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Abstract

This paper explores the environmental consequences of illegal drug production, specifically focusing on the impact of coca prices and cultivation on tree cover density in Peru. Using satellite imagery and granular data on the economic value of coca cultivation, I show that fluctuations in coca profitability significantly drive deforestation in the Peruvian Amazon. My findings show that the 40% increase in coca prices observed during the study period led to an estimated loss of 6,450 km^2 of tree cover—roughly eight times the land area of New York City. Additionally, I provide suggestive evidence of a technological revolution — marked by the widespread use of agrochemicals — that has expanded the coca cultivation frontier to remote areas of the Amazon, transforming it into a diffuse source of environmental degradation. This shift has enabled illegal coca farming in previously unsuitable strategic locations. The technological advancements, increasing productivity of forest-derived land uses, presented Narcos with fresh economic opportunities for environmental crimes.

JEL codes: O13, Q01, Q02, Q12, Q15, Q23, Q50, Q55, K42
Keywords: Tropical Deforestation, Illegal Markets, Amazon Forest, Coca, Latin America

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1 Introduction

> *What coca/cocaine has done as an economic and social phenomenon is to provide the financial means and motives for deforestation* (Young, 2004a). *One of the ironies of this deforestation is that the expected spatial patterns are reversed. [...] When the goal is to plant coca, this must be done in isolated places, far from military and civil control. [...]* (Young, 2004b).

Understanding the drivers of global legal and illegal deforestation is a significant policy concern. Between the years 2001 and 2020, approximately 9% of the Amazon forest – the earth's largest tropical rainforest – has been deforested (RAISG, 2022). In some areas, the Amazon is now emitting more carbon than it can absorb (Gatti et al., 2021), and its CO_2 emissions are comparable to the ones of Japan (European Commission. Joint Research Centre, 2021) – the 5th biggest polluter in the world (Harris et al., 2021). Curtis et al. (2018) estimates that 51% of global forest loss occurred between 2001 and 2015 is either commodity or agriculture driven, i.e. conversion of forests to non-forest land uses such as agriculture, mining, and drug production. Furthermore, the World Economic Forum (2020) reports that half of tropical deforestation worldwide is illegal, and particularly driven by demand for illegal or unsustainable commodities. While extensive research has examined environmental externalities in legal markets, there is limited understanding on how market forces within illegal markets contribute to natural resource degradation.

This paper addresses this gap by investigating how coca market prices influence local deforestation in Peru. Peru not only hosts the second-largest portion of the Amazon forest but also approximately one-fourth of the global area under coca bush cultivation (UNODC, 2021).

Estimating this relationship presents several challenges, particularly due to the limited availability of reliable, granular data on forest cover and illicit crop cultivation. Furthermore, two primary sources of bias require careful consideration. First, unobserved characteristics at the cell level may correlate with both illegal coca cultivation and tree cover levels—such as local political corruption, which could simultaneously enable coca production and drive deforestation through other illegal activities. Second, Dávalos et al. (2016) finds that proximity to abandoned state-sponsored projects from the 1960s and 1970s (which themselves led to deforestation) significantly increases coca cultivation. To overcome these challenges, I exploit *(i.)* remote sensing satellite imagery, and *(ii.)* geographic variation in coca-prone areas along with time variation in coca leaf prices in the Peruvian black market.

Thus, I construct a novel panel dataset spanning from 2003 to 2019, processing and gathering high-resolution yearly satellite images and model-based geographical raster data at a spatial resolution of 12km x 12km. It includes information on Coca Density from the United Nations Office on Drugs and Crime (UNODC), Percent Tree Cover (MODIS-VCF), an index of soil suitability for coca cultivation (Sviatschi, 2022), prices of coca leaves in the Peruvian black market (UNODC), nightlights (Li and Zhou, 2017), prices and suitability indexes for other commodities (MIDAGRI, BCRP, the World Bank, FAO).

To evaluate the environmental impact of rising coca prices and expanded cultivation, I leverage cell-level variations in the economic value of potential coca cultivation and a two-way fixed effects model with cell and year fixed effects. Similar to related literature on commodity shocks and deforestation, I follow a shift-share approach or Bartik (1991) method and interact a cell-level measure of exposure to coca ("share") with the prices of coca leaves in the Peruvian black market ("shift"). Using two primary sources of cross-sectional variation in coca-growing areas, I construct two distinct measures of Price Shocks for coca. Specifically, each definition combines a source of geographic variation, namely, Coca Suitability and Proximity to the Colombian border, with lagged yearly national price of coca leaves in the Peruvian black market. In both settings, the empirical strategy is comparable to a difference-in-differences model, where areas more suitable to coca cultivation are compared to areas less suitable, in years following high coca prices versus years following low coca prices. Finally, I leverage the coca price shock as an instrument for yearly coca cultivation density, as fluctuations in coca prices influence deforestation rates by altering the economic incentives for coca cultivation. I assume that in the absence of rising returns to coca cultivation, areas with higher suitability or proximity to the Colombian border would have experienced similar deforestation levels as less suitable or more distant areas.

I first show that increases in coca prices are associated with significant rises in deforestation. A one standard deviation increase in coca leaf prices leads to an average reduction in tree cover of approximately 2 percentage points, corresponding to about 4% of the average tree cover level. The estimate remains robust even when considering the impact of price shocks to agricultural and gold commodities. These commodities may share similar geographical cultivation patterns and simultaneously have price trends correlated with coca leaf prices. My findings show that the 40% increase in coca prices observed during the study period led to a loss of approximately 6,450 km^2 of tree cover in Peru - equivalent to more than eight times the land area of New York City. To assess the share of coca-driven deforestation, I perform a simple back-of-the-envelope calculation. I focus on the year with the highest tree cover loss (2013-2014) and estimate that, in regions suitable for coca cultivation (which account for 36.5% of the country), the 30% increase in coca prices, such that observed during this period, explains approximately 18% of the total deforestation that occurred in Peru that year.

Secondly, I provide suggestive evidence of a technological revolution which intensified the country wide effect and significantly impacted coca cultivation patterns. In line with anecdotal evidence, I find spatial heterogeneous effects and suggestive evidence of a technical change that concerned the coca cultivation process in Loreto. The adoption of agro-chemicals in the coca production lowers the costs associated with coca cultivation in non-suitable areas and emerges as a dominant economic rationale for coca cultivation and forest clearing in areas where the benefits are deemed to be higher (near the Colombian border). Consequently, the technological change makes previously unsuitable areas viable options for illegal cultivation, allowing an expansion of the coca cultivation frontier to a new coca-growing region in the middle of the Amazon, and specifically, in the region of Loreto – already a crucial cross-border trafficking hub. In line with Tomich et al. (2001) and Angelsen and Kaimowitz (2001)'s dispute[1] of the subsistence hypothesis (*Borlaug hypothesis*), the introduction of new chemical inputs increases productivity of forest-derived land uses. In turn, it presents fresh economic opportunities for conversion and increases the opportunity costs of conserving natural forests (Angelsen and Kaimowitz, 2001).

Lastly, due to the technological revolution and the expansion of the illegal coca cultivation frontier, deforestation in border areas exhibits a unique price sensitivity for coca relatively to other commodities, with only coffee and sugar cane showing any negative environmental impact, although this is statistically insignificant. Border regions, such as Loreto, show notably higher tree density than areas deemed suitable for coca cultivation, with average tree cover exceeding that of coca-suitable regions by over 20 percentage points. The stylized facts support the evidence that the illicit nature of coca drives its cultivation into remote areas, where it first-order stochastically dominates other crops, both in terms of presence in densely forested areas and deforestation impact.

The policy relevance of these results extends beyond Peru, highlighting the broader significance of this phenomenon. The anecdotal evidence reports comparable environmental

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[1] "Thus, if a new technology presents fresh economic opportunities, farmers are likely to expand their agricultural land unless their labour and/or capital constraints keep them from doing so. [...] In addition, technologies that create new economic opportunities can stimulate migration to forest frontiers, increasing forest conversion." (Angelsen and Kaimowitz, 2001)

impacts of other illegal crops, such as cannabis in North America and opium poppy in Colombia, Mexico, Peru, and Myanmar, as well as with coca cultivation in Colombia and Bolivia. Furthermore, in recent years, technological advancements have facilitated the cultivation of coca in regions once deemed unsuitable for this crop. The widespread use of toxic and highly polluting agrochemicals has enabled coca to expand into non-traditional, strategically significant countries such as Belize, Mexico, Honduras, and Guatemala, where criminal groups are reportedly experimenting[2] with coca cultivation (Héctor Molina, 2021; Shuldiner, 2022; The Economist, 2025)

The results have strong policy implications. It is estimated that half of all tropical deforestation worldwide is illegal, yet there remains limited empirical evidence on the underlying sources and mechanisms. By documenting the effects of drug cultivation, and the role of incentives and technological adoption, this study helps inform targeted policies aimed at mitigating forest loss and, more broadly, environmental degradation. Addressing the environmental impact of illicit coca cultivation requires a comprehensive policy framework that integrates both supply-side and demand-side interventions. On the supply side, two key policy tools emerge: regulation and economic incentives. Regarding regulation, the expansion of coca cultivation beyond traditional Andean regions into Central American countries, such as Mexico and Guatemala, highlights the need for a transnational drug policy that integrates both development and environmental considerations. The role of international cooperation in addressing climate change provides a relevant comparison for its potential in shaping responses to the environmental and social consequences of illicit economies. Since tropical deforestation generates global externalities—such as weakening the Amazon's resilience—enhanced monitoring and coordinated enforcement across national borders are essential to curbing illegal land conversion and mitigating deforestation. In addition to regulatory measures, this paper highlights the role of economic incentives in shaping land-use decisions among coca farmers. In this regard, alternative development interventions, such as those led and financed by national governments, the UNODC, the US and the European Union (EU), aim to assist farmers in transitioning from coca cultivation to legal and sustainable agricultural practices. Several crop substitution programs exist to en-

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[2] "The scene of unusual coca crop discoveries that suggest drug cartels are adapting to shifts in the multimillion-dollar narcotics trade. [...] The result is that Mexican traffickers are now experimenting with growing coca leaves, whose production has historically been dominated by Bolivia, Peru and Colombia. [...] Organized crime groups are trying to diversify their activities and experiment with coca planting.[...] Mexican cartels have come to control almost the entire cocaine trafficking chain in Colombia. Now coca crops are also flourishing in Honduras and Guatemala, once just transit points for the drug from South America" (France 24, 2023).

courage a transition away from coca cultivation, yet few empirical studies - such as (Prem et al., 2021b) - have rigorously assessed their effectiveness. A stronger evidence base is required to determine whether these programs provide sustainable economic alternatives that meaningfully reduce illegal coca cultivation and deforestation. On the demand side, consumer countries, particularly within the EU, can play a transformative role by reshaping market dynamics through targeted policies. One key strategy involves incentivizing the demand for alternative crops by integrating sustainable standards into trade frameworks. Drawing on experiences from initiatives such as the Sustainable Cocoa Initiative (European Commission, 2022) —where sustainability standards in the cocoa industry incorporate both environmental and social safeguards – the EU could tailor similar standards to the South American context. By promoting legally produced alternatives like cocoa or coffee, such measures would not only reduce the economic reliance on coca cultivation but also encourage a broader shift towards deforestation-free practices. Furthermore, demand-side interventions should include the integration of these environmental considerations into deforestation laws. Current European deforestation regulation[3], for instance, may inadvertently penalize farmers who have transitioned from coca cultivation to sustainable crops if their land was previously deforested (POLITICO, 2024). Revising these legal frameworks to recognize and reward nature-positive land-use changes is essential. By incorporating provisions that account for historical land-use practices while incentivizing sustainable transitions, policymakers can ensure that deforestation laws support rather than hinder efforts to promote legal and sustainable agricultural production.

The paper contributes to two main strands of economic literature, namely the economic literature on tropical deforestation and the literature on illicit drug markets. First, this paper adds to the third wave of empirical economic research on tropical deforestation, which utilizes high-resolution and high-frequency satellite data to monitor global land use changes (Balboni et al., 2022). Existing literature on the drivers of tropical deforestation has focused on several factors: political economy factors (Burgess et al., 2011; Fetzer and Marden, 2017; Burgess et al., 2019; Asher et al., 2020; Araujo et al., 2023; Assunção et al., 2023), environmental regulation (Hsiao, 2022; Souza-Rodrigues, 2019; Assunção et al., 2020; Bragança and Dahis, 2022), conflicts (Burgess et al., 2015; Smith et al., 2015; Vargas et al., 2019; Prem et al., 2021a), changes in values of alternative land use, such as prices of agricultural (Assunção et al., 2015; Ferraz, 2015; Curtis et al., 2018; Pendrill et al., 2019; Berman et al., 2023; Chort

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[3] EU Deforestation Regulation (EUDR) - Regulation (EU) 2023/1115 on deforestation-free products (European Commission, 2023).

and Öktem, 2024) and mineral (Caballero Espejo et al., 2018; Girard et al., 2022) commodities, and the role of technological change (Angelsen and Kaimowitz, 1999, 2001; Tomich et al., 2001; Abman and Carney, 2020; Szerman et al., 2022). Unlike legal crops, coca cultivation represents an illegal activity and, as such, does not adhere to regulations. Coca is not only illegal to produce but also illegal to sell, especially on international markets. This status significantly restricts the economic policy tools available to address issues related to coca cultivation and its environmental impact. While other commodities, such as cocoa, are produced and sold legally, allowing for the implementation of policy measures, such as taxes, to mitigate deforestation and other environmental concerns, coca's illegal status necessitates alternative approaches. Furthermore, its cultivation requires remote and difficult-to-detect locations, far from military and civil control. Lastly, the technological innovation has expanded the coca cultivation frontier, transforming it from a localized activity to a non-point source of environmental degradation that now affects previously unsuitable areas. This expansion contrasts with illegal gold mining, which remains a point source of degradation largely concentrated in the Madre de Dios region.

Second, the literature on illegal drug markets and the effects of the war on drugs has focused on its effectiveness (Mejia and Restrepo, 2015) and the unintended consequences, such as increased violence and trafficking (Dell, 2015), escalation of cocaine production (Prem et al., 2021b), and displacement of coca crops to other producer countries (Mejia and Restrepo, 2015). This paper complements the literature on the unexpected consequences of illegal markets by providing evidence that their externalities are not limited to increased violence (Angrist and Kugler, 2008; Mejia and Restrepo, 2013; Chimeli and Soares, 2017) and criminal capital formation (Sviatschi, 2022). I show that Narcos' repeated search for new land (capital) results in environmental crimes, particularly forestry crimes. In terms of context, the closest related paper is Sviatschi (2022). It provides evidence that higher returns to illegal activities, in areas more prone to coca cultivation in Peru, are associated with higher employment levels of children in coca fields. This causes children to develop criminal capital and enter a criminal life path.

Lastly, to the best of my knowledge, this is the first paper that combines the aforementioned strands of economic literature by investigating the environmental impact of drug production. By doing so, it speaks directly to the interdisciplinary literature on illicit drug markets and deforestation, which originally uncovered this phenomenon. In the Geography, Environmental, and Bioscience literatures, Dávalos et al. (2011) and Sesnie et al. (2017) directly analyze the effects of drug cultivation and anti-drug policies on deforestation. The former investigates the relevant relationship at the municipality level in the department of Choco and the Amazon forest of Colombia. The latter performs a spatio-temporal analysis on the impact of drug trafficking on forest loss in Central America. This study contributes to the broader scientific literature by focusing on drug cultivation (rather than drug trafficking), broadening the scope of analysis (constructing a cell-level panel dataset for the entire producer country instead of focusing solely on Biodiversity Hotspots), and, therefore, utilizing reduced form econometric analysis to comprehend the marginal impact and extent of the *Narco-Deforestation* phenomenon.

The remainder of the paper is organized as follows: Section 2 provides an overview of the Peruvian Amazon forest, the coca cultivation process, regulatory framework, and relevant institutional context. Section 3 details the comprehensive set of satellite, geographical, commodity price, and suitability data utilized. Section 4 outlines the empirical approach and discusses how endogeneity is addressed through the Bartik identification strategy. Section 5 presents the main findings and the suggestive evidence on the technological advancements and expansion of the illegal coca cultivation frontier. Finally, Section 6 concludes.

2 Institutional Context

In this section, I present the institutional context. First, I provide information on the Peruvian Amazon and its drivers of deforestation. Second, I describe the botany of coca, the coca cultivation process, and its regulation. Lastly, I summarize the main events and effects of the Colombian and Peruvian war on drugs.

2.1 The Peruvian Amazon and the Main Drivers of Deforestation

Peru is considered one of the most biodiverse countries in the world, with 60% of its territory covered by the Amazon forest. Within this, 90% is primary forest, and most of the remaining intact forest landscapes (IFLs)[4] are located in Loreto, Ucayali, and Madre de Dios (Rojas et al., 2021). Peru hosts 11% of the Amazon forest (Bardales et al., 2022), second largest portion after Brazil, and it possesses the fourth largest area of tropical forest in the

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[4] "Both terms [primary and IFLs] indicate a forest with no significant human disturbances in recent record. While primary forests refer to areas of forest having reached the final stage of succession, IFLs encompass a broader patchwork of undisturbed area. Within the boundary of an IFL you might find younger forests, clearings and areas of rock or ice in addition to primary forests. However, these younger patches must have been caused by natural disturbance patterns like floods or wildfire." (Ruiz, 2020)

world (Zelli et al., 2014). The forest not only preserves biodiversity but is also essential to the cultural identity and social cohesion of indigenous people, as it is home to 42 of Peru's 44 different ethnic groups (Zelli et al., 2014). Forest cover levels have been slowly but steadily declining since 1975, with deforestation and forest degradation accounting for nearly half of all GHG emissions in the country (Zelli et al., 2014).[5] Agricultural expansion is considered the major driver of deforestation. According to Vale Costa H (2021), 56% of the forest loss occurred in the Peruvian Amazon between 2001 and 2017 corresponds to agricultural areas in 2018. Other causes of deforestation include population growth in forested regions, institutional and legal weaknesses (Rosa da Conceição et al., 2015; Zelli et al., 2014), (illegal) logging, mining, gas/oil operations, and drug production (Zelli et al., 2014).[6] Young (2004a) in Steinberg et al. (2004) estimates that about one-third of Peruvian deforestation occurs in places where coca is grown. The authors also report that coca fields are often 0.25 to 1.0 hectares in size, leaving forest margins around the field. The perturbation of the forest edge conditions indirectly affects surrounding forests by limiting or preventing the survival of plant and animal species that require large tracts of undisturbed forest. Additionally, the establishment of new fields in even more isolated places worsens forest fragmentation. Finally, "there seems to be little likelihood of ecological restoration of these deforested and degraded landscapes" (Steinberg et al., 2004).

2.2 Coca Cultivation

Bolivia, Colombia, and Peru[7] are the only countries in the world that have the optimal conditions to grow coca[8] (Sviatschi, 2022). The eastern slopes of the Andean countries and the adjacent areas of the Amazon basin fully satisfy certain geographical and ecological conditions (altitude, slope, and soil characteristics) required for coca growing (Henman, 1978). Coca bushes usually grow between 500 and 1500 meters above sea level, reaching a height of 2 to 3 meters. The leaves of coca plants, which belong to the genus *Erythroxylum coca*, are used to extract cocaine alkaloid for cocaine production (Mejia and Posada, 2008).

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[5] As reported by Rosa da Conceição et al. (2015), environmental policy making in Peru, similar to the rest of Latin America, is perceived as a low priority by Peruvian voters. It is mostly undertaken by the executive branch of the government and, therefore, not subject to legislative processes.

[6] To the best of my knowledge, neither the Government of Peru nor any other reliable source reports the share of deforestation driven by any of these factors.

[7] I refer to these three countries as producer countries or source countries or Andean countries.

[8] The biomes (i.e., type of vegetation) of the Andean regions provide ideal conditions for growing coca and opium poppy. The lowland and montane forests (ideal biome for coca growing) form the major part of the natural resources of Colombia, Peru, and Bolivia, accounting for between 48% and 58% of these countries' land areas (UNODC, 2006).

The *Erythroxylum coca* genus is large and may contain up to 250 species, usually growing in the form of shrubs or small trees.[9] Coca cultivation and harvesting can occur throughout the year, but the majority of coca growth occurs from December to April. Depending on the variety and conditions, harvesting can take place between six and nine months after sowing. Coca is harvested between three and eight times per year. After harvesting, dried coca leaves are first transformed into coca paste, then into coca base, and ultimately into cocaine (Mejia and Posada, 2008).

In Peru, coca cultivation is not intrinsically illegal. Its legal production and uses are regulated by the state-owned Empresa Nacional de la Coca (ENACO), which holds a monopoly on the coca trade and manages registered coca farmers. As reported by DEVIDA (2021), in 1978, Peru enacted Legislative Decree 22095, known as the Law on the Suppression of Illicit Drug Trafficking (Ley de Represión del Tráfico Ilícito de Drogas). This law prohibited the cultivation of coca leaves and seedlings in new areas of the national territory, stipulating that no additional crops could be established beyond those already existing. To regulate the coca leaf market—particularly regarding the area and amount permitted by the state for traditional purposes—the government established a registry of state-recognized farmers, identifying them as coca leaf producers. The first transitional provision of Legislative Decree 22095 mandated that all agricultural producers with properties dedicated to coca cultivation must register in ENACO's Producer Registry. This registry includes 36,464 producers from whom ENACO can purchase coca leaves, covering a total permitted area of 22,094 hectares. Figure 1a reports DEVIDA (2021) and ENACO regional level data in a visual format. Regions shown in red indicate areas where coca cultivation may be legal, with at least one state-recognized coca leaf producer, while regions in white, e.g. Loreto, denote areas where coca cultivation is entirely illegal- no state-recognized producers.

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[9] Within the family of Erythroxylaceae, four different varieties of cultivated coca can be found: Erythroxylum coca var. coca (or Bolivian Coca), Erythroxylum coca var. ipadu (or Amazonian Coca), Erythroxylum novogranatense var. novogranatense (or Colombian Coca), and Erythroxylum novogranatense var. truxillense (or Trujillo Coca). While the names refer to the past geographical distribution of each of the four varieties, the current predominant species in the Andes is Bolivian coca. It represents the "master" variety from which all others are derived and is the most traded variety in the Colombian cocaine market (Mejia and Restrepo, 2013).

2.3 Anti-Drug Policies and Their Effects

Colombia and Peru have alternatively been the world's biggest producers of coca.[10] Both countries often relied on foreign aid, especially from the United States, to carry out the "war on drugs" and, more specifically, to implement eradication policies, alternative livelihood programs, and/or attempts to disrupt the cocaine market chain. However, the two countries have implemented substantially different strategies over the years. In the early '90s, Peru was the number one producer of coca in the world. The Peruvian government implemented policies aimed at disrupting the cocaine manufacturing chain by targeting the air bridge used to transport Peruvian cocaine paste to refining laboratories in Colombia. As a direct result, coca cultivation in Peru dropped from 115,000 hectares in 1995 to 48,000 hectares in 2005 (Mejia and Posada, 2008). However, as an indirect result, coca cultivation increased dramatically in Colombia, reaching a new historical peak. In response to these events, since 1997, the Colombian government, in a military alliance with US Foreign Assistance[11], has conducted an eradication program known as the *Plan Colombia*, aimed at preventing national coca cultivation through aerial spraying of herbicides. The US-driven spraying program targeted not only drug production and trafficking but also the organized criminal groups—the Fuerzas Armadas Revolucionarias de Colombia (FARC) and the Autodefensas Unidas de Colombia (AUC)—associated with these activities (Mejia and Restrepo, 2015). Similar to what happened a few years earlier, the drug trade displaced (displacement effect or "balloon effect") to other producer countries, particularly Peru. Figure 2a shows the evolution of coca leaf prices in the Peruvian black market from the mid-1990s. During the early 2000s, prices steadily increased. Between 2004 and 2009, Peru's share of coca leaf production rose from 27% to 39%, as a result of a decline in coca leaf production in Colombia and an increase in production in Peru over the same period (UNODC, 2010).

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[10] The two countries have very dissimilar histories regarding the crop. In Colombia, the first coca leaves were found on the properties of the "emeralds," who became the first drug traffickers and forced Colombian peasants to grow coca. On the other hand, in Peru, coca leaves were found much earlier, before the 19th century. The production of coca has always been legal, either for medicinal purposes or for chewing. No violence was exerted by cartels in their extraction (Sviatschi, 2022).

[11] "North America, in particular the United States, remains the main final destination of cocaine smuggled from the Andean countries." (UNODC, 2021)

3 Data

In this paper, I utilize information from remote sensing satellite imagery (for percent tree cover, nightlights, and coca density) and model-based geographical raster data (for suitability indexes) to overcome challenges arising from the lack of reliable administrative data. Additionally, I explore a measure of coca suitability (alongside proximity to the Colombian border) and the temporal variation in coca leaf prices. To examine the relation of interest, geoprocessing of the raw data is initially conducted, followed by the construction of the measures of interest at the 12km x 12km cell-year level. The study period spans from 2003 to 2019. Table 1 provides the summary statistics for the main variables included in the analysis. Forested areas and Coca cultivation cover respectively about 43 % and 0.09 % of the country's total land.

3.1 Main Variables

3.1.1 Percent Tree Cover

I identify forested areas using global satellite data from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument aboard NASA's Terra satellite. More specifically, I utilize the MODIS/Terra Vegetation Continuous Fields (VCF) yearly product provided by DiMiceli et al. (2016).[12] VCF offers a continuous, quantitative portrayal of land surface cover at a spatial resolution of 250 meters, with a sub-pixel depiction of percent cover in reference to the three ground cover components (DiMiceli et al., 2016). VCF presents a significant improvement over data sources used in previous deforestation studies. It can distinguish forests from non-forest plantations, surpassing the limitations of the Normalized Difference Vegetation Index (NDVI) employed by previous studies such as Foster and Rosenzweig (2003). Moreover, the "continuous" nature of the VCF enables the capture of partial forest loss, improving upon the binary deforestation indicators used in the Global Forest Cover (Hansen et al., 2013). The primary VCF data layer used in this study is *Percent Tree Cover*, which reports the percentage of each pixel covered by tree canopy. Tree canopy is defined as woody vegetation higher than 5 meters. Figures 3 is a map of Peru that visually represents the country's *Percent Tree Cover* (raw-data) for the year 2000, using a grayscale color scheme. The darker regions, indicating lower tree cover, are concentrated in the western part of Peru, corresponding to the coastal areas and the Andean mountain range. In contrast, the lighter

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[12] The product has been generated using a supervised machine-learning algorithm, that exploits imagery from Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 from 1998 to 2013 as training data (DiMiceli et al., 2021).

regions, which indicate higher tree cover, are found primarily in the eastern part of the country, where the Amazon rainforest is located.

3.1.2 Coca Suitability

I use coca suitability as the initial source of geographical variation. Due to the unavailability of spatial data on soil suitability for coca cultivation, I rely on the coca agro-ecological index developed by Sviatschi (2022). This index, ranging from 0 to 1 at the district/GADM3 level, is based on time-invariant agro-ecological conditions, including precipitation, temperature, slope, altitude, and soil characteristics. Figure 1b illustrates the geographical distribution of this index across Peru, showing that approximately 36% of the country's land area is suitable to some extent for coca cultivation. The geographical distribution of licenses for legal & traditional coca cultivation (Figure 1a) aligns closely with the areas identified by this index.

As shown in Figure 1c, only the southern districts of Loreto region (Peru's northern border with Colombia) exhibit any coca suitability, and all cultivation in this region is illegal - i.e. no state-recognized coca leaf producers. At the cell level, I define coca suitability as the weighted average of coca suitability values of areas intersecting the cell, where the weights correspond to the percentage of intersection.

3.1.3 Prices of Coca Leaves

Since 1990, the UNODC has been reporting average monthly prices of sun-dried coca leaves in the Peruvian black market. The prices are collected by project staff in focal regions[13] across the country. The semi-structured interviews target key informants, including farmers, storekeepers, and other stakeholders involved in the illicit drug business (UNODC and DEVIDA, 2006). These prices are available at the country level. Figure 2a and A1 report the evolution of prices of coca leaves (in $\$/kg$) over time, revealing a clear long-term upward trajectory, and a shift in demand from Colombian to Peruvian coca leaves. This trend is particularly evident from the late 1990s onward, with prices steadily increasing over the years.

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[13] The reporting of regional prices is not conducted systematically by UNODC. While country-average data is available for all years considered, the same is not true for the singular regional markets.

3.1.4 Coca Density

The United Nations Office on Drugs and Crime (UNODC), in conjunction with national governments, gathers internationally comparable data on illegal crop cultivation through the Global Illicit Crop Monitoring Programme (ICMP). For Peru, yearly coca cultivation geo-data is obtained from *(i.)* the UNODC (for the period 2003-2017) and *(ii.)* its Peruvian governmental counterpart, the Comisión Nacional para el Desarrollo y Vida sin Drogas (DEVIDA), for the period 2018-2019. The data on coca crops is derived from the interpretation and validation of satellite images from various sources. Remote sensing experts define interpretation patterns for five different categories and stages of coca fields: young coca field, mature coca field, harvested coca field, rehabilitated coca field, and mixed crops. These patterns are then refined through field verification (image pre-processing), and a preliminary visual interpretation is conducted using historical coca series and secondary information from diverse sources. Identification is achieved through the use of several chromatic compositions that highlight coca fields among other coverings. Verification over-flight further validates the results in the territories affected by coca crops (UNODC and DEVIDA, 2006; Biesimci, 2019). In the raw data, coca density is a categorical variable ranging from zero to five. Zero indicates the absence of coca crops, one denotes 0.1 to 1 ha of coca per km^2, two denotes 1.1 to 2 ha/km^2, three denotes 2.1 to 4 ha/km^2, four denotes 4.1 to 8 ha/km^2, and five denotes more than 8 ha/km^2. Given the non-linearity and undercounting threat associated with this variable, I create a new coca density variable, representing the maximum value among the aforementioned coca density intervals, and measured in ha/km^2.

Figure 4 illustrates the evolution of the number of cells with coca crops. Specifically, it focuses on the variation over time in the number of cells with a positive coca density ($CocaDensity > 0$). The green markers represent values for Loreto region, while the blue markers correspond to the rest of the country, excluding Loreto. It is notable that no coca field was detected in Loreto prior to 2006. Between 2009 and 2010, there was a sharp rise in the number of cells with coca cultivation. At the national level, the number of such cells increased by approximately 60%. By the end of the study period, the number of cells with coca fields in Loreto constituted about 40 % of the rest of the country. This temporal and spatial variation is visually evident in in Figure 5a and Figure 5b. Figure 5a shows Percent Tree Cover and coca crops at the baseline, while Figure 5b illustrates the distribution of coca crops in 2019 (highlighted in red), overlaid with deforestation and reforestation gradients in various shades of brown and green, spanning the entire analysis period. As visible in the latter figure, there is a clear correlation between deforested areas and coca fields across the country — from the extreme south, near the Bolivian border, through Peru's main illicit coca-producing region in the Apurímac, Ene, and Mantaro River Valleys (VRAEM), to the Loreto region in the extreme north, bordering Colombia.

This data is the most reliable source[14] of information on coca cultivation. Figure 6 shows the clear correlation between the evolution of Coca Density over time and the variation of price of coca leaves in the Peruvian black market. Nonetheless, it has limitations due to the complexity of monitoring this illegal activity. The undercounting of coca density is highly plausible given the nature of the data. As stated by UNODC (2017), "under-registration of the area with coca is likely." Geographical factors, such as precision in delimiting the polygons identified with coca (e.g., presence of clouds in satellite images), may hinder detection. Additionally, human error in interpreting satellite images and strategic behavior of coca farmers could compromise the detection. For instance, UNODC and DEVIDA (2006) mentions that "the decrease [in coca cultivation in Peru between 2004 and 2005] was attributed to the limitation of satellite images to detect coca cultivation below tree canopy." The Puno region, for instance, often had coca cultivation interspersed with other crops or bushes, making detection more challenging. Coca farmers are not solely dependent on coca cultivation but also have other crops or activities in neighboring areas, contributing to the difficulty in identification.[15]

3.1.5 Nightlights

Nightlight data is included in the analysis as the best measure of economic activity available at disaggregated level. This data is derived from yearly global satellite data at a spatial resolution of 30 arc-seconds (approximately 1km at the equator). Nightlights data is obtained from Li and Zhou (2017), which uses temporally calibrated Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS) stable nighttime light (NTL) time series data from 1992-2013 and converted NTL time series from the VIIRS data (2014-2021).

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[14] Illegal drug production in suspected drug-growing areas is also monitored by the US government's White House Office of Drug Control Policy (ONDCP). However, UNODC is considered more reliable because *(i.)* it collects data on coca cultivation throughout the producer countries' entire territories, whereas ONDCP's data only covers a representative sample; *(ii.)* UNODC applies more corrections than ONDCP for possible biases and mistakes in aerial imagery interpretation.

[15] Further evidence of under-reporting is provided by UNODC (2006) for Colombia's monitoring in 2005: "Potential small coca fields have been detected in remote areas outside the established agricultural areas of the departments of the Orinoco and Amazon river basins. Field verification has not been carried out in these areas because it was considered too time-consuming and too costly to verify small and isolated patches of coca cultivation. Because of the absence of field verification, the estimate for coca cultivation in these areas are presented as indicative and not included in the final estimate."

3.1.6 Price Shocks to Other Commodities

For soil suitability to other agricultural commodities (coffee, cocoa, palm oil, cotton, and sugarcane), I utilize raster data from the FAO-Global Agro-Ecological Zones (GAEZ) suitability indexes at 30 arc-second resolution. The indexes are constructed based on input levels such as climate data, soil, and crop characteristics from the period 1961-1990. Data on gold deposits is obtained from the US Geological Survey's Mineral Resource Database.

Prices for other commodities are collected from various sources. National data on cocoa and coffee prices is obtained from the Ministry of Agricultural Development and Irrigation (Ministerio de Desarrollo Agrario y Riego - MIDAGRI), which provides information on the evolution of the average monetary value received by agricultural producers (Precio en Chacra). National gold price data is downloaded from the Central Reserve Bank of Peru (Banco Central de Reserva del Perú - BCRP) and reflects export prices. To the best of my knowledge, price data for other commodities (cotton, sugar, and palm oil) is not available at national level for the entire period of interest. Thus, international prices are sourced from the World Bank's Global Economic Monitor. All prices are expressed in $\$/kg$. Figure 2b llustrates the indexed evolution (2003 = 100) of coca prices together with the relevant commodities.

3.1.7 Administrative Areas

Administrative areas of Peru are sourced from the Database of Global Administrative Areas (GADM, 2021), version 3.6. Peru consists of 26 regions (GADM1 level administrative units), with Loreto being the largest and bordering Colombia, Brazil, and Ecuador. The lowest administrative level available for Peru is GADM3, corresponding to districts. District size varies across the country, with smaller districts situated along the mountain regions on the west side of the country. Figure 1c illustrates the administrative levels considered in the model.

3.2 Other Geographical and Time Level Variables

3.2.1 Cultivation density data for other crops

Cultivation density data for other crops (cocoa, coffee, cotton, and sugarcane) is obtained from MINAGRI and covers the period 2015–2019, available at the monthly and district levels. This data, reported in hectares, is converted to hectares per square kilometer (ha/km^2)

for consistency with other variables. This data originates from the National Agricultural Survey (ENA) under the PIADER project, which combines probabilistic sampling and census data to create a comprehensive sampling framework for agricultural activities across the country. The framework was initially constructed using 2012 RapidEye satellite images to map land cover and agricultural area, later updated with 2018 Sentinel-2 images for greater accuracy (DIRECCIÓN GENERAL DE ESTADÍSTICA, SEGUIMIENTO Y EVALUACIÓN DE POLÍTICAS, 2021). Although limited in time span and relatively aggregated, to the best of my knowledge, this represents the best available source of cultivation data in Peru.

3.2.2 International Coca and Cocaine Market

International prices for cocaine are sourced from UNODC. The data includes street prices of cocaine in the United States (USD per gram), later converted to USD per kilogram ($\$/kg$) for consistency. To the best of my knowledge, international prices for coca leaves are not publicly available. Quantification of the hectares of coca crops existing in Colombia as of December 31 of each year is obtained from the Government of Colombia.

4 Empirical Strategy

To examine how illegal market forces drive environmental degradation, I exploit cell-level variation in the economic value of potential coca cultivation induced by fluctuations in Peruvian black-market prices. Using two primary sources of cross-sectional variation, I construct two distinct measures of Price Shocks for coca, both relying on time variation in coca leaf prices. Specifically, each potential instrumental variable combines a source of geographic variation in coca-growing areas—Coca Suitability ($Coca\ Suitability_c$) or Proximity to the Colombian border ($Proximity\ to\ border_c$)—with $Standardised\ Coca\ Price_{t-1}$, the lagged yearly national price of coca leaves in the Peruvian black market. Both empirical strategies can be interpreted as a shift–share, or Bartik (1991), instrument, in which I interact a cell-level measure of exposure to coca ("share") with the price of coca leaves in the Peruvian black market ("shift"). This approach is widely used in the literature on commodity shocks (Dube and Vargas, 2013; Sviatschi, 2022) and their effects on deforestation (Assunção et al., 2015; Girard et al., 2022; Berman et al., 2023).[16] To ensure comparability of

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[16] To determine the extent to which the price of a relevant commodity (e.g., cattle, soybeans, palm oil) affects demand in a specific location, the (inter)national time series of the price is interacted with a cross-sectional measure of exposure (Balboni et al., 2022).

estimates, Price Shocks for coca and other commodities are defined such that: *(i.)* commodity suitability indexes are defined between 0 and 1; *(ii.)* prices are standardised (std), and *(iii.)* lagged to account for time delays. The use of lagged prices reflects the time it may take for coca farmers and traffickers to react to changes in prices.

4.1 Econometric Specification using Coca Suitability

4.1.1 Economic Incentives

Figure 1b illustrates the agro-ecological coca suitability index proposed by Sviatschi (2022). Starting from the district-level data, I define the time-invariant coca suitability of cell c ($Coca\ Suitability_c$) as the weighted average of coca suitability values for areas that intersect the cell, where the weights are given by the percentage of intersection. The Price Shock to coca $Z_{1,c,t-1}$ is defined as:

$$Z_{1,c,t-1} = Coca\ Suitability_c \times Std\ Coca\ Price_{t-1}$$

To study how variation in incentives to grow coca affects deforestation, I estimate a two-way fixed-effects reduced-form model. The outcome $Y_{c,t}$ is either $Coca\ Density_{c,t}$ (first-stage) or $Perc\ Tree\ Cover_{c,t}$ (reduced-form), where $Coca\ Density_{c,t}$ denotes actual coca density in cell c and year t, and $Perc\ Tree\ Cover_{c,t}$ denotes the percentage of each cell covered by tree canopy in year t. To analyze the marginal effect of an increase in coca density of 1 ha/km^2, I construct a transformed coca density variable. To alleviate undercounting concerns related to data construction, this variable is defined as the maximum value of the original Coca Density data within each category. The resulting categorical variable takes values from 0 to 8 (ha/km^2): it is equal to zero in the absence of coca crops; one denotes from 0.1 to 1 ha of coca per km^2; two denotes from 1.1 to 2 ha/km^2; four denotes from 2.1 to 4 ha/km^2; and eight denotes from 4.1 to 8 ha/km^2.[17] The empirical specification is:

$$Y_{c,t} = \beta_0 + \beta_1 Z_{1,c,t-1} + \beta_2 X_{c,t} + \alpha_c + \alpha_t + \epsilon_{c,t} \tag{1}$$

where c represents the 12 km × 12 km cell and t denotes the year. $Y_{c,t}$ is the outcome of interest—either actual coca crops observed or forest cover levels—both defined as measures

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[17] Observations with more than 8 ha/km^2 of coca density are dropped, as they represent about 0.02% of the sample.

of density over $[0, 100]$. The preferred specification includes cell fixed effects α_c, year fixed effects α_t, and a vector of controls for average nightlights and price shocks to other relevant commodities $X_{c,t}$. All reported standard errors are heteroskedasticity-robust and clustered at the district level[18] to account for correlation over time within districts. The strategy is akin to a difference-in-differences design, comparing areas more suitable for coca cultivation to areas less suitable in years following high coca prices *versus* years following low coca prices. In other words, I analyze the magnitude of coca-driven deforestation by exploiting heterogeneous effects of prices, assuming that, in the absence of an increase in the returns to cultivating coca, suitable and unsuitable areas would have experienced the same level of deforestation.

4.1.2 The role of coca cultivation

Variations in coca prices affect deforestation levels by changing the incentives to cultivate coca. In the following OLS model, Price Shocks to coca serve as an instrumental variable for actual observed Coca Density:

$$Perc\ Tree\ Cover_{c,t} = \beta_0 + \beta_1 Coca\ Density_{c,t} + \beta_2 X_{c,t} + \alpha_c + \alpha_t + \epsilon_{c,t} \tag{2}$$

Both the dependent and independent variables are defined as measures of percentage or density, potentially within the range $[0, 100]$.

4.2 Proximity to the Colombian Border and Technological Revolution

Figure 1b shows that most of the Loreto region is unsuitable for coca cultivation. As explained in Section 2, coca plants require specific geographical conditions, particularly an altitude between 500 and 1500 meters. The Andean hills represent the ideal biome for growing coca, whereas the Loreto region[19], which was 98% covered by natural forest as of 2000 (Global Forest Watch, 2023), is not considered suitable. Moreover, coca cultivation in Loreto is entirely illegal (shown in white in Figure 1a), as the state does not recognize any coca leaf producers in the region. However, Figures 4 and 5b reveal that this bordering region has become an important coca cultivation area.

The border between Peru, Brazil, and Colombia, known as the *Triple Frontier* or *Amazon Trapeze*, has traditionally served as a transit zone in the global cocaine trade. Over the last

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[18] Peruvian districts are demarcated with blue lines in Figure 1c.

[19] The region is highlighted in green in Figure 1c.

few decades, it has evolved from a trafficking enclave to an emerging site of coca cultivation and cocaine production (López and Tuesta, 2015). According to anecdotal evidence, coca cultivation in this region has been made possible by a technological innovation that artificially creates the ecological conditions required to grow the crop.[20] The use of agrochemicals[21]—in their maximum possible doses (UNODC, 2009)—allows not only higher leaf yields (and, therefore, potential cocaine hydrochloride production) but also the expansion of the coca cultivation frontier into new areas (UNODC, 2010). The greater use of chemical inputs (fertilizers, insecticides, etc.), leading to yield increases, makes extensive production systems more profitable, providing the economic rationale for forest clearing in previously inaccessible areas (Angelsen and Kaimowitz, 2001).

The growth and expansion of Loreto's "Narco-Infrastructure" (Silverstein, 2021) is shaped by geography, with a "tangle of forests and rivers creating a web of opportunities for clandestine transit" (López and Tuesta, 2015). The Amazon River serves as *(i.)* a direct connection to Brazil and *(ii.)* a "door" to the European and African markets through the Atlantic Ocean. Additionally, cocaleros in Loreto are only hours away by river from Peruvian cities and institutions. Furthermore, the narco-infrastructure knows no borders and "supports the *balloon effect* of failed counter-narcotics policy" (Silverstein, 2021), allowing for the dis-

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[20] "The technological improvement of cultivation and the handling of large volumes of agrochemicals causes severe and irremediable problems for the environment. For many years, Sevín was one of the products most frequently used in coca cultivation. This product has currently been replaced by others much more toxic and highly polluting such as Cypermec, Monitor, Caporal, Benomil, Faramate, Tamarón, Thiodan, Antracol, among many others, whose use has been restricted and/or prohibited in other countries, essentially due to the great damage they cause to the environment." (UNODC, 2009)

[21] **Similarities are found with the methodologies used in the non-traditional yet extractive cultivation of coca in Colombia, implying that the technological improvement might have been imported by Colombian Narcos.** "In Colombia, coca farmers do not use traditional cultivation methods as in parts of Peru and Bolivia, as coca cultivation is mostly for cocaine production. Coca growers are frequently people displaced from other areas, with no knowledge of local and traditional agricultural activities. Their main goal is to maximize the harvest rather than to maintain long-term soil productivity." (UNODC, 2006)

placement[22] of Colombian Narcos targeted by anti-drug policies.[23]

> *The cultivation, implementation, chemical handling, and processing of leaves [in Putumayo and Bajo Amazonas] continue to be given under the "Colombian" modality; that is, the police interventions have not found either "drying places" nor maceration ponds in coca farms, as is typical in the rest of the country [of Peru].* (UNODC and DEVIDA, 2016)

To capture this source of geographic variation, the second definition of Price Shock to coca, $Z_{2,c,t-1}$, exploits Proximity to the Colombian border (measured in 100 km units, 0 at the border, negative further away), shown as the red line in Figure 1c.

$$Z_{2,c,t-1} = Proximity\ to\ border_c \times Std\ Coca\ Price_{t-1}$$

In analogy with equation (1), a baseline border-based specification relates outcomes to this price shock as follows:

$$Y_{c,t} = \gamma_0 + \gamma_1 Z_{2,c,t-1} + \gamma_2 X_{c,t} + \alpha_c + \alpha_t + \upsilon_{c,t}. \tag{3}$$

In this context, technological change permits cultivation of the crop regardless of soil characteristics. Colombian traffickers and farmers can relocate just across the border and exploit the returns to higher prices while escaping national anti-drug policies. Thus, the empirical strategy mirrors equation (1), exploiting the differential impact of price variation by comparing $Coca\ Density$ and $Perc\ Tree\ Cover$ in areas closer to the border with areas farther from Colombia. In the empirical analysis, I combine this joint inclusion of $Z_{1,c,t-1}$ and $Z_{2,c,t-1}$ with the full set of shift–share shocks for legal crops and gold. Lastly, I interact

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[22] "Coca cultivation has continued to spread in the country [of Peru], **with the northern border seeing the most pronounced increase in the final years of the previous decade. This is a complicated area for a number of reasons, including allegations that Colombians have moved into the zone to cultivate coca.** The Peruvian government suspects that members of the Revolutionary Armed Forces of Colombia (FARC) rebels who have not demobilized are also taking advantage of the remote area." (Grisaffi, 2020)

[23] Silverstein (2021) on the narco-partnership between Amazonian Colombia and Loreto: "Antinarcotics operations in the region targeted air traffic, with the authorization to shoot down planes for suspicion of narco-involvement. In the wake of these drug war policies, and in conjunction with glyphosate-spraying coca eradication campaigns in Colombia, the province of Ramón Castilla (Peru) was reinvented as a coca-growing zone. Thus, Mishkiyacu's participation in illicit coca cultivation is relatively new; people estimated that they began growing coca somewhere in the early 2000s. Around this time, representatives from drug trafficking organizations arrived in Mishkiyacu, as well as surrounding communities, seeking to establish new spaces to house both coca plants and maceration operations. They did not arrive as strangers. Rather, they drew on historical ties to rural communities with whom they, or their associates, had partnered to help facilitate the transfer of PBC for the past several decades."

both suitability-based price shocks and border-based price shocks with a post-technology indicator. to investigate time-heterogeneous effects.

4.2.1 Share endogeneity and the exogenous-shares perspective

I interpret the empirical design as a shift–share strategy in which the "shares" are fixed geographic characteristics and the "shift" is the national coca leaf price. Formally, the price shocks $Z_{1,ct-1}$ and $Z_{2,ct-1}$ combine cell-level exposure (coca suitability or proximity to the Colombian border) with a common time shock to coca profitability. Following Borusyak et al. (2025), this places the identifying assumption in the *exogenous-shares* class rather than the "many exogenous shifts" class: conditional on controls and fixed effects, units with different shares are assumed to follow similar counterfactual trends in forest cover in the absence of changes in coca profitability.

In this framework, the shares are explicitly tailored to coca. The coca suitability index is an agro-ecological measure that captures the biophysical feasibility of coca cultivation in each grid cell; it is time-invariant and is not intended to proxy general agricultural productivity or generic forest-frontier potential. Proximity to the Colombian border captures differential access to cross-border narco-infrastructure and to the "Colombian" cultivation technology, rather than generic market access or suitability for legal crops. This tailoring is in line with the guidance in Borusyak et al. (2025), who stress that shares closely tied to the treatment mechanism are more credible than broad composition measures.

A natural concern is that coca-suitable or border-proximate areas may exhibit different underlying trends in forest cover, or may be exposed to other shocks that load on the same shares. A key limitation of this setting is that there is no clean pre-treatment period without coca: coca cultivation and coca-related deforestation pre-date the availability of coca data, and the tree-cover series start in 2000. This is consistent with historical evidence that coca-driven deforestation is already underway at the beginning of the sample, so standard pre-trend tests necessarily reflect a mixture of structural differences and pre-existing coca dynamics.

Given this limitation, I interpret identification as resting on an exogenous-shares assumption that holds conditional on the included controls and fixed effects. All specifications include cell and year fixed effects, which absorb time-invariant geographic heterogeneity and aggregate shocks. To address the possibility that other markets might load on similar geography, I further include a full set of shift–share price shocks for legal crops and gold—constructed by interacting their prices with their own suitability (or deposit) shares—whenever I use coca suitability as the share, and an analogous set of border-based price shocks when I use proximity to the Colombian border. As shown in the results section, conditioning on this vector of other commodity shocks leaves the estimated coca effect unchanged, and in the border-based design the coca price shock interacted with border proximity is quantitatively important while analogous shocks for other commodities are small and statistically insignificant. Under the maintained assumption that, conditional on these controls and fixed effects, the residual variation in the coca shift–share is orthogonal to other unobserved forces correlated with coca suitability and border proximity, the estimated coefficients can be interpreted as the incremental effect of changes in coca profitability on deforestation.

5 Results

5.1 Main Results

Table 2 presents the main results of this paper and shows that an increase in coca prices is associated with reductions in tree cover. In Column 1, I report the estimated coefficients of the baseline specification (equation 1). A one-standard-deviation increase in coca prices leads, on average, to a 1.7 percentage point reduction in tree cover, equivalent to a 4% decrease relative to the average Percent Tree Cover. This finding is consistent with arguments by Young (2004a) and with the spatial correlation in Figure 5b, both of which show concentrated deforestation in coca-growing areas. Column 2 includes nightlight data as a proxy for economic activity; the results remain robust.

5.1.1 Other commodities shocks

Exclusion restrictions could be violated if there are other commodities whose production is closely linked to coca cultivation and, in turn, contributes to deforestation. These commodities should meet two conditions: *(i)* they are geographically concentrated in areas prone to coca cultivation, and *(ii)* their price trends are correlated with coca leaf prices. Consequently, price shocks to these commodities could introduce confounding variation.

I address these concerns by including controls for price shocks to other key commodities, using national-level data for the most relevant commodities, e.g., cocoa, coffee, and gold, while data for other important commodities, e.g., palm oil, cotton, and sugar cane, are only available at the international level.[24] For each crop, the price shock is defined analogously to Price Shocks to coca, as the interaction between the soil suitability index and the standardised lagged price. For gold, the geographical prediction is derived from the share of mineral gold deposits per cell in the 1970s. Column 3 of Table 2 shows that the estimate for coca remains robust with the inclusion of price shocks to these commodities.

5.1.2 Back-of-the-envelope calculation

My findings show that the 40% increase in coca prices observed during the study period led to an estimated loss of 6,450 km^2 of tree cover. To estimate the share of deforestation attributable to coca cultivation, I perform a back-of-the-envelope calculation. A 30% increase in coca prices, such as that observed between 2013 and 2014, in cells that are at least partially suitable (accounting for 36.5% of the country) is estimated to have contributed approximately 18% of the total tree cover loss that occurred in Peru in 2014—the year that witnessed the highest tree cover loss over the time horizon considered (37,000 km^2, representing a 6% decrease compared to 2013). To calculate this share, I multiply the predicted narco-deforestation estimate (derived from the results of Column 2, Table A1) by the increase in coca price ($+1\$/kg$) observed between 2013 and 2014, the proportion of suitable areas, and the tree cover area in 2013.

Given the available data, it is not possible to disentangle, within a given cell-year, the share of tree cover loss that corresponds to intact or primary forest from the share that corresponds to reforested areas with woody vegetation taller than 5 meters (e.g., palm oil). As a result, I cannot accurately determine the extent of intact or primary forest loss from year to year. These limitations prevent a precise quantification of the overall share of coca-driven deforestation over the entire period under consideration.

5.1.3 The effects of coca density

Changes in coca prices affect deforestation rates through changes in the incentives to grow coca. Columns 4–7 of Table 2 complement the analysis by incorporating data on Coca

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[24] As explained in Section 2.1, anecdotal evidence suggests that agricultural expansion to forested areas and illegal gold mining are important drivers of deforestation in the Peruvian Amazon. The choice of relevant commodities aligns with the existing economic literature on coca cultivation: coffee and gold (Sviatschi, 2022), and cocoa, palm oil, and sugar cane (Mejia and Restrepo, 2013). According to data from MIDAGRI (Ministerio de Agricultura y Riego, 2019), in 2018, the relevant crops represented the following shares of the total Peruvian cultivated area (leading permanent and semi-permanent crops): coffee 33%, cocoa 12%, palm oil trees 5%, sugar cane 6%, and cotton 1%.

Density and presenting results using Ordinary Least Squares (OLS), First-Stage (FS), and Two-Stage Least Squares (2SLS) methods. Column 4 re-establishes the negative correlation between coca cultivation and tree cover visible in Figure 5b. Column 5 reports that a one-standard-deviation increase in coca prices is associated with a statistically significant increase in Coca Density of about 74% relative to its average value. In turn, a marginal increase in Coca Density corresponds to an average reduction in tree cover of approximately 24 percentage points (Column 6), and this relationship remains robust when controlling for price shocks in other commodities (Column 7). However, as explained in Sections 3.1.4 and 4, the 2SLS estimates may appear large, both in absolute terms and relative to the OLS estimates in Column 4, because of an unmeasured undercount in coca density.

5.1.4 Robustness

Table A2 addresses endogeneity concerns related to the *shift* component of the design, i.e., the national coca price, arising from supply-side dynamics. For comparability, Column 1 of Table A2 again reports the coefficients for the environmental effect of Price Shocks to coca and other relevant commodities (Column 3 of Table 2). One concern is *reverse causality*: deforestation may affect coca prices rather than the other way around. If producers expand coca cultivation and clear forest, the resulting increase in supply could depress coca prices. In that case, contemporaneous movements in prices and deforestation would partly reflect this feedback, complicating the interpretation of the reduced-form relationship between coca price shocks and tree-cover loss. More generally, coca prices and deforestation may be jointly determined: higher prices raise incentives to expand coca and clear forest, while changes in supply conditions induced by deforestation can feed back into prices.

To mitigate these supply-side concerns about the shift, Columns 2 and 3 of Table A2 replace the national coca leaf price with two external proxies for coca profitability: international cocaine prices (U.S. retail prices) and reductions in coca cultivation in Colombia. These proxies are plausibly exogenous to local deforestation in Peru but still affect the profitability of Peruvian coca through international markets. Figure A1 shows that these external series are empirically relevant for Peruvian coca prices. The Peruvian coca leaf price co-moves positively with U.S. retail cocaine prices, while it is strongly negatively correlated with coca cultivation in Colombia, especially after 2007. This pattern is consistent with the idea that reductions in Colombian supply shift demand towards Peruvian producers and increase farm-gate coca prices.

As expected, because these proxies are noisier measures of local coca profitability, the point estimates are smaller in magnitude; however, the results are qualitatively unchanged. This evidence complements the exogenous-shares discussion in Section 4: while that section focuses on the exogeneity of the *shares* (coca suitability and border proximity), Table A2 shows that the main findings are robust to using plausibly exogenous *shifts* in coca profitability instead of domestic coca prices.

5.2 Technological Revolution

The results above show that coca market forces play a central role in driving local deforestation in the Peruvian Amazon rainforest. These aggregate patterns, however, mask spatial heterogeneity. As discussed in Section 4.2, the northern region of Loreto plays a distinctive role in the coca economy of the broader area.

Table 3 documents this spatial heterogeneity using a specification that includes both the suitability-based and the border-based price shocks and allows their coefficients to differ between Loreto and the rest of Peru. Column 1 shows that outside Loreto, coca suitability is the dominant predictor of coca density: the coefficient on the suitability-based price shock is large and precisely estimated, while the border-based shock is small and not statistically related to coca outcomes. In contrast, within Loreto (Column 2) the pattern reverses. Coca density responds strongly to price shocks interacted with proximity to the Colombian border, whereas the suitability-based shock becomes weakly correlated with coca cultivation. This pattern is consistent with the idea that, in this strategic frontier region, the relevant margin of adjustment is not agronomic suitability per se—more prevalent in the south of Loreto (see Figure 1b)—but rather access to the border and trafficking routes. In the context of coca cultivation, producers therefore face a location-choice problem in which they trade off agronomic productivity against market access. Before 2006, coca cultivation was constrained to high-suitability areas and the marginal return to clearing forest in remote, low-suitability border cells was low. The introduction of agro-chemical inputs around 2006 can be interpreted as a technological change that relaxes this constraint: it lowers the marginal cost of cultivating coca in non-suitable areas and increases the relative profitability of remote cells with good access to the border, thus potentially reshaping where coca-related deforestation occurs.

Building on this evidence, Table 4 investigates how the 2006 technological revolution reshaped the relative importance of the two geographic channels. All columns estimate variants of equation 1 that include both exposure measures to national coca price shocks: a suitability-based price shock, $\text{Suit}_i \times P_t$, and a border-based price shock, $\text{Border}_i \times P_t$. Columns 1–3 pool the entire 2003–2019 period, while Columns 4–5 and 6–7 allow the coefficients on the suitability-based and border-based shocks, respectively, to differ before and after 2006 by interacting them with the post-technology indicator.

Columns 1 and 2 replicate, with the inclusion of the border-based price shock, the first-stage and reduced-form estimates that use coca suitability as the source of cross-sectional variation in exposure (Columns 5 and 2 of Table 2). The suitability-based price shock remains the main driver of coca outcomes: a one-standard-deviation increase in the price shock raises coca density (Column 1) and reduces Percent Tree Cover by about 1.9 percentage points, or 4.4 percent of its mean value (Column 2). Importantly, the border-based price shock also has a statistically significant but much smaller association with coca density and forest loss. Column 3 introduces an interaction between the border-based price shock and an indicator for Loreto; the coefficient shows that, in Loreto, the effect of border-based price shocks on tree-cover loss is roughly three times larger than in the rest of the country, consistent with the descriptive patterns in Figure 5b.

Columns 4 and 5 turn to the role of technological change in the suitability channel. The specification interacts the suitability-based price shock with an indicator for the post-2006 period, while still conditioning on the border-based shock. The first-stage estimates in Column 4 show that the sensitivity of coca density to suitability-based price shocks is unchanged by the technological shift: the pre-2006 coefficient is 0.089 and the post-2006 differential is economically negligible and statistically indistinguishable from zero. In contrast, the reduced-form estimates for Percent Tree Cover in Column 5 reveal a large change in how deforestation responds to suitability-based price shocks. Before 2006, a one-standard-deviation increase in the suitability-based shock reduces tree cover by 7.7 percentage points, corresponding to about 17.7 % of the mean tree-cover level; after 2006, the implied effect falls to roughly 3.8 % of the mean. Taken together, Columns 4 and 5 indicate that price shocks in suitable areas continue to translate into higher coca density, but each additional unit of price increase is associated with substantially less forest loss. This points to a shift from extensive to more intensive production systems in traditional coca-growing zones.

Columns 6 and 7 then focus on the border channel, allowing the coefficient on the border-based price shock to change after 2006, while controlling for the suitability-based shock. Before the technological change, the border-based price shock has essentially no effect on coca density (Column 6) and is associated with a small increase in tree cover (Column 7). I do not attach a structural interpretation to this positive pre-2006 coefficient: conditional on suitability-based price shocks and other commodity shocks, cells closer to the border experience slightly weaker deforestation pressure than more distant cells when the coca price increases, likely reflecting other land-use dynamics. After 2006, however, the coefficient on the border-based price shock becomes positive and statistically significant for coca density and turns negative for tree cover. The interaction term in Column 7 implies that the effect on tree cover switches to significantly negative after the technological shift. In other words, only after the technological revolution do price shocks transmitted through border proximity become a strong predictor of both coca cultivation and forest loss. This pattern supports the interpretation that the adoption of agro-chemicals made previously marginal, low-suitability border areas profitable for coca, thereby shifting the locus of narco-deforestation towards the Colombian border.

5.2.1 Coca vs other commodities

Table 5 presents elasticity estimates across different commodities. Column 1 highlights the impact of price shocks in areas suitable for each specific crop, showing that the elasticity estimate for coca aligns closely with that of cocoa, which is known to be one of the main drivers of deforestation (Vale Costa H, 2021; Earthsight, 2016). The coefficients of coca and cocoa are not statistically different from each other.[25] Additionally, as expected, price shocks to gold are associated with tree cover loss. However, this estimate is not statistically significant, likely because deforestation driven by gold mining is highly localized. A positive estimate is found for palm oil, which is consistent with Percent Tree Cover satellite images capturing woody vegetation higher than 5 meters.

A clearer difference between coca and other commodities appears when examining geographic variation based on proximity to the border. Cultivation in those border areas is highly sensitive to prices, and this is true only for coca. Only coffee and sugar cane show a negative environmental impact, though these estimates are statistically insignificant. For other commodities, effects on the environment are positive but not significant, with gold as the exception, showing positive and significant effects, possibly due to the concentration of gold mining activity in the southern area of Madre de Dios. This pattern connects directly to the exogenous-shares discussion: the same border share that strongly amplifies coca price shocks does not systematically transmit price shocks to other commodities, reinforcing the

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[25] The lincom test (linear combination of coefficients) returns a P-value of about 0.8.

interpretation that border proximity mediates coca-specific rather than generic agricultural or mining forces.

These border areas are characterized by higher tree density than coca-suitable areas: as reported in Table 5, at baseline, the average tree cover in Loreto exceeds that in coca-suitable areas by more than 20 percentage points. This finding supports the argument that coca's illegal status drives its cultivation into remote, densely forested areas, making it an outlier in terms of environmental impact. Figure 7 illustrates this by depicting the cumulative distribution functions of baseline tree cover levels (PTC_{2003}) and changes in tree cover from 2003 to 2019 ($PTC_{2019-2003}$), conditional on: *(i.)* the presence of coca and absence of other crops (in red), and *(ii.)* the presence of other crops and absence of coca (in purple). Figure 7a indicates that areas with coca have, on average, higher levels of tree cover than areas with other crops. Additionally, Figure 7b displays the distribution of changes in tree cover between 2003 and 2019 across locations associated with different crop types. For coca-growing areas, tree cover decreases in approximately 70% of locations, as evidenced by the red line's dominance on the left (negative) side of the distribution. In contrast, for locations associated with other crops, tree cover decreases in only 30% of cases, with the majority showing positive values, indicating an increase in tree cover. Together, these figures demonstrate that coca cultivation first-order stochastically dominates other crops, both in terms of presence in densely forested areas and in terms of deforestation impact (Figure 7b).

6 Conclusion

World's forests, and in particular, tropical rainforests have a key role in the fight against climate change. As explained by Brown (1996), they can either provide a carbon sink, absorbing carbon through photosynthesis and respiration, or a carbon source – releasing into the air the carbon previously stored. Increasing evidence from Geography and Environmental studies experts indicates that criminal activities associated with drug production and trafficking are among the main drivers of forest loss in the entire American continent. While extensive research examines environmental externalities in legal markets, the impact of market dynamics within illegal markets — such as those influencing coca cultivation — remains largely unexamined. Regarding the narco-deforestation phenomenon specifically, satellite remote sensing has enabled scientific studies to emerge; however, research quantifying its scale and significance remains limited.

I contribute to the interdisciplinary literature by investigating this phenomenon in Peru.

I construct a novel panel dataset spanning from 2003 to 2019, gathering and processing high-resolution yearly satellite images and model-based geographical raster data at a spatial resolution of 12km x 12km. The results are relevant both from an economic and policy point of view. Leveraging geographic variation in coca-growing areas and yearly fluctuations in coca prices in the Peruvian black market, I demonstrate that variation in the return to cultivate coca lead to deforestation of the Peruvian Amazon Forest. I show that the 40% increase in coca prices observed during the study period led to a loss of more than 6,450 km^2 of tree cover - equivalent to more than eight times the land area of New York City. Furthermore, consistent with anecdotal evidence, I find spatially heterogeneous effects and suggestive evidence of the technical change which involved the widespread use of toxic and highly polluting agrochemicals. This shift has expanded the illegal coca cultivation frontier to previously unsuitable strategic locations. The illegal nature of coca production pushes cultivation into isolated forested areas, where it dominates other crops in terms of both prevalence and environmental impact.

References

ABMAN, R. AND C. CARNEY (2020): "Agricultural productivity and deforestation: Evidence from input subsidies and ethnic favoritism in Malawi," *Journal of Environmental Economics and Management*, 103.

ANGELSEN, A. AND D. KAIMOWITZ (1999): "Rethinking the Causes of Deforestation: Lessons from Economic Models," *The World Bank Research Observer*, 14, 73–98, publisher: Oxford University Press.

——— (2001): "Introduction: the role of agricultural technologies in tropical deforestation," CAB International, accepted: 2012-06-04T09:06:19Z.

ANGRIST, J. AND A. KUGLER (2008): "Rural Windfall or a New Resource Curse? Coca, Income, and Civil Conflict in Colombia," *The Review of Economics and Statistics*, 90, 191–215.

ARAUJO, R., J. ASSUNÇÃO, AND A. A. BRAGANÇA (2023): *The Effects of Transportation Infrastructure on Deforestation in the Amazon: A General Equilibrium Approach*, World Bank, Washington, DC.

ASHER, S., T. GARG, AND P. NOVOSAD (2020): "The Ecological Impact of Transportation Infrastructure," *Economic Journal*, 130, 1173–1199, publisher: Royal Economic Society.

ASSUNÇÃO, J., C. GANDOUR, AND R. ROCHA (2015): "Deforestation slowdown in the Brazilian Amazon: prices or policies?" *Environment and Development Economics*, 20, 697–722, publisher: Cambridge University Press.

——— (2023): "DETER-ing Deforestation in the Amazon: Environmental Monitoring and Law Enforcement," *American Economic Journal: Applied Economics*, 15, 125–156.

ASSUNÇÃO, J., C. GANDOUR, R. ROCHA, AND R. ROCHA (2020): "The Effect of Rural Credit on Deforestation: Evidence from the Brazilian Amazon," *The Economic Journal*, 130, 290–330.

BALBONI, C., A. BERMAN, R. BURGESS, AND B. A. OLKEN (2022): "The Economics of Tropical Deforestation," .

BARDALES, R., M. HYDE, J. GALLO, AND V. BORON (2022): "National parks and conservation concessions: a comparison between mammal populations in two types of tropical protected areas in Ucayali, Peru," *Journal of Tropical Ecology*, 39.

BARTIK, T. J. (1991): *Who Benefits from State and Local Economic Development Policies?*, W.E. Upjohn Institute.

BERMAN, N., M. COUTTENIER, A. LEBLOIS, AND R. SOUBEYRAN (2023): "Crop prices and deforestation in the tropics," *Journal of Environmental Economics and Management*, 119, 102819.

BIESIMCI (2019): "Metodología censo cultivo de coca," .

BORUSYAK, K., P. HULL, AND X. JARAVEL (2025): "A Practical Guide to Shift-Share Instruments," *Journal of Economic Perspectives*, 39, 181–204.

BRAGANÇA, A. AND R. DAHIS (2022): "Cutting special interests by the roots: Evidence from the Brazilian Amazon," *Journal of Public Economics*, 215, 104753.

BROWN, S. (1996): "Unasylva - No. 185 - Forest influences - Present and potential roles of forests in the global climate change debate," .

BURGESS, R., F. J. M. COSTA, AND B. OLKEN (2019): "The Brazilian Amazon's Double Reversal of Fortune," preprint, SocArXiv.

BURGESS, R., M. HANSEN, B. OLKEN, P. POTAPOV, AND S. ONDER (2011): "The Political Economy of Deforestation in the Tropics," *The Quarterly Journal of Economics*, 127.

BURGESS, R., E. MIGUEL, AND C. STANTON (2015): "War and deforestation in Sierra Leone," *Environmental Research Letters*, 10.

CABALLERO ESPEJO, J., M. MESSINGER, F. ROMÁN-DAÑOBEYTIA, C. ASCORRA, L. FERNANDEZ, AND M. SILMAN (2018): "Deforestation and Forest Degradation Due to Gold Mining in the Peruvian Amazon: A 34-Year Perspective," *Remote Sensing*, 10, 1903.

CHIMELI, A. B. AND R. R. SOARES (2017): "The Use of Violence in Illegal Markets: Evidence from Mahogany Trade in the Brazilian Amazon," *American Economic Journal: Applied Economics*, 9, 30–57.

CHORT, I. AND B. ÖKTEM (2024): "Agricultural shocks, coping policies and deforestation: Evidence from the coffee leaf rust epidemic in Mexico," *American Journal of Agricultural Economics*, 106, 1020–1057, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ajae.12441.

CURTIS, P. G., C. M. SLAY, N. L. HARRIS, A. TYUKAVINA, AND M. C. HANSEN (2018): "Classifying drivers of global forest loss," *Science*, 361, 1108–1111, publisher: American Association for the Advancement of Science.

DELL, M. (2015): "Trafficking Networks and the Mexican Drug War," *American Economic Review*, 105, 1738–79.

DEVIDA (2021): "Análisis de compra y venta de hoja de coca en el Perú," .

DIMICELI, C., K. M. SANCHEZ, AND D. ARMENTERAS (2016): "MOD44B MODIS/Terra Vegetation Continuous Fields Yearly L3 Global 250m SIN Grid V006." .

DIMICELI, C., J. TOWNSHEND, M. CARROLL, AND R. SOHLBERG (2021): "Evolution of the representation of global vegetation by vegetation continuous fields," *Remote Sensing of Environment*, 254, 112271.

DIRECCIÓN GENERAL DE ESTADÍSTICA, SEGUIMIENTO Y EVALUACIÓN DE

POLÍTICAS (2021): "ATLAS DE LA SUPERFICIE AGRÍCOLA DEL PERÚ," .

DUBE, O. AND J. F. VARGAS (2013): "Commodity Price Shocks and Civil Conflict: Evidence from Colombia," *The Review of Economic Studies*, 80, 1384–1421, publisher: [Oxford University Press, The Review of Economic Studies, Ltd.].

DÁVALOS, L. M., A. BEJARANO, M. HALL, H. CORREA, A. CORTHALS, AND J. ESPEJO (2011): "Forests and Drugs: Coca-Driven Deforestation in Tropical Biodiversity Hotspots," *Environmental science & technology*, 45.

DÁVALOS, L. M., K. M. SANCHEZ, AND D. ARMENTERAS (2016): "Deforestation and Coca Cultivation Rooted in Twentieth-Century Development Projects," *BioScience*, 66, 974–982.

EARTHSIGHT (2016): "Illegal cocoa and palm plantations cause $111m damage in Peruvian Amazon," .

EUROPEAN COMMISSION (2022): "The Sustainable Cocoa Initiative - European Commission," .

——— (2023): "Regulation on Deforestation-free products - European Commission," .

EUROPEAN COMMISSION. JOINT RESEARCH CENTRE (2021): *GHG emissions of all world: 2021 report.*, LU: Publications Office.

FERRAZ, C. (2015): "Explaining Agriculture Expansion and Deforestation: Evidence from the Brazilian Amazon – 1980/98," Discussion Paper 0106, Instituto de Pesquisa Econômica Aplicada - IPEA.

FETZER, T. AND S. MARDEN (2017): "Take What You Can: Property Rights, Contestability and Conflict," *The Economic Journal*, 127, 757–783, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecoj.12487.

FOSTER, A. D. AND M. R. ROSENZWEIG (2003): "Economic Growth and the Rise of Forests," *The Quarterly Journal of Economics*, 118, 601–637, publisher: Oxford University Press.

FRANCE 24 (2023): "Coca crops take root in Mexico as opium demand wanes," .

GADM (2021): "GADM database of Global Administrative Areas," .

GATTI, L. V., L. S. BASSO, J. B. MILLER, M. GLOOR, L. GATTI DOMINGUES, H. L. G. CASSOL, G. TEJADA, L. E. O. C. ARAGÃO, C. NOBRE, W. PETERS, L. MARANI, E. ARAI, A. H. SANCHES, S. M. CORRÊA, L. ANDERSON, C. VON RANDOW, C. S. C. CORREIA, S. P. CRISPIM, AND R. A. L. NEVES (2021): "Amazonia as a carbon source linked to deforestation and climate change," *Nature*, 595, 388–393.

GIRARD, V., T. MOLINA-MILLÁN, AND G. VIC (2022): "Artisanal mining in Africa," NOVAFRICA Working Paper Series, Universidade Nova de Lisboa, Nova School of Business and Economics, NOVAFRICA.

GLOBAL FOREST WATCH (2023): "Loreto, Peru Deforestation Rates & Statistics | GFW," .

GRISAFFI, T. (2020): "Peru's coca control strategy: Mixed messages and ambiguous data," .

HANSEN, M. C., P. V. POTAPOV, R. MOORE, M. HANCHER, S. A. TURUBANOVA, A. TYUKAVINA, D. THAU, S. V. STEHMAN, S. J. GOETZ, T. R. LOVELAND, A. KOMMAREDDY, A. EGOROV, L. CHINI, C. O. JUSTICE, AND J. R. G. TOWNSHEND (2013): "High-Resolution Global Maps of 21st-Century Forest Cover Change," *Science*, 342, 850–853, publisher: American Association for the Advancement of Science Section: Report.

HARRIS, N. L., D. A. GIBBS, A. BACCINI, R. A. BIRDSEY, S. DE BRUIN, M. FARINA, L. FATOYINBO, M. C. HANSEN, M. HEROLD, R. A. HOUGHTON, P. V. POTAPOV, D. R. SUAREZ, R. M. ROMAN-CUESTA, S. S. SAATCHI, C. M. SLAY, S. A. TURUBANOVA, AND A. TYUKAVINA (2021): "Global maps of twenty-first century forest carbon fluxes," *Nature*

Climate Change, 11, 234–240.

Henman, A. (1978): *Mama Coca*, London: Hassle Free Press.

Hsiao, A. (2022): "Coordination and Commitment in International Climate Action," .

Héctor Molina (2021): "Narco incursiona con la producción de coca en México," .

Li, X. and Y. Zhou (2017): "A Stepwise Calibration of Global DMSP/OLS Stable Nighttime Light Data (1992–2013)," *Remote Sensing*, 9, 637.

López, N. and D. Tuesta (2015): "Economías ilícitas y orden social: la frontera de Perú, Brasil y Colombia Illicit economies and social order: the border area of Peru, Brazil and Colombia," *Cidob d'Afers Internacionals*, 79–104.

Mejia, D. and C. E. Posada (2008): "Cocaine Production and Trafficking: What Do We Know?" SSRN Scholarly Paper ID 1149121, Social Science Research Network, Rochester, NY.

Mejia, D. and P. Restrepo (2013): "Bushes and Bullets: Illegal Cocaine Markets and Violence in Colombia," *SSRN Electronic Journal*.

——— (2015): "The Economics of the War on Illegal Drug Production and Trafficking," 49.

Ministerio de Agricultura y Riego (2019): "Plan Nacional de Cultivo 2019-2020," *Ministerio de Agricultura y Riego*, accepted: 2020-04-13T18:53:12Z Publisher: Ministerio de Agricultura y Riego.

Pendrill, F., U. M. Persson, J. Godar, T. Kastner, D. Moran, S. Schmidt, and R. Wood (2019): "Agricultural and forestry trade drives large share of tropical deforestation emissions," *Global Environmental Change*, 56, 1–10.

POLITICO (2024): "Anti-deforestation law will deepen Europe's cocaine problem, warn ambassadors – POLITICO," .

Prem, M., M. E. Purroy, and J. F. Vargas (2021a): "Landmines: The Local Effects of Demining," SSRN Scholarly Paper ID 3924929, Social Science Research Network, Rochester, NY.

Prem, M., J. F. Vargas, and D. Mejia (2021b): "The Rise and Persistence of Illegal Crops: Evidence from a Naive Policy Announcement," SSRN Scholarly Paper ID 3466363, Social Science Research Network, Rochester, NY.

RAISG (2022): "Deforestación en la Amazonía al 2025: Pasado y Futuro de la Deforestación en la Amazonía." .

Rojas, E., B. R. Zutta, Y. K. Velazco, J. G. Montoya-Zumaeta, and M. Salvà-Catarineu (2021): "Deforestation risk in the Peruvian Amazon basin," *Environmental Conservation*, 48, 310–319.

Rosa da Conceição, H., J. Börner, and S. Wunder (2015): "Why were upscaled incentive programs for forest conservation adopted? Comparing policy choices in Brazil, Ecuador, and Peru," *Ecosystem Services*, 16, 243–252.

Ruiz, S. (2020): "What are Primary Forests and Why Should We Protect Them? \textbar Data and Research \textbar Global Forest Watch Blog," Publication Title: Global Forest Watch Content.

Sesnie, S. E., B. Tellman, D. Wrathall, K. McSweeney, E. Nielsen, K. Benessaiah, O. Wang, and L. Rey (2017): "A spatio-temporal analysis of forest loss related to cocaine trafficking in Central America," *Environmental Research Letters*, 12, 054015, publisher: IOP Publishing.

Shuldiner, H. (2022): "Coca Cultivation Grows in Guerrero, Mexico, but Scalability Remains Doubtful," .

SILVERSTEIN, S. M. (2021): "Narco-Infrastructures and the Persistence of Illicit Coca in Loreto," *The Journal of Latin American and Caribbean Anthropology*, 26, 427–450, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jlca.12582.

SMITH, C., G. HOOKS, AND M. LENGEFELD (2015): "The War on Drugs in Colombia: The Environment, the Treadmill of Destruction and Risk-Transfer Militarism," *Journal of World-Systems Research*, 20, 185.

SOUZA-RODRIGUES, E. (2019): "Deforestation in the Amazon: A Unified Framework for Estimation and Policy Analysis," *The Review of Economic Studies*, 86, 2713–2744.

STEINBERG, M. K., J. J. HOBBS, AND K. MATHEWSON (2004): *Dangerous Harvest: Drug Plants and the Transformation of Indigenous Landscapes*, Oxford University Press.

SVIATSCHI, M. M. (2022): "Making a *NARCO* : Childhood Exposure to Illegal Labor Markets and Criminal Life Paths," *Econometrica*, 90, 1835–1878.

SZERMAN, D., J. ASSUNÇÃO, M. LIPSCOMB, AND A. MOBARAK (2022): "Agricultural Productivity and Deforestation: Evidence from Brazil," *Discussion Papers*.

THE ECONOMIST (2025): "The traffickers are winning the war on drugs," *The Economist*.

TOMICH, T. P., M. VAN NOORDWJIK, S. BUDIDARSONO, A. N. GILLISON, T. KUSUMANTO, D. MURDIYARSO, F. STOLLE, AND A. M. FAGI (2001): "Array - CIFOR Knowledge," .

UNODC (2006): "COCA CULTIVATION IN THE ANDEAN REGION A survey of Bolivia, Colombia and Peru," .

——— (2009): "Peru Monitoreo de cultivos de coca 2008," .

UNODC (2010): "Informe Analítico: Problemática ambiental y la utilización de agroquímicos en la producción de coca," .

UNODC (2010): "World Drug Report 2010," .

——— (2017): "Colombia: Survey of territories affected by illicit crops – 2016," .

——— (2021): "World Drug Report 2021," .

UNODC AND DEVIDA (2006): "Peru Coca Survey for 2005," .

——— (2016): "Peru Coca Survey for 2015," .

VALE COSTA H, F. M. (2021): "MAAP #134: Agriculture and Deforestation in the Peruvian Amazon," .

VARGAS, J. F., M. PREM, AND S. SAAVEDRA (2019): "End-of-Conflict Deforestation: Evidence from Colombia's Peace Agreement – HiCN," *HiCN Working Paper No. 288*.

WORLD ECONOMIC FORUM (2020): "Illegal logging has to be stopped - here's how," .

YOUNG, K. R. (2004a): "Environmental and Social Consequences of Coca/Cocaine in Peru: Policy Alternatives and a Research Agenda," in *Dangerous Harvest: Drug Plants and the Transformation of Indigenous Landscapes*, ed. by M. K. Steinberg, J. J. Hobbs, and K. Mathewson, Oxford University Press, 0.

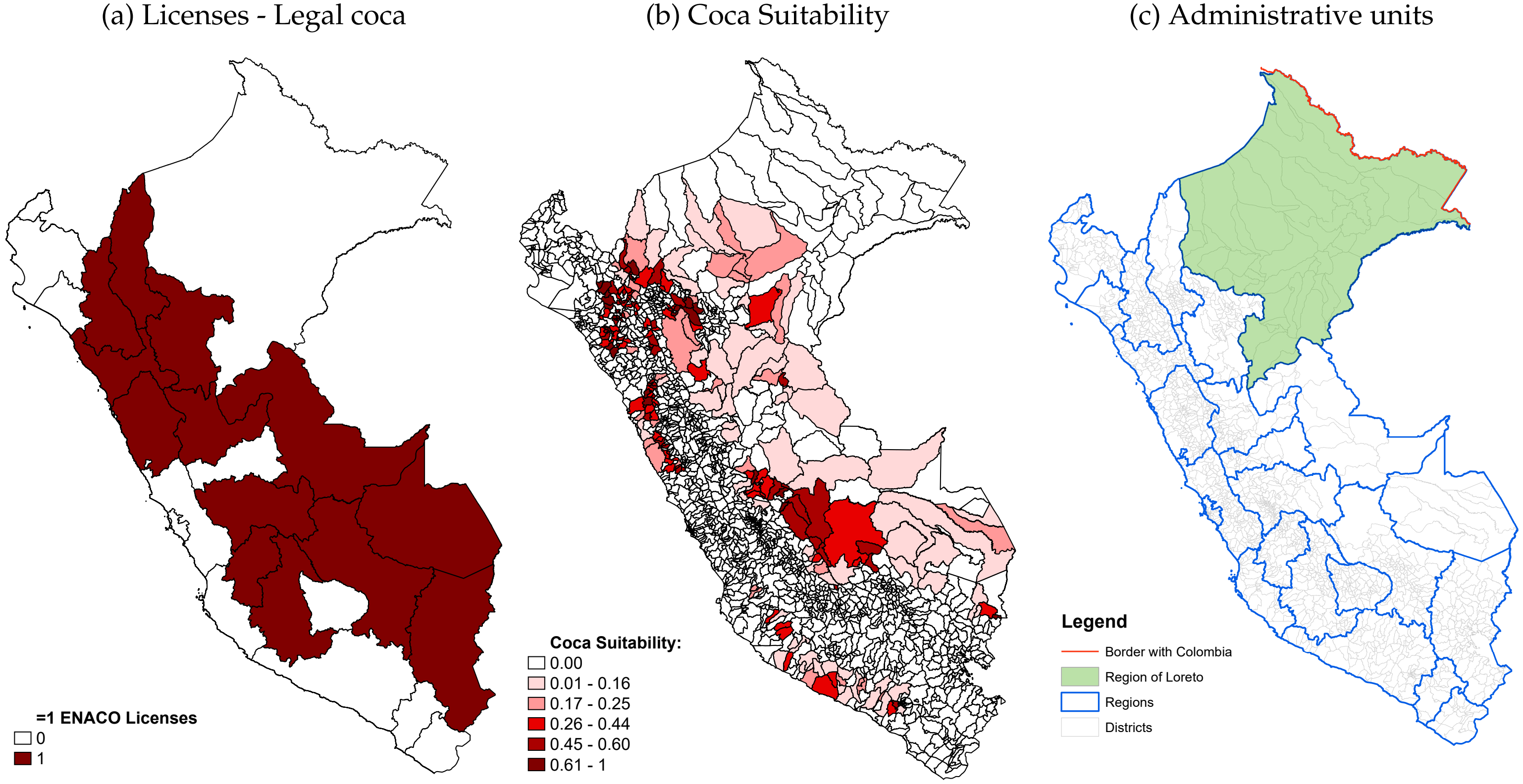
——— (2004b): "A Geographical Perspective on Coca/Cocaine Impacts in South America," in *WorldMinds: Geographical Perspectives on 100 Problems: Commemorating the 100th Anniversary of the Association of American Geographers 1904–2004*, ed. by D. G. Janelle, B. Warf, and K. Hansen, Dordrecht: Springer Netherlands, 363–367.

ZELLI, F., J.-I. HEIN, D. ERLER, AND A.-M. SANTA CRUZ MELGAREJO (2014): "Reducing emissions from deforestation and forest degradation (REDD) in Peru: a challenge to social inclusion and multi-level governance," Research Report 85, Studies, iSBN:

9783889856517.

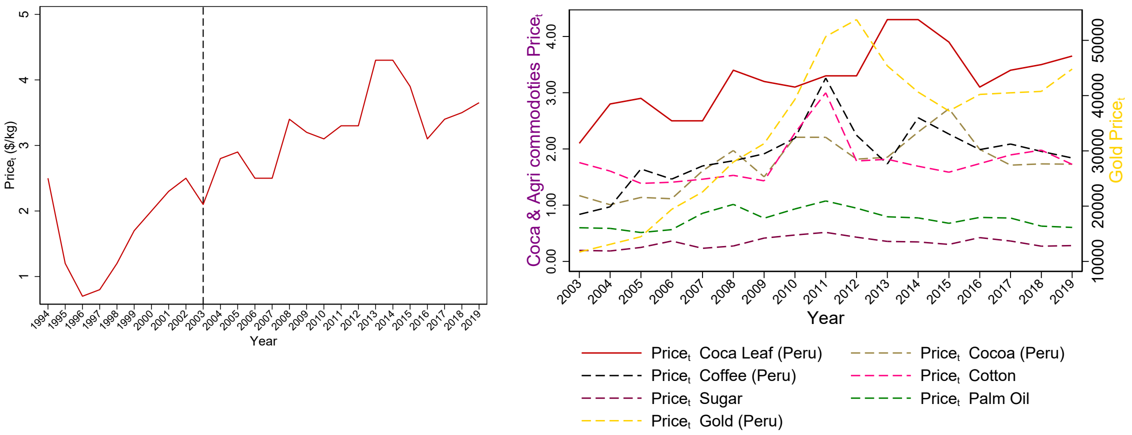
7 Figures

Figure 1: Geographical Variation



Notes: Panel a reports DEVIDA (2021) and ENACO regional level data. It shows in red the regions where coca cultivation might be legal - there is at least one state-recognised coca leaf producers, while in white regions where coca leaf cultivation is entirely illegal (no state-recognised coca leaf producers). *Panel b* shows geographical variation of Sviatschi (2022)'s coca suitability index at district level. In white non-suitable areas. *Panel c* maps the administrative levels used in the empirical analysis: in gray the layer of Peruvian districts (GADM3); in blue the layer of Peruvian regions (GADM1). Lastly, in green the region of Loreto and in red the border between Peru and Colombia. See Section 3 for a full description of the data sources.

Figure 2: Coca Leaf Prices in Peru

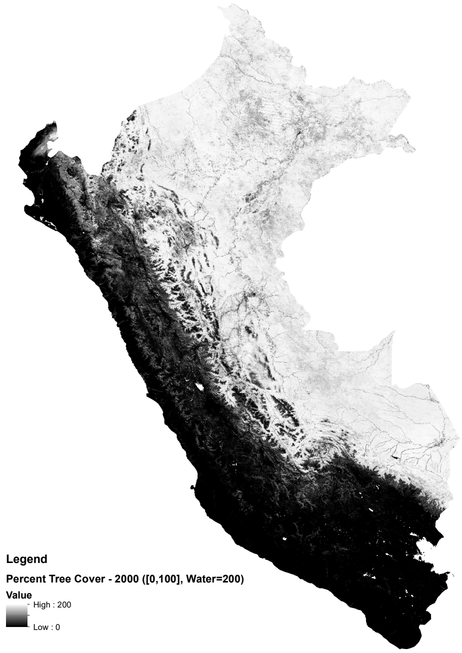


(a) Coca

(b) Coca *vs* other commodities

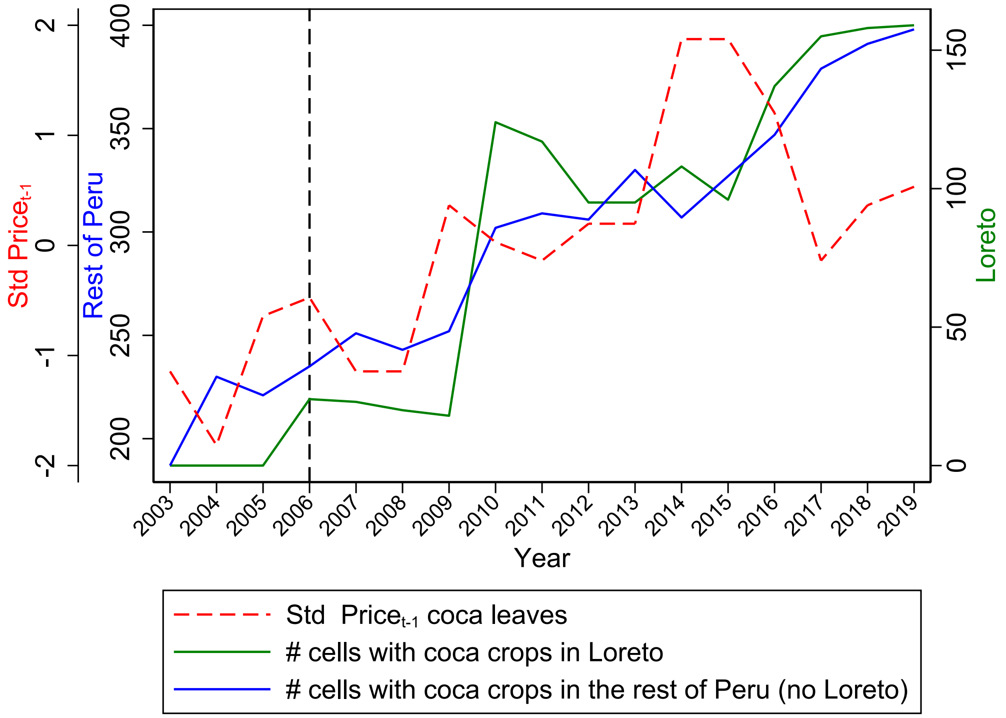
Notes: Panel a shows the evolution of average yearly prices of sun-dried coca leaf in the Peruvian black market, from 1994 to 2019. Prices are in $\$/kg$. The black dashed vertical line represents the beginning of the period of analysis. *Panel b* reports the indexed evolution (2003 = 100) of coca prices in comparison with other commodities (e.g. cocoa, coffee, gold, cotton, palm oil and sugarcane). See Section 3 for a full description of the data sources.

Figure 3: Tree Cover - MODIS/Terra VCF



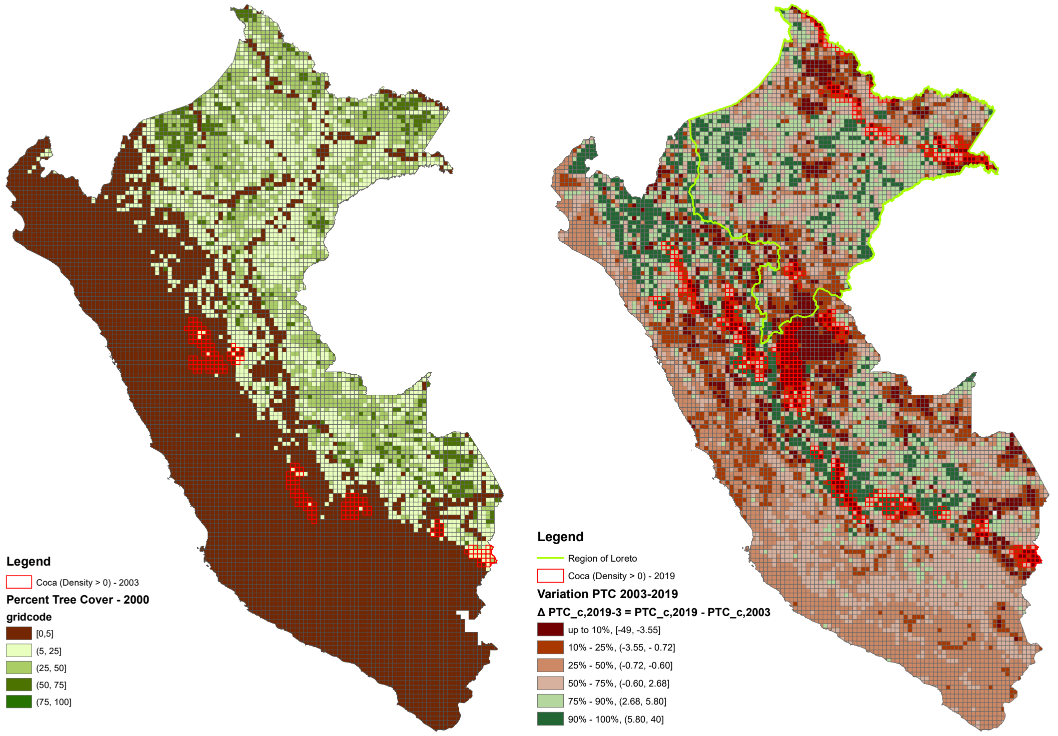
Notes: Panel a provides a visual representation of *MODIS VCF* satellite data for Peru (year 2000). Please zoom in for a more detailed visualization. See Section 3 for a full description of the data sources.

Figure 4: Summary Statistics



Notes: This Figure shows how coca crops expanded over time. It reports the evolution for the region of Loreto (green line) and the rest of Peru (blue line – i.e. without considering the northern region at the border to Colombia), together with the time series of standardised lagged prices of coca leaf in the Peruvian black market. In particular, for each geographical area, it shows variation over time of the number of cells with coca fields. The gray vertical line (Year 2006) highlights when coca first appeared in Loreto. See Section 3 for a full description of the data sources and concerns related to undercount in Coca Density.

Figure 5: Tree Cover and Coca Density

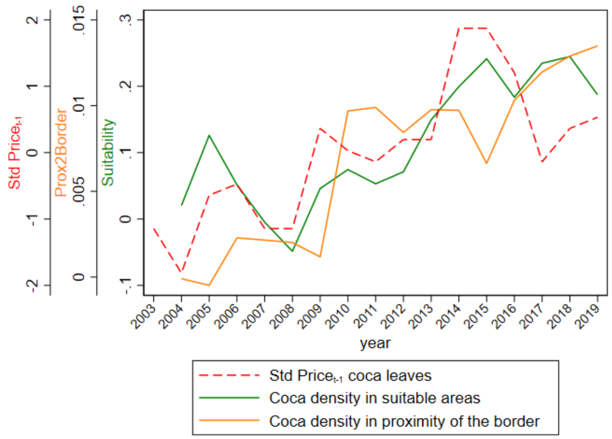


(a) Baseline Map

(b) Endline Map

Notes: Panel a provides the Baseline Map, showing the location of *(i.)* 2003 coca crops in red (first available year) and *(ii.)* Percent Tree Cover as of year 2000 (geo-processing of *Figure 3*). *Panel b* provides the Endline Map, showing the location of *(i.)* 2019 coca crops in red (last available year), *(ii.)* deforestation/reforestation occurred between 2003 and 2019 (percentile distribution of $\Delta PTC_{c,2019-03}$), and *(iii.)* the region of Loreto (contoured in green). Please zoom in for a more detailed visualization. See Section 3 for a full description of the data sources and concerns related to undercount in Coca Density.

Figure 6: Coca Density Variation

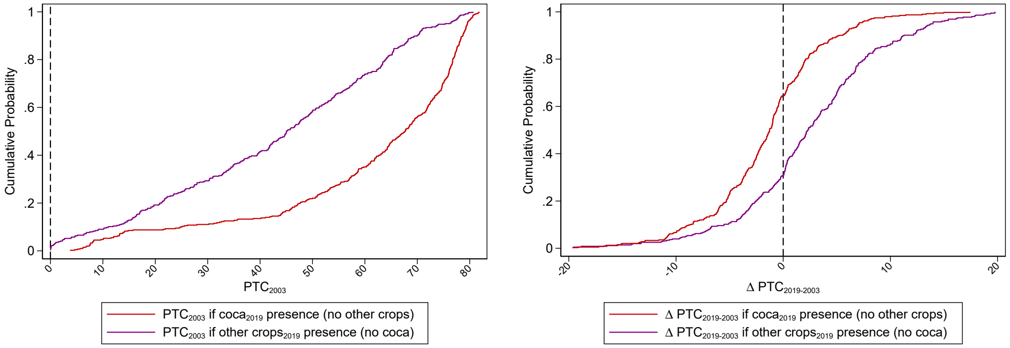


Notes: The Figure shows the evolution of Coca Density over time in (*i.*) suitable areas (green line) and (*ii.*) proximity to the Colombian border (orange line), estimating, for each geographic source of variation, the following equation:

$$Coca\ Density_{c,t} = \gamma_0 + \sum_{t=2003}^{2019} \gamma_{1t}(\alpha_t \times Geo\ Source_c) + \gamma_2 X_{c,t} + \alpha_c + \alpha_t + \nu_{c,t}$$

2003 is the reference year. The dashed red line indicates the evolution of standardised lagged coca leaf prices in Peru. Regressions include the full set of fixed effects and nightlights. Standard errors clustered at district level. See Section 3 for a full description of the data sources and concerns related to undercount in Coca Density.

Figure 7: Coca *vs* other crops



(a) Tree Cover

(b) Change in Tree Cover

Notes: Panel a illustrates the distribution of tree coverage in 2003, conditional on the *(i.)* presence of coca and absence of any other crop (in red) and *(ii.)* presence of other crops and absence of coca (in purple). *Panel b* reports the cumulative distribution function plot which compares 2019 coca presence (in red) and 2019 other crops presence (in purple) in terms of overall deforestation patterns. See Section 3 for a full description of the data sources and concerns related to undercount in Coca Density.

8 Tables

Table 1: Summary Statistics

	Obs.	**Mean**	**Std. Dev**	**Min**	**Max**
Main Variables					
Avg Percent Tree cover [0,100]	161616	43.49	32.80	0.00	85.34
Coca Density	162923	0.09	0.54	0.00	8.00
Prox to border (100 km)	162962	-7.65	3.94	-15.92	0.00
Prox to river (5km)	162962	-4.20	7.09	-39.34	0.00
coca suit	162962	0.07	0.13	0.00	1.00
Std Coca $Price_{t-1}$	162962	0.00	1.00	-1.82	1.87
Avg Nightlights	162273	0.94	3.50	0.00	63.00
Other Commodities					
coffee suit	161653	0.23	0.23	0.00	0.88
cocoa suit	161653	0.21	0.23	0.00	0.73
palm oil suit	161653	0.24	0.28	0.00	0.84
cotton suit	161653	0.03	0.06	0.00	0.53
sugar suit	161653	0.21	0.22	0.00	0.77
Share of gold deposits (MRDS)	162962	0.00	0.02	0.00	1.00
Std coffee $Price_{t-1}$	162962	0.13	0.97	-1.71	2.37
Std cocoa $Price_{t-1}$	162962	0.21	0.85	-1.10	1.94
Std gold $Price_{t-1}$	162962	0.16	0.93	-1.30	1.66
Std Inter palm oil $Price_{t-1}$	162962	0.20	0.85	-1.04	1.86
Std Inter cotton $Price_{t-1}$	162962	0.07	1.03	-0.99	3.35
Std Inter sugar $Price_{t-1}$	162962	0.10	1.01	-1.38	2.04

Notes: This Table reports the summary statistics for the main set of variables employed in the analysis. See Section 3 for a description of the variables and sources.

Table 2: Main Results (Coca Suitability)

	(1) Perc Tree Cover RF	(2) Perc Tree Cover RF	(3) Perc Tree Cover RF	(4) Perc Tree Cover OLS	(5) Coca Density FS	(6) Perc Tree Cover 2sls	(7) Perc Tree Cover 2sls
Coca Density				-0.323***		-23.896**	-23.826**
				[0.076]		[10.552]	[9.268]
Std Coca $Price_{t-1} \times$ coca suit	-1.685***	-1.678***	-1.849***		0.069**		
	[0.382]	[0.372]	[0.348]		[0.028]		
Std cocoa $Price_{t-1} \times$ cocoa suit			-1.719***				-0.702
			[0.336]				[0.618]
Std gold $Price_{t-1} \times$ Share of gold deposits			-2.473				-0.200
			[1.553]				[3.156]
Std coffee $Price_{t-1} \times$ coffee suit			-0.243				-0.538
			[0.362]				[0.460]
Std inter cotton $Price_{t-1} \times$ cotton suit			0.253				-1.184
			[0.288]				[0.808]
Std inter sugar $Price_{t-1} \times$ sugar suit			-0.091				0.701
			[0.222]				[0.523]
Std inter palmoil $Price_{t-1} \times$ palmoil suit			1.227***				0.763*
			[0.228]				[0.390]
Cell FEs (9,586)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs (2003-19)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.988	0.988	0.988	0.988	0.741	-3.397	-3.397
Control for Nighlight	No	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var.	43.490	43.527	43.535	43.527	0.093	43.527	43.534
F-test of excluded instrument					6.3		
Districts	1,369	1,366	1,366	1,366	1,369	1,366	1,366
Observations	161616	161270	160709	161231	162234	161231	160670

Notes: This Table reports the main results of the paper. Column 1 and 2 report the RF estimates of the baseline specification (equation 1), respectively without and with nightlights. Column 3 addresses potential confounding concerns by additionally controlling for price shocks to coffee, cocoa, palm oil, cotton, sugar cane, and gold. Columns 4-7 report respectively OLS, FS, 2sls results, and 2sls results with controls for price shocks to other commodities. If not otherwise specified, all the columns include nightlights, Cell and Year FE. Standard errors in brackets: clustered at district level. Stars indicate significance in the usual way. See Section 3 for a full description of the data sources and concerns related to undercount in Coca Density. See Section 5.1 for a full explanation of the results.

Table 3: Spatial Heterogeneity - Peru *vs* Loreto

	(1) Coca Density Rest of Peru	(2) Coca Density Loreto
Std Coca $Price_{t-1}$ × coca suit	0.104***	0.055
	[0.028]	[0.037]
Std Coca $Price_{t-1}$ × Prox to border (100 km)	0.000	0.017***
	[0.001]	[0.004]
Cell FEs (9,586)	Yes	Yes
Year FEs (2003-19)	Yes	Yes
R^2	0.779	0.496
Control for Nighlight	Yes	Yes
Control for Price shocks to other commodities	Yes	Yes
Mean dep. var.	0.108	0.057
Districts	1,321	47
Observations	114779	46472

Notes: This Table reports the main results of the paper. It investigate FS spatial heterogeneous effects by comparing the impact of coca suitability and proximity to the Colombian border on coca density in Peru (no Loreto) – Column 1 – versus Loreto (Column 2). If not otherwise specified, all the columns include nightlights, controls for price shocks to other commodities, Cell and Year FE. Standard errors in brackets: clustered at district level. Stars indicate significance in the usual way. See Section 3 for a full description of the data sources and concerns related to undercount in Coca Density. See Section 5.1 for a full explanation of the results.

Table 4: 2006 Technological Change and Proximity to Border

	(1) Coca Density	(2) Perc Tree Cover	(3) Perc Tree Cover	(4) Coca Density	(5) Perc Tree Cover	(6) Coca Density	(7) Perc Tree Cover
Std Coca $Price_{t-1}$ × coca suit	0.080***	-1.918***	-1.730***	0.089**	-7.731***	0.080***	-1.876***
	[0.027]	[0.348]	[0.322]	[0.039]	[1.676]	[0.027]	[0.345]
Post Tech Revolution=1 × Std Coca $Price_{t-1}$ × coca suit				-0.001	6.071***		
				[0.035]	[1.624]		
Std Coca $Price_{t-1}$ × Prox to border (100 km)	0.003***	-0.067***		0.003***	-0.068***	0.000	0.223***
	[0.001]	[0.017]		[0.001]	[0.017]	[0.000]	[0.060]
Loreto=1 × Std Coca $Price_{t-1}$ × Prox to border (100 km)			-0.220***				
			[0.052]				
Post Tech Revolution=1 × Std Coca $Price_{t-1}$ × Prox to border (100 km)						0.002**	-0.328***
						[0.001]	[0.061]
Cell FEs (9,586)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs (2003-19)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.741	0.989	0.989	0.741	0.989	0.742	0.989
Control for Nighlight	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for Price shocks to other commodities	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var.	0.093	43.535	43.535	0.093	43.535	0.093	43.535
Districts	1,366	1,366	1,366	1,366	1,366	1,366	1,366
Observations	161251	160709	160709	161251	160709	161251	160709

Notes: This Table reports the main results of the paper. Columns 1 and 2 focus on Coca Suitability and report the FS and RF estimates of the baseline specification (equation 1), further controlling for coca price shocks at the border. Column 3 adds an interaction between the border-based price shock and a dummy for Loreto to capture spatial heterogeneity. Columns 4 and 5 investigate time-heterogeneous effects of the suitability-based price shock (before/after the 2006 technological change), by interacting it with a post-2006 indicator. Columns 6 and 7 analogously estimate pre-/post-2006 effects for the border-based price shock. All the columns include nightlights, controls for price shocks to other commodities, Cell and Year FE. Standard errors in brackets: clustered at district level. Stars indicate significance in the usual way. See Section 3 for a full description of the data sources and concerns related to undercount in Coca Density. See Section 5.1 for a full explanation of the results.

Table 5: Geographical distribution: Coca vs other commodities

	(1) Perc Tree Cover (RF) Entire study period	(2) Perc Tree Cover (RF) Post Tech Revolution=1
Std Coca $Price_{t-1}$ × coca suit	-1.849***	
	[0.348]	
Std cocoa $Price_{t-1}$ × cocoa suit	-1.719***	
	[0.336]	
Std gold $Price_{t-1}$ × Share of gold deposits	-2.473	
	[1.553]	
Std coffee $Price_{t-1}$ × coffee suit	-0.243	
	[0.362]	
Std inter cotton $Price_{t-1}$ × cotton suit	0.253	
	[0.288]	
Std inter sugar $Price_{t-1}$ × sugar suit	-0.091	
	[0.222]	
Std inter palmoil $Price_{t-1}$ × palmoil suit	1.227***	
	[0.228]	
Std Coca $Price_{t-1}$ × Prox to border (100 km)		-0.148***
		[0.031]
Std cocoa $Price_{t-1}$ × Prox to border (100 km)		0.043
		[0.031]
Std gold $Price_{t-1}$ × Prox to border (100 km)		0.048**
		[0.019]
Std coffee $Price_{t-1}$ × Prox to border (100 km)		-0.040
		[0.052]
Std inter cotton $Price_{t-1}$ × Prox to border (100 km)		0.002
		[0.029]
Std inter sugar $Price_{t-1}$ × Prox to border (100 km)		-0.019
		[0.021]
Std inter palmoil $Price_{t-1}$ × Prox to border (100 km)		0.045***
		[0.014]
Cell FEs (9,586)	Yes	Yes
Year FEs (2003-19)	Yes	Yes
R^2	0.988	0.989
Control for Nighlight	Yes	Yes
Mean PTC in 2003 in suitable areas	53.073	
Mean PTC in 2003 in Loreto		74.106
Lincom P-value (Suit): coca vs cocoa	0.812	
Lincom P-value (Post Tech Revolution=1): coca vs cocoa		0.001
Districts	1,366	1,366
Observations	160709	132426

Notes: This table examines how the impact of price shocks on forest cover varies across commodities and geographic dimensions. The dependent variable is Percent Tree Cover. Column (1) reports reduced-form estimates for the full sample period; Column (2) restricts the sample to the post–technological revolution period (Post Tech Revolution$=1$). All the columns include nightlights, Cell and Year FE. Standard errors in brackets: clustered at district level. Stars indicate significance in the usual way. See Section 3 for a full description of the data sources. See Section 5.1 for a full explanation of the results.

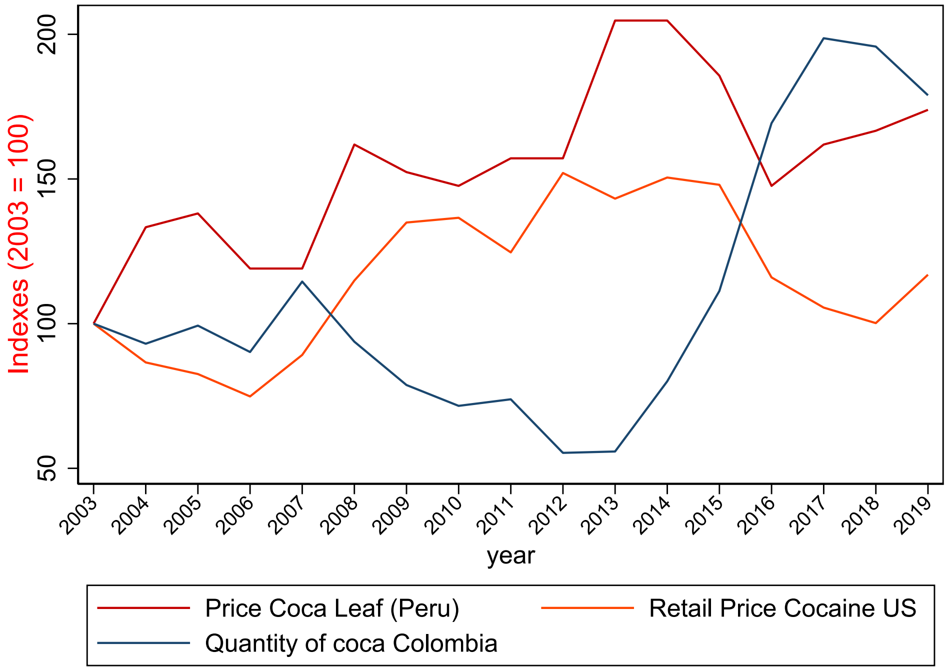
A Appendix

Table A1: Back-of-the-envelope

	(1) Perc Tree Cover RF	(2) Perc Tree Cover RF
Coca $Price_{t-1}$ × coca suit	-2.815***	-3.100***
	[0.623]	[0.584]
cocoa $Price_{t-1}$ × cocoa suit		-2.952***
		[0.577]
gold $Price_{t-1}$ × Share of gold deposits		-0.000
		[0.000]
coffee $Price_{t-1}$ × coffee suit		-0.381
		[0.569]
cotton $Price_{t-1}$ × cotton suit		0.666
		[0.756]
sugar $Price_{t-1}$ × sugar suit		-0.944
		[2.302]
palmoil $Price_{t-1}$ × palmoil suit		6.332***
		[1.179]
Cell FEs (9,586)	Yes	Yes
Year FEs (2003-19)	Yes	Yes
R^2	0.988	0.988
Control for Nighlight	Yes	Yes
Mean dep. var.	43.527	43.535
Districts	1,366	1,366
Observations	161270	160709

Notes: This Table reports RF estimates for the Back-of-the-envelope calculation - Price shocks to coca defined using prices in level. Column 1 includes only the interaction between coca prices and coca suitability. Column 2 addresses potential confounding concerns by additionally controlling for price shocks to coffee, cocoa, palm oil, cotton, sugar cane, and gold. If not otherwise specified, all the columns include nightlights, Cell and Year FE. Standard errors in brackets: clustered at district level. Stars indicate significance in the usual way. See Section 3 for a full description of the data sources and concerns related to undercount in Coca Density. See Section 5.1 for a full explanation of the results.

Figure A1: Coca & Cocaine Market



Notes: This figure illustrates the indexed evolution (2003 = 100) of key variables in the coca and cocaine market from 2003 to 2019. The red line represents the price of coca leaf in Peru, while the orange line shows the retail price of cocaine in the United States. The blue line indicates the hectares of coca crops existing as of December 31 of each year in Colombia. See Section 3 for a full description of the data sources and concerns related to undercount in Coca Density.

Table A2: Robustness check

	(1) Perc Tree Cover Baseline	(2) Perc Tree Cover International Prices	(3) Perc Tree Cover Colombian Quantity
Std Coca $Price_{t-1}$ × coca suit	-1.849***		
	[0.348]		
Std inter cocaine $Price_{t-1}$ × coca suit		-0.639**	
		[0.273]	
Reduction in hectares in Colombia - Std Ha_{t-1} Colombia × coca suit			-0.511**
			[0.228]
Cell FEs (9,586)	Yes	Yes	Yes
Year FEs (2003-19)	Yes	Yes	Yes
Control for Nighlight	Yes	Yes	Yes
Control for Price shocks to other commodities	Yes	Yes	Yes
Mean dep. var.	43.535	43.535	43.535
Districts	1,366	1,366	1,366
Observations	160709	160709	160709

Notes: This Table presents robustness checks to address potential endogeneity concerns arising from supply-side dynamics in the relationship between coca price shocks and deforestation. Column 1 reproduces the main estimates from Table 2, Column 3, for comparability. Columns 2 and 3 introduce alternative proxies for coca price fluctuations to mitigate concerns of reverse causality and simultaneity. Specifically, Column 2 uses international cocaine prices (U.S. retail prices), while Column 3 employs reductions in coca cultivation in Colombia as an external measure of supply shocks. These results reinforce the robustness of the main findings, suggesting that the observed relationship between coca price shocks and deforestation is not merely driven by endogenous supply-side adjustments. Standard errors in brackets: clustered at district level. Stars indicate significance in the usual way. See Section 3 for a full description of the data sources. See Section 5.1.3 for a full explanation of the results.

Table A3: Additional Results (Prox to border)

	(1) Perc Tree Cover OLS	(2) Coca Density FS	(3) Perc Tree Cover RF	(4) Perc Tree Cover 2sls
Coca Density	-0.323***			-25.515***
	[0.076]			[8.072]
Std Coca $Price_{t-1}$ × Prox to border (100 km)		0.003***	-0.074***	
		[0.001]	[0.013]	
Cell FEs (9,586)	Yes	Yes	Yes	Yes
Year FEs (2003-19)	Yes	Yes	Yes	Yes
R^2	0.988	0.741	0.988	-3.880
Control for Nighlight	Yes	Yes	Yes	Yes
Mean dep. var.	43.527	0.093	43.527	43.527
F-test of excluded instrument		10.0		
Districts	1,366	1,369	1,366	1,366
Observations	161231	162234	161270	161231

Notes: This Table reports OLS (Column 1), First Stage (Column 2), Reduced Form (Column 3) and 2sls (Column 4), employing Proximity to Border in the definition of Price Shocks to coca, and, therefore, IV for Coca Density. If not otherwise specified, all the columns include nightlights, Cell and Year FE. Standard errors in brackets: clustered at district level. Stars indicate significance in the usual way. See Section 3 for a full description of the data sources and concerns related to undercount in Coca Density. See Section 5.1.3 for a full explanation of the results.

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