalities above and below the median predicted treatment effect. Table 7 presents these comparisons, alongside standardized differences in means and p-values adjusted for multiple hypothesis testing (List et al., 2019). The results indicate that municipalities with above-median CATEs tend to have higher population, a greater number of active criminal organizations in the decade before the period we analyse, a lower share of employment in agriculture, and to be closer to a route's origin or endpoint, and departmental capitals. The only exceptions, where standardized differences are not significantly different from zero, are the poverty index and FARC presence.

Figure 10 plots the average predicted treatment effects across deciles of key baseline observables, revealing additional patterns. Panel A suggests that the number of active criminal actors at the baseline shapes the violent response to the volume of drug traffic. When a single criminal organization was active between 2000 and 2010 in the department d where m is located, the estimated effects are the lowest, consistent with the idea that a strong incumbent may deter the entrance of new competitors, thereby leading to a lower homicide rate. CATE is substantially higher both in areas with no previously active criminal organizations - indicating that a power vacuum may fuel violent competition among new entrants - and in areas with multiple active groups, implying that violent competition intensifies as more groups contest control. Overall, these findings provide empirical support for the idea that criminal competition may influence the dynamic of violence along drug trafficking routes.

Estimated impacts also increase with proximity to key nodes along trafficking routes. Municipalities located closer to a route's endpoint (panel c) or origin (panel d), or to a departmental capital (panel d), exhibit substantially larger estimated effects. These locations may indeed carry greater strategic value for controlling trafficking flows. The origin and endpoint of a trafficking route often represent the most strategically salient locations - where refinement activities may take place in the former case, or where shipments are organized, consolidated, or transferred in the latter. Departmental capitals — more populous and often larger hubs of domestic drug consumption — may represent particularly attractive locations for criminal groups seeking to secure dominance. This interpretation is further supported by the fact that the estimated impacts also increase with population (panel g).

The results for the poverty index and the share of agricultural employment - shown in panels (b) and (f), respectively — provide mixed evidence and do not reveal a clear pattern. For the poverty index, the first two deciles display very high treatment effects, while from the third decile onward, the CATE increases only slightly with poverty levels. A similar pattern emerges for the share of agricultural employment: the first two deciles exhibit higher impacts, whereas the remaining deciles present a relatively flat profile.

6 Conclusion

This study examines the effects of local exposure to illicit drug trafficking on violence and economic well-being in Colombian municipalities located along trafficking routes. Focusing on the period from 2011 to 2021, we leverage confidential data on geolocated coca crops and crime records provided by the Colombian Ministry of Defense. By identifying a network of predicted cocaine transportation routes, we construct a measure of each municipality's exposure to drug trafficking and provide causal evidence of its impact on homicide rate and nighttime light intensity, which we employ as a proxy of economic well-being.

To address potential endogeneity concerns arising from unobserved local factors influencing both coca production and violence along trafficking routes, we exploit the quasi-experimental setting generated by the unanticipated 2014 announcement of the PNIS crop substitution program. As documented by Prem et al. (2023), the policy induced a sizable increase in coca production in areas with higher cultivation suitability. We leverage this shock to construct an instrumental variable for the amount of cocaine trafficked along the routes, allowing us to isolate the causal effect of drug trafficking on local outcomes.

Our findings indicate a strong and positive effect of cocaine trafficking on violence. Two-stage least squares (2SLS) estimates suggest that a 1% increase in trafficked cocaine raises the homicide rate by 0.065 per 100,000 inhabitants. Given the 42.1% annual increase in predicted trafficked cocaine from 2014 onward, this effect translates to approximately 2.3 additional homicides per 100,000 inhabitants annually, or 10.22% of the sample mean homicide rate. In contrast, we find no significant effect on nighttime light intensity, suggesting that cocaine trafficking does not generate meaningful economic spillovers in transit areas.

The violent impact of drug trafficking is highly heterogeneous across municipalities, shaped by both criminal competition and geographic proximity to key trafficking nodes. The effect is strongest in municipalities with multiple competing criminal organizations, where contestation over trafficking corridors fuels violent disputes, and in municipalities with no previous criminal presence, where a power vacuum may incentivize violent competition among emerging groups. By contrast, areas previously controlled by a single dominant organization experience smaller increases in violence, consistent with a monopolistic enforcement structure that deters rival entry. Geographic proximity also matters: municipalities located nearer to a route's endpoint or origin exhibit a higher homicide rate, likely reflecting the strategic salience of these areas, where instrumental activities such as refinement, consolidation, or shipment organization typically occur. These patterns underscore the importance of considering trafficking corridors and export hubs — not only production zones — when assessing the broader externalities of illicit markets. Finally, the estimated impacts are larger in more populous municipalities and in those closer to departmental capitals, plausibly because these areas constitute sizable domestic markets for cocaine consumption.

Our results are robust to an extensive set of controls and alternative route definitions. To test whether traffickers systematically avoid the shortest routes to evade law enforcement, we conduct a placebo analysis with 100,000 iterations, where our predicted measure of trafficked cocaine is randomly reassigned across municipalities. The placebo estimates never replicate our baseline results, reinforcing the validity of our identification strategy.

Overall, this study contributes to the broader debate on illicit economies and their externalities, providing compelling evidence that drug trafficking fuels violence but does not generate economic gains for transit areas. These findings have important policy implications. While supply-reduction policies could help curb violence, their effectiveness depends on local criminal dynamics. In areas with fragmented criminal control, enforcement measures may trigger further violent contestation rather than reducing overall conflict. Future research should explore the longer-term effects of drug trafficking on labor markets, education, and institutional trust. Additionally, policymakers must account for the unintended spillover effects of crime policies, ensuring that enforcement strategies do not merely displace violence but address the underlying institutional and governance weaknesses that allow illicit economies to thrive.

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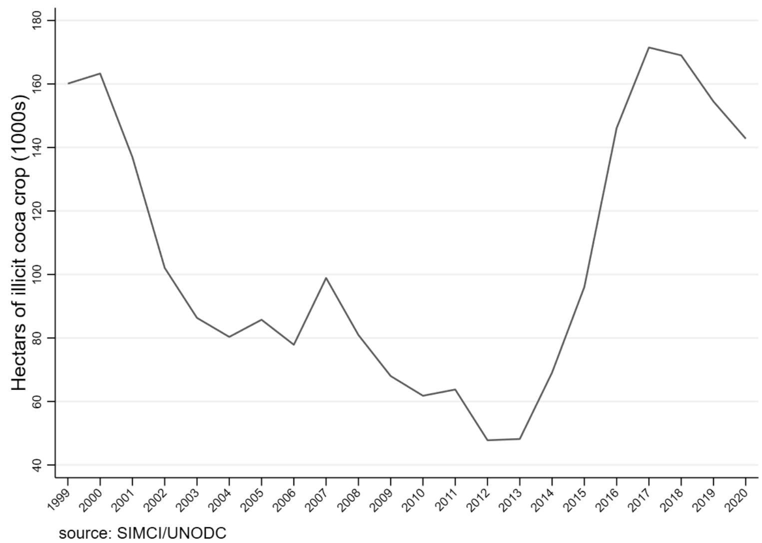
Figures and Tables

Figure 1: Coca cultivation trend in Colombia (1999-2020)

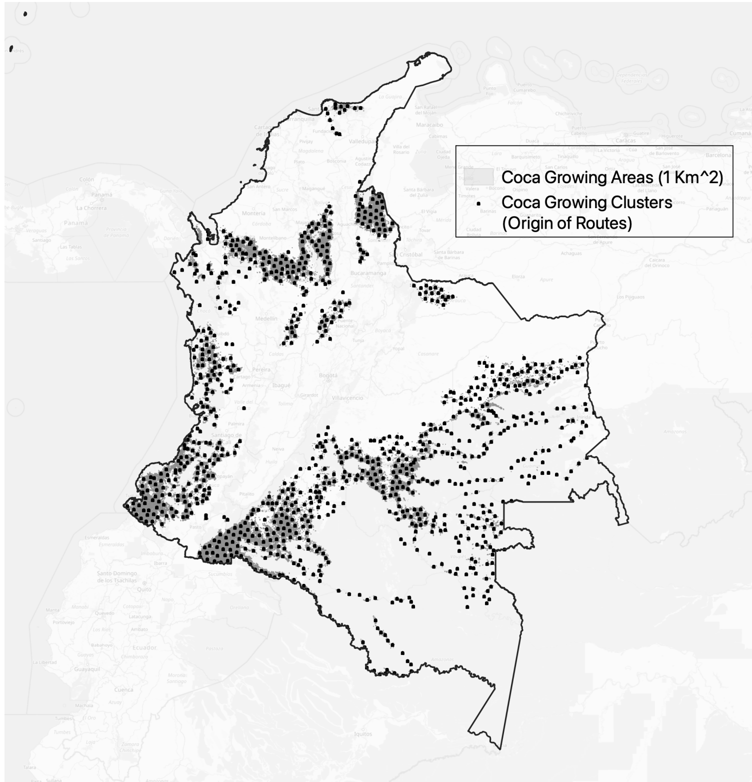


Source: Calculations conducted by the authors based on UNODC data. To compute the overall quantity of coca cultivated in Colombia, we aggregated the coca amounts from each grid cell across the country.

Figure 2: Coca Growing Areas (1 km^2 Grid-Level)

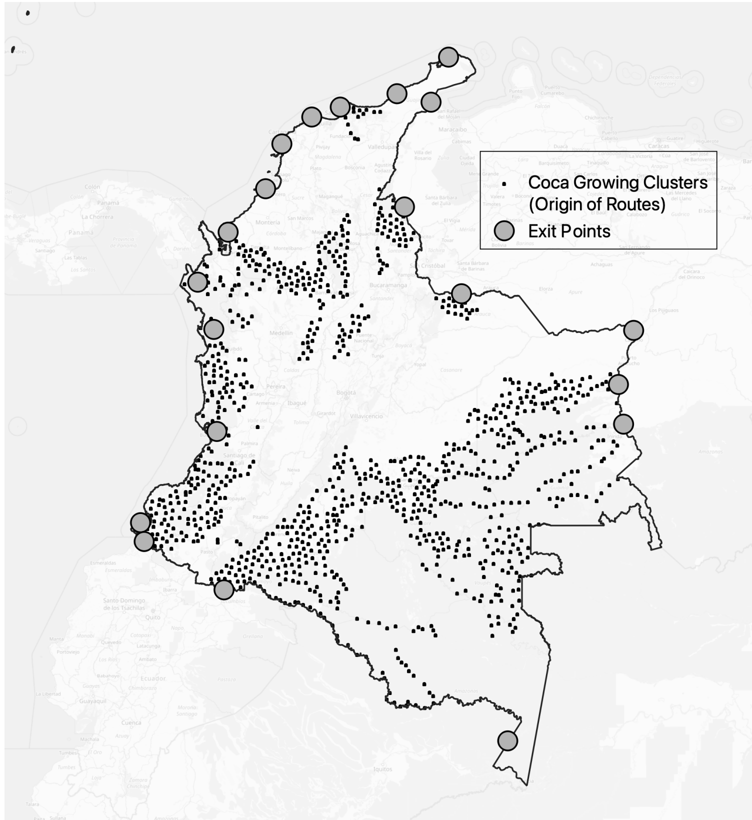
Source: Calculations conducted by the authors utilizing data from the United Nations Office on Drugs and Crime (UNODC) for coca crop information, and OpenStreetMap data for identifying roads, rivers, and ports.
Notes: This figure illustrates the grid areas that experienced coca cultivation at least once between 2011 and 2021.

Figure 3: Creation of Coca Growing Clusters



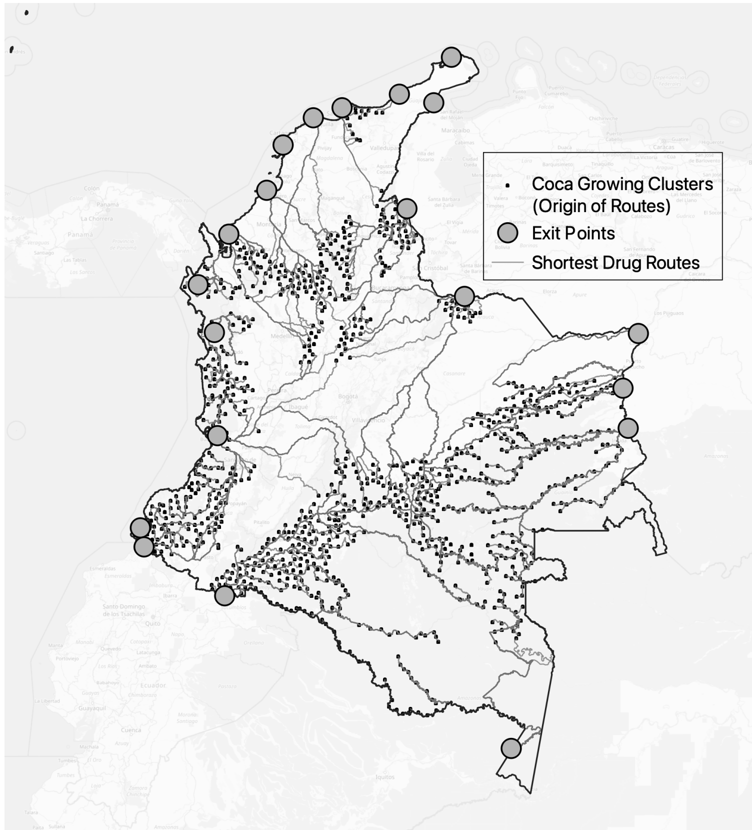
Notes: This figure depicts the process of constructing the 1000 coca clusters, with the largest cluster covering an area of approximately 15 km^2.

Figure 4: Coca Growing Clusters and Exit Points



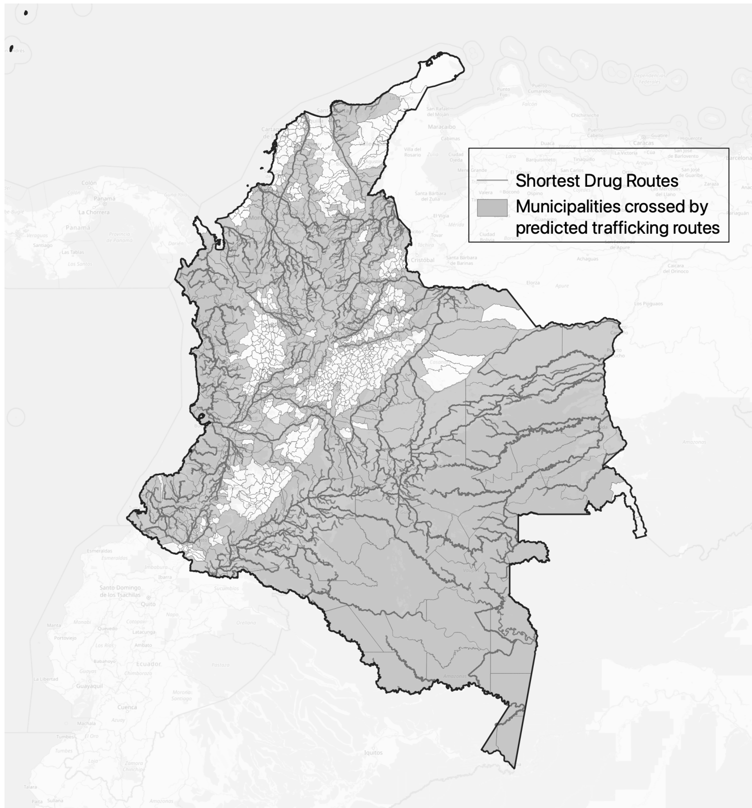
Notes: This figure displays the 1000 clusters alongside the 16 designated exit points.

Figure 5: Predicted Trafficking Routes



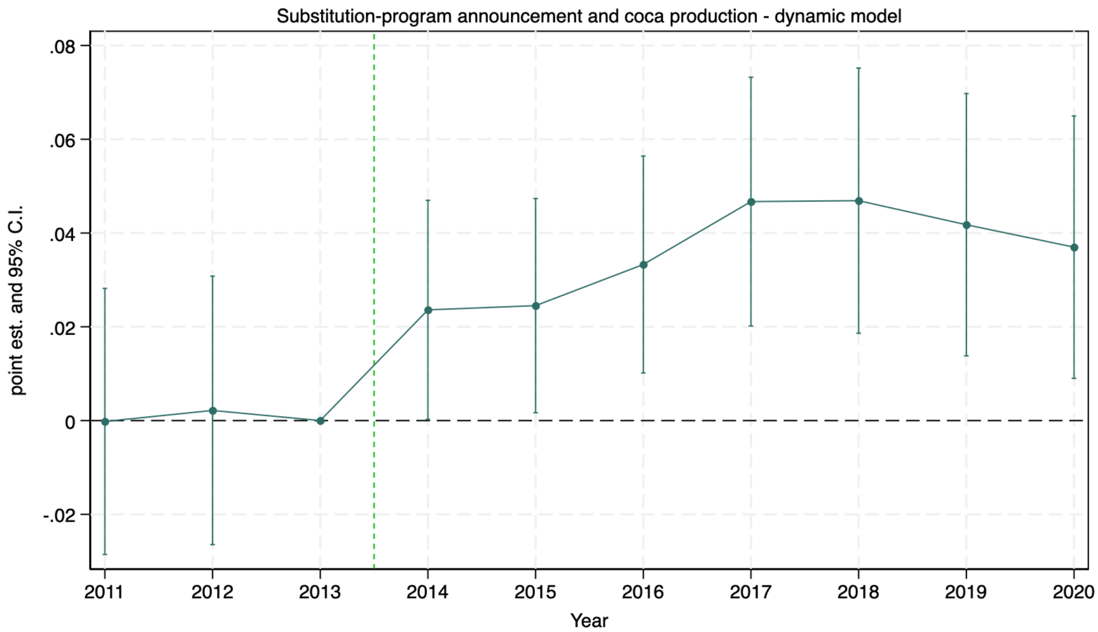
Notes: This figure showcases the 1000 predicted trafficking routes.

Figure 6: Municipalities crossed by Predicted Trafficking Routes



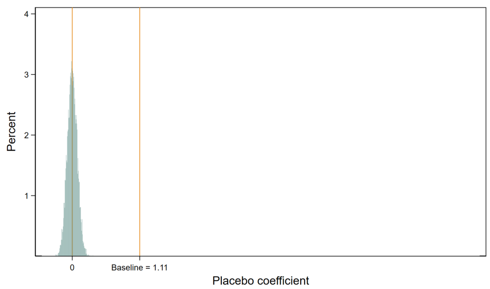
Notes: This figure depicts municipalities crossed by the 1000 predicted trafficking routes.

Figure 7: PNIS announcement and coca production: event-study specification

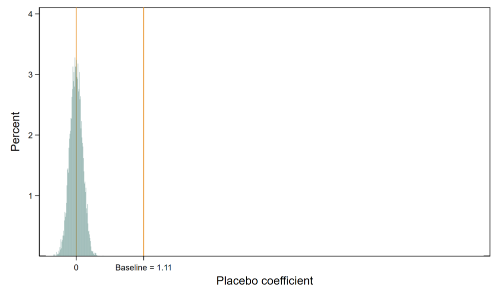


Notes: This figure shows potential pre-existing trends in coca production across grid cells with different suitability, using 2013 as the baseline year – one year prior to the PNIS announcement.

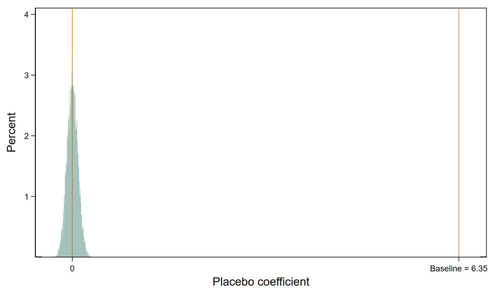
Figure 8: Distribution of placebo effects



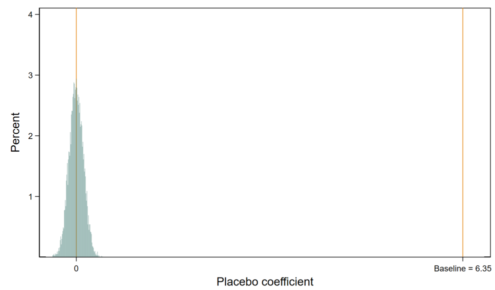
(a) OLS - Within year reshuffling



(b) OLS - Within year and dept. reshuffling



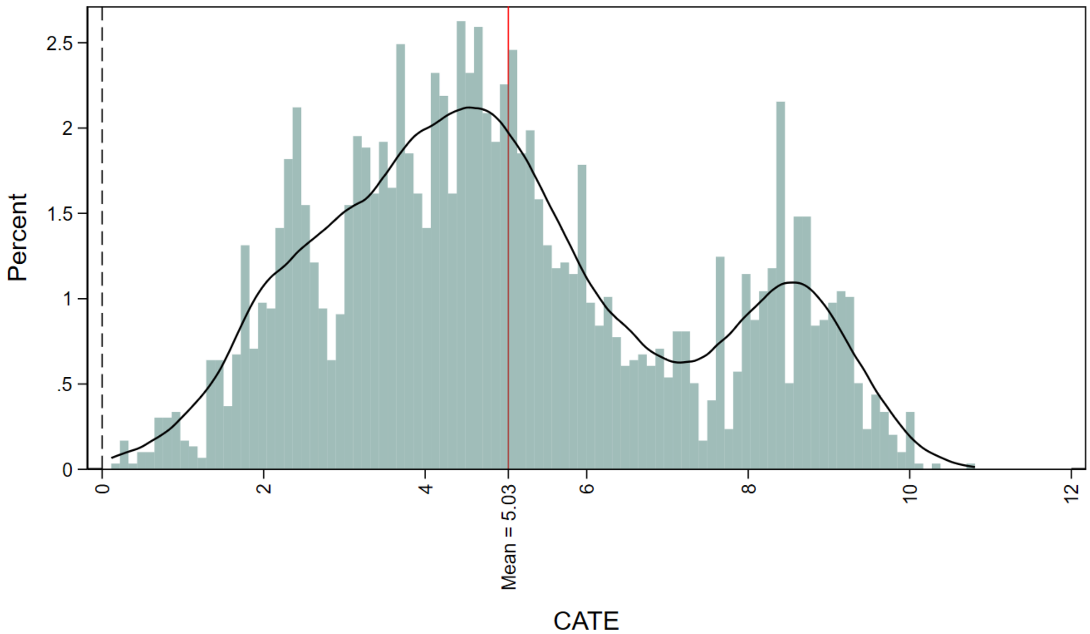
(c) 2SLS - Within year reshuffling



(d) 2SLS - Within year and dept. reshuffling

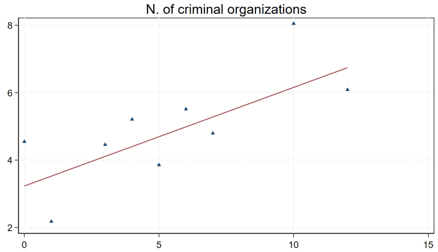
Notes: This Figure displays the distribution of placebo-estimated effects for each type of estimation and sample with the indication of the corresponding baseline estimate coefficient.

Figure 9: Distribution of Conditional average treatment effect (CATE)

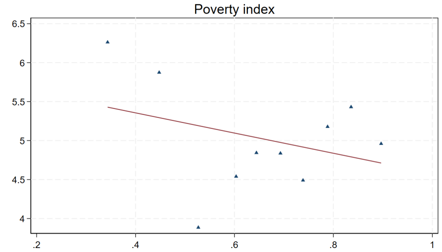


Notes: This Figure shows how the predicted Conditional Average Treatment Effect (CATE) varies over its rank distribution. The red line depicts the mean of the Conditional Average Treatment Effects.

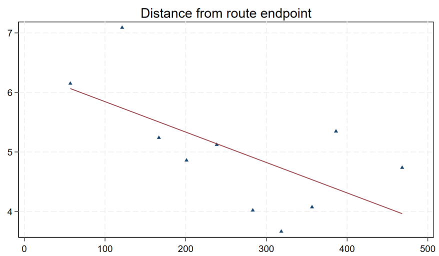
Figure 10: Conditional Average Treatment Effects



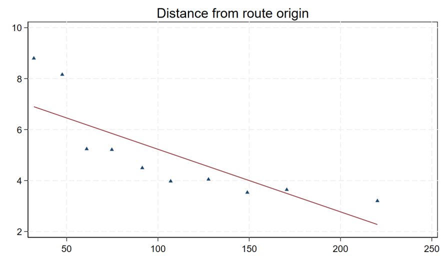
(a) CATE and n. of criminal organization



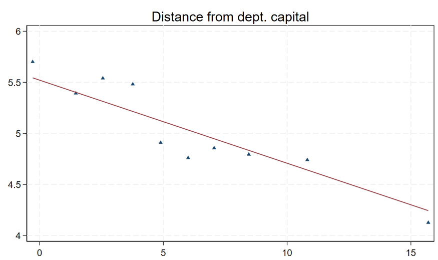
(b) CATE and poverty index



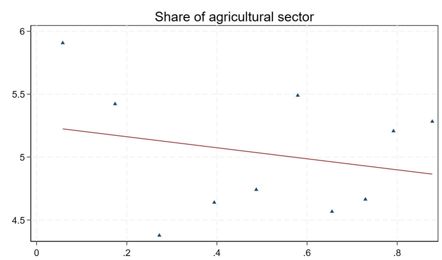
(c) CATE and distance froma route's endpoint



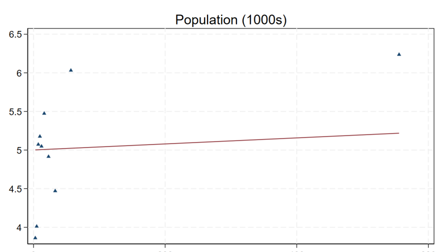
(d) CATE and distance from a route's origin



(e) CATE and distance from department capital



(f) CATE and share of people working in agricultural sector



(g) CATE and population

Notes: This figure presents the estimated Conditional Average Treatment Effects of cocaine trafficking exposure on homicide rate across deciles of baseline municipal characteristics. Panel (a) plots CATE against the number of criminal organizations. Panel (b) shows the relationship between CATE and the poverty index. Panels (c), (d), and (e) display CATE estimates as a function of distance from the closest route's endpoint, origin, and from departmental capital, respectively. Panel (f) relates CATE to the share of people working in the agricultural sector. Panel (g) plots CATE against municipal population size.

Table 1: Descriptive Statistics (2011-2021)

	(1) Mean	(2) Std. Dev.	(3) Min	(4) Max	(5) Mean	(6) Std. Dev.	(7) Min	(8) Max
PANEL A: Coca crops (Grid Level) - 2011-2020								
	All Grids				Grids in Growing Areas			
Hectares of coca per grid	0.10	0.90	0.00	83.74	0.96	2.72	0.00	83.74
Observations	11,533,600				1,145,080			
Number of grids	1,153,360				114,508			
PANEL B: Municipality Characteristics - 2012-2021								
	All Municipalities				Municipalities on the routes			
Coca Trafficked (hectares of coca)	672.7	2,885.012	0	50,888.9	1,233.243	3,816.946	0	50,888.95
Homicide Index (100k inhabitants)	25.50	32.26	0.00	494.95	31.08	35.73	0.00	494.95
Nightlights Intensity	6.47	8.30	0.00	62.92	5.59	7.63	0.00	61.04
Observations	11,150				6,070			
Number of municipalities	1,115				607			
PANEL C: Road network characteristics								
Length routes (Km)	449.07	307.11	8.7	1,405.548				
Number of routes	1,000							

Notes: Descriptive summary statistics of the main variables of the analysis. PANEL A provides the summary statistics for the hectares of coca cultivated at grid level. Columns 1-4 examine the full sample of grids. Columns 5-8 examine the subsample of grids where at least once coca was cultivated between 2010-2021. PANEL B provides the summary statistics for municipalities characteristics. Columns 1-4 examine the full sample of municipalities. Columns 5-8 examine the subsample of municipalities located along the drug trafficking routes. PANEL C provides the summary statistics for the drug trafficking routes.

Table 2: Descriptive Statistics of municipal baseline characteristics

	Mean	SD	Min	Max	Obs
2005 Poverty Index	0.65	0.17	0.24	0.97	330
2010 Population (1000s)	10.42	1.31	7.60	16.51	330
2005 Share of agricultural sector	0.50	0.26	0.00	1.00	330
Distance from dept. capital (km)	6.09	4.56	0.00	24.71	330
2000-2010 N. of criminal organizations	6.15	2.84	0.00	12.00	330
Distance from route endpoint (km)	259.70	122.94	6.54	583.75	330
Distance from route origin (km)	108.11	59.30	15.94	477.07	330
FARC presence	0.03	0.16	0.00	1.00	330

Notes: This table reports descriptive statistics for the set of baseline municipality-level variables used in the analysis. These are: the 2005 Multidimensional Poverty Index, 2010 population, 2005 sectoral employment shares are drawn from DANE. Distances from the origin and endpoint of trafficking routes are computed along the predicted cocaine trafficking network. Information on the number of criminal organizations and FARC presence is constructed using event and actor data from the VIIPA dataset (Osorio et al., 2019). The sample includes the full set of municipalities intersecting predicted trafficking routes, excluding areas primarily devoted to coca cultivation.

Table 3: Substitution program announcement and coca production

	(1)	(2)
	Dependent variable: Hectares of coca	
Post-announcement × Coca suitability	0.0671***	0.0356***
	(0.0113)	(0.0067)
Observations	11,533,600	11,533,600
Mean hectares of coca at baseline	0.031	0.031
Grid cell FE	Yes	Yes
Department-by-Year FE	Yes	
Municipality-by-Year FE		Yes

Notes: Conley's standard errors, accounting for spatial clustering up to 100 km and serial correlation until $t-2$, in parentheses. Asterisks denote statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The outcome variable is the number of hectares of coca grown in a grid-cell. $Post-announcement$ is an indicator for post-crop substitution program announcement years, i.e., from 2014 onward. *Coca suitability* is a coca suitability index at the grid-cell level. All specifications include grid-cell fixed effects. Columns 1 features department-by-year fixed effects, while column 2 municipality-by-year fixed effects.

Table 4: First stage - PNIS announcement IV

	(1)	(2)
	Outcome variable:	
	Trafficked cocaine	
Trafficked cocaine - PNIS ann. IV	1.275***	1.281***
	(0.161)	(0.146)
Observations	2970	2970
F-statistic	62.51	76.68
Municipality FE	Yes	Yes
Department-by-Year FE	Yes	Yes
Baseline mun. contr. by year		Yes

Notes: Standard errors in parentheses are clustered at the municipality level. Asterisks denote statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The outcome is the predicted amount of cocaine trafficked through the municipality, which is defined in section 3.1, while the main explanatory variable is the instrumental variable constructed by exploiting the 2014 PNIS announcement described in section 4.1. All specifications include municipality and department-by-year fixed effects. Column 2 adds a set of baseline municipality control variables (defined in section 4) interacted with year dummies.

Table 5: The impact of cocaine traffic on homicides rate and nightlights

	(1)	(2)	(3)	(4)
	Panel A. Homicides rate			
	OLS		2SLS	
Trafficked cocaine	1.112**	1.158**	6.351**	6.466**
	(0.435)	(0.455)	(2.777)	(2.545)
	[0.034]	[0.031]	[0.009]	[0.005]
Observations	2970	2970	2970	2970
Mean outcome variable	22.57	22.57	22.57	22.57
	Panel B. Nightlights			
	OLS		2SLS	
Trafficked cocaine	-0.009	-0.004	-0.032	-0.021
	(0.006)	(0.005)	(0.025)	(0.018)
	[0.270]	[0.428]	[0.257]	[0.263]
Observations	2970	2970	2970	2970
Mean outcome variable	9.92	9.92	9.92	9.92
Municipality FE	Yes	Yes	Yes	Yes
Department by year FE	Yes	Yes	Yes	Yes
Baseline mun. contr. by year		Yes		Yes

Notes: Standard errors in parentheses are clustered at the municipality level. Asterisks denote statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. In panel A, the outcome variable is the homicide rate per 100,000 inhabitants. The main explanatory variable is the predicted amount of cocaine trafficked through the municipality, which is defined in section 3.1. In Panel B, the outcome variable is the average nighttime light intensity. All specifications include municipality and department-by-year fixed effects. Column 2 and 4 add a set of baseline municipality control variables (defined in section 4) interacted with year dummies. Columns 1 and 2 collect the OLS estimates, columns 3 and 4 the 2SLS estimates using the PNIS announcement IV defined in section 4.1.

Table 6: Placebo estimates statistics. Homicides rate - 10,000 simulations

Estimation	Reshuffle within	Baseline est. coefficients	Placebo coefficients: Mean	Min	Max	Rejection rate (%) [pval $<$ 0.05]
OLS	Year	1.11	0.00	-0.28	0.35	4.99
OLS	Department-Year	1.11	0.00	-0.38	0.44	5.04
2SLS	Year	6.35	0.00	-0.33	0.31	5.00
2SLS	Department-Year	6.35	0.00	-0.39	0.43	4.97

Notes: This table reports descriptive statistics from the placebo simulations. Column 1 indicates the estimation method, and Column 2 specifies the reshuffling strategy. Column 3 presents the estimated coefficients. Columns 4, 5, and 6 report the mean, minimum, and maximum of the placebo distribution, respectively. The final column shows the rejection rate, defined as the percentage of simulations with a p-value below 5%.

Table 7: CATE - Std. diff. and MHT

	(1)	(2)	(3)	(4)
	CATE		Std. diff.	MHT p-value
Baseline characteristics	Below median	Above median	(1)-(2)	(1)-(2)
Poverty index	0.656	0.648	0.047	0.377
Population (1000s)	21.458	122.633	-0.235	0.001
Share of agricultural sector	0.535	0.469	0.252	0.001
Distance from dept. capital	7.173	4.908	0.505	0.001
N. of criminal organizations	5.385	6.912	-0.559	0.001
FARC presence	0.024	0.030	-0.037	0.321
Distance from route endpoint	303.101	216.296	0.756	0.001
Distance from route origin	133.870	82.352	0.966	0.001

Notes: This table reports the average value of each characteristic for municipalities below and above the median distribution of predicted treatment effects, together with standardized differences in the mean and p-values adjusted for multiple hypothesis testing.