Coca's Return and the American Overdose Fallout*

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Abstract

Colombian coca cultivation fell dramatically between 2000 and 2015, a period that saw intense U.S.-backed eradication and interdiction efforts. That progress reversed in 2015, when peace talks and legal rulings in Colombia opened enforcement gaps. Coca plantation has since increased to record levels, which coincided with a sharp rise in cocaine-related overdose deaths in the U.S. We estimate how much of that rise can be causally attributed to Colombia's new coca boom. Leveraging the unforeseen coca supply shock and cross-county differences in pre-shock cocaine exposure, we find that the surge in supply caused an immediate rise in overdose mortality in the U.S. Our analysis estimates on the order of 1,000–1,500 additional U.S. deaths per year in the late 2010s can be attributed to Colombia's cocaine boom. Implicit annual loss in American statistical life values about $48,000 per hectare of cultivation in Colombia. If left untamed, the current level of coca cultivation (over 230,000 ha in 2022) may impose on the order of $10 billion per year in costs via overdose fatalities.

Keywords: Drug overdose; international drug policy; foreign aid.

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1. Introduction

Illicit drug markets are transnational in scope. Shifts in supply in one part of the world can have profound consequences for public health and safety in consuming regions elsewhere (Dell 2015; Csete et al., 2016; Castillo, Mejía, and Restrepo, 2020; Moore, Olney, and Hansen, 2023; Donahoe and Soliman, 2025). In the 2000s, with heavy U.S. support, Colombia waged an aggressive campaign against the plantation of coca, the raw plant used to make cocaine. Initiatives like *Plan Colombia* combined aerial herbicide spraying with manual crop eradication to contain cocaine supply at its source. Colombia's coca fields shrank from about 168,000 hectares in 2000 to just 48,000 by 2013, and cocaine became much less available in the United States (Office of National Drug Control Policy, 2012).

However, this progress abruptly unraveled in the mid-2010s as enforcement efforts weakened. Two major policy changes in 2015–2016 created a perfect storm for coca's resurgence. First, in May 2015 the Colombian government halted its U.S.-backed aerial fumigation program for coca crops after health authorities warned that the spray chemical glyphosate was likely carcinogenic.[1] Second, Colombia's government signed a landmark peace accord in late 2016 with the Revolutionary Armed Forces of Colombia (FARC) guerrilla group, ending a 52-year civil conflict. While peace was welcome, it had unintended consequences for the drug trade. For years, the FARC had tightly controlled and taxed coca production in the areas it dominated. When the rebels demobilized, a power vacuum formed in remote coca-growing regions. A variety of other armed groups ranging from dissident FARC factions to cartels rushed in to seize these territories. These new traffickers actively encouraged local farmers to plant more coca as they consolidated control. At the same time, the peace deal introduced a coca crop substitution program that promised stipends and development aid to farmers who eradicated their coca. This well-intentioned plan backfired. Farmers quickly realized they needed to have coca plants in the ground to qualify for compensation, which led many to start new coca plots or expand existing ones in hopes of securing the promised subsidies (Gelvez and Serrano, 2023; Prem, Vargas, and Mejía, 2023).

[1] It is worth noting while ariel eradication is one of the main methods used to control coca cultivation since the launch of *Plan Colombia* in 2000, its effectiveness relative to ground-level, manual eradication is a subject of scientific debate (e.g., Rozo, 2014; Mejía, 2016; Camacho and Mejía, 2017; Mejía, Restrepo, and Rozo, 2017).

By 2022, Colombia's coca cultivation area and potential cocaine output were more than three times their 2015 levels (Figure 1, panel A).[2] This coca boom translated directly into greater cocaine availability abroad. U.S. officials reported a "flood of cheap drugs" entering the United States by 2016–2017, as cocaine purity on the street rose and prices fell (Miroff, 2017). Consistent with those reports, Drug Enforcement Administration (DEA) data show that after 2015 the average size of cocaine seizures jumped markedly, while seizures of other drugs did not follow the same pattern (Figure 1, panel B).

The surge in supply was accompanied by an alarming increase in U.S. drug deaths. By the late 2010s, cocaine-involved overdose fatalities in the United States had climbed to their highest level in over a decade, breaking a long period of stable cocaine-related mortality (Jalal et al., 2018). Many analysts and officials drew a direct line between Colombia's coca boom and the rise in American overdose deaths. As one U.S. State Department official warned: "Between 2013 and 2016, coca cultivation in Colombia increased by more than 130 percent and cocaine production by more than 200 percent. The explosion in Colombian cocaine is driving an increase in cocaine use and overdose deaths in the United States and threatening Colombia's internal security and successful implementation of its peace accord" (Glenn, 2018).

Of course, simply observing that Colombian coca surged and U.S. overdoses spiked does not prove causality. Overdose trends are influenced by many factors such as the spread of fentanyl to broader socioeconomic shifts, so rigorous analysis is needed to isolate the impact of Colombia's supply boom from other developments. To our knowledge, no prior study has quantitatively estimated how much of the recent U.S. drug overdose crisis can be attributed to Colombia's cocaine resurgence. In this paper, we provide the first causal evidence on this link by exploiting the natural experiment created by Colombia's 2015–2016 policy pivot.

Our research design leverages exogenous increase in Colombia's aggregate coca production and differences in local exposure to Colombian cocaine across U.S. counties. Before the shock, some U.S. counties were major transshipment hubs or had high cocaine consumption, while others saw minimal cocaine traffic. When the Colombian coca surge hit, areas more

[2] Potential production refers to the amount of cocaine that would be produced if all the leaves harvested from the area under coca cultivation in one year would be converted into 100% pure cocaine hydrochloride (United Nations Office on Drugs and Crime, 2010).

entwined with the cocaine trade experienced a larger increase in supply than less-exposed areas. We combine detailed data on Colombia's coca production with U.S. county-level overdose death records and compare changes in overdose rates in high-exposure versus low-exposure counties after 2015. This approach allows us to isolate the effect of the Colombian supply shock on U.S. overdose mortality, under the assumption (which we confirm in tests) that absent the shock those counties would have followed similar overdose trends.

Our results show a clear pattern: starting in 2016, overdose death rates rose significantly faster in the U.S. counties most exposed to Colombian cocaine than in otherwise similar counties with little exposure. This divergence did not exist before 2015, which strengthens the case that the Colombian supply shock, rather than any pre-existing local trend, was responsible for the change. By 2017–2018, the hardest-hit areas were suffering dozens of extra overdose deaths per million residents each year relative to low-exposure areas. Aggregating these local impacts, we estimate that Colombia's coca boom caused on the order of 1,500 additional U.S. drug overdose deaths per year in the late 2010s and early 2020s. For context, U.S. cocaine overdose fatalities surpassed 20,000 per year in the early 2020s, so a significant share of the recent surge in cocaine deaths can be traced directly to Colombia's policy reversal.

We conduct a variety of robustness and falsification checks. The result holds under alternative definitions of the coca boom (using different measures of cultivation and production, or simply a post-2015 indicator) and is consistent when we use different data sources to measure pre-shock drug exposure. We find no comparable increase in overdose deaths involving drugs other than cocaine, i.e., the effect is specific to cocaine's supply surge. We also run falsification tests by applying our methodology to "placebo" shocks (for example, pretending that another drug or an unrelated factor experienced a similar supply jump). These placebo tests produce no effect, which confirms that the coca surge is behind the observed mortality increase.

Our empirical findings carry several policy lessons. First, they highlight how lapses in international drug enforcement can produce health spillovers. Colombia's halt to aerial eradication and the peace accord's unintended consequences created a health externality abroad. Even well-intended domestic policies like ending a civil war can generate serious cross-border repercussions when they undermine drug supply control. This episode shows that a breakdown in supply-side enforcement abroad can swiftly undercut public health progress at home.

Second, our results suggest that U.S. investments in overseas counter-narcotics efforts may have delivered large domestic benefits. American support helped Colombia drastically reduce its coca crop in the 2000s, likely saving many American lives. For example, *Plan Colombia*, provided roughly $10 billion in aid between 1999 and 2015. Now that those gains have been reversed, the cost to the United States is stark. We estimate that Colombia's current coca boom is inflicting on the order of $10 billion *per year* in damages to the U.S. in the form of overdose fatalities. In concrete terms, each additional hectare of coca cultivated in Colombia ultimately causes roughly $45,000 per year in harm to the United States when valuing the statistical lives lost to drug overdose. By this empirical benchmark, programs like *Plan Colombia* had provided substantial values in the long run. Renewing enforcement efforts to contain the coca supply would yield significant returns in lives saved and economic value.

Third, we find that a major surge in drug supply can drive up overdose deaths even without any increase in domestic demand, and that U.S. demand-side interventions alone were unable to counteract the flood of cocaine. In our data, the effect of Colombia's supply shock on U.S. mortality was rapid: overdose death rates in highly exposed areas began climbing within about a year of the coca surge. Domestic drug treatment, education, and enforcement efforts did not significantly blunt this rise. This implies that when supply explodes, it can overwhelm even a stable demand base. Such situations demand an immediate and coordinated policy response before the damage mounts.

Related Literature. We are most directly related to the literature on the economics of cocaine drug market. Prior research has analyzed the effects of *Plan Colombia* drug eradication policies both on production (Mejía and Posada, 2008; Camacho and Mejía, 2016; Mejía, Restrepo, and Rozo, 2017; Gelvez and Serrano, 2023; Prem, Vargas, and Mejía, 2023) and the downstream effect to user markets (Mejía and Restrepo, 2016). We are most related to Mejía and Restrepo (2016), who combine predictions from a calibrated model with time-series evidence to show that reductions in supply under *Plan Colombia* had limited effects on cocaine prices and retail availability. To our knowledge, ours is the first analysis to directly estimate the end-point health consequences of cocaine using a quasi-experimental framework, and we find these health effects to be substantial. It is important to note that our exercise focuses exclusively on measuring health spillovers to the U.S. rather than capturing broader local effects. For example, both the expansion and suppression of drug markets have been shown to impose substantial costs on local communities through

increased violence (Angrist and Kugler, 2008; Mejía and Restrepo, 2013; Dube and Naidu, 2015; Dube, García-Ponce, and Thom, 2017), natural resource depletion (Negret et al., 2019; Dávalos et al., 2011), and weakened state capacity (Acemoglu, Robinson, and Santos, 2013).

Our work also adds to the understanding of several features of the illicit trade market. First, measurement of illicit trade is difficult by nature, and thus the study of such markets is intrinsically challenging (Fisman and Wei, 2009; Moore, Olney, and Hansen, 2023). Our framework instead exploits how a common shock lands differentially across counties with varying degrees of prior exposure to the drug. While we are not able to directly measure usage, our strategy does produce estimates of the overdose fatality cost per hectare of cultivation at the source, which is the policy-relevant variable. Second, drug production and trade adapt strongly to enforcement changes and often have transboundary spillover effects (Miron and Zwiebel, 1995; Dobkin and Nicosia, 2009; Dell, 2015; Galenianos and Gavazza, 2017; Chimeli and Soares, 2017; Bellégo and Drouard, 2024; Donahoe and Soliman, 2025). Colombia's post-2015 experience provides another example of a full, rapid comeback of a globally traded drug as enforcement gaps emerge. Finally, drug diffusion has profound health ramifications, although in the prior literature, much more evidence is available on the opioid crisis (e.g., Alpert, Powell, and Pacula, 2018; Evans, Lieber, and Power, 2019; Balestra et al., 2021; Alpert et al., 2022; Cornaggia et al., 2022; Eichmeyer and Zhang, 2022; Evans, Harris, and Kessler, 2022) and less so on other imported drugs such as cocaine (Evans, Garthwaite, and Moore, 2016).

Before proceeding, it is worthwhile to highlight scholarly work that offers alternative perspectives on *Plan Colombia* and on supply-side drug regulation more generally, and to clarify how our conclusions would be affected if those perspectives are correct. First, in our policy discussion we implicitly treat *Plan Colombia* as a major contributor to Colombia's coca decline between 2000 and 2013. This interpretation is motivated by the close alignment between the timing of the decline and the period of intensive U.S.-backed eradication, and by the fact that most large-scale crop suppression efforts during this period were supported by U.S. funding and technical assistance under *Plan Colombia*. That said, the academic literature on the effectiveness and efficiency of *Plan Colombia* is considerably more nuanced. For example, Mejía (2016) documents diminishing effectiveness of eradication efforts over time, and some studies argue that *Plan Colombia* may have been largely ineffective in reducing aggregate coca cultivation (Moreno-Sanchez, Kraybill, and Thompson, 2003; Rincón-Ruiz et al., 2016). If U.S. interventions

were not in fact the primary driver of the coca decline between 2000 and 2013, this would not affect our econometric analysis of how the post-2013 coca boom translated into health costs in the United States. It would, however, limit our ability to interpret earlier supply suppression efforts under *Plan Colombia* as having saved lives.

Second, prior work argues that historical supply-side interventions can be inefficient and costly. For example, Mejía and Restrepo (2008) show that reductions in cultivated area need not translate proportionally or contemporaneously into reductions in cocaine production. Related work highlights displacement or "balloon" effects, whereby eradication shifts cultivation and trafficking across regions rather than reducing overall supply (Mejía, 2016; Mejía and Restrepo, 2008). Other studies document additional externalities of eradication policies, including adverse health impacts from aerial spraying and forced displacement of rural households (Dion and Russler, 2008; Camacho and Mejía, 2017). Mejía (2016) further argues that demand-side policies such as interdiction may be more cost-effective by avoiding supply-side adaptation and unintended consequences. Our findings show that large positive supply shocks generate substantial health externalities in consumer markets. Although it follows logically that reductions in cocaine supply could reduce these harms, our analysis does not speak to the relative effectiveness of alternative policy instruments. Nor do we claim that a return to *Plan Colombia*–style interventions would necessarily be the most efficient or welfare-maximizing approach.

Section 2 continues with institutional background and data description. Section 3 presents our main empirical analysis. Section 4 discusses policy implications and then concludes the paper.

2. Background and Data

2.1 Background

History of Colombia coca, conflict, and U.S. involvement. Colombia's coca cultivation has long been entwined with its internal conflict. Starting in the 1980s, cocaine cartels and guerrilla groups like the Revolutionary Armed Forces of Colombia (FARC) built their operations around the coca economy. FARC rebels taxed coca-growing farmers in areas under their control and played a major role in trafficking. For decades, cocaine profits fueled Colombia's civil war: leftist guerrillas and right-wing paramilitaries alike financed their fighting through the drug trade.

In response, the United States stepped in as a key partner in Colombia's counter-narcotics efforts. The most prominent initiative was *Plan Colombia*, launched in 2000 and backed by over $10 billion in U.S. aid. *Plan Colombia* combined military operations with aggressive coca eradication campaigns ranging from aerial herbicide spraying to manual crop destruction on the ground in an effort to weaken insurgents and curtail cocaine production. These efforts appeared highly successful. Colombia's coca cultivation area fell from roughly 168,000 hectares in 2000 to about 48,000 hectares by 2013, which was a historic low.

The reversal of coca's decline. This progress began to unravel in 2015 due to a convergence of policy shifts and peace developments. In May 2015, the Colombian government suspended its U.S.-backed aerial fumigation program for coca fields. For over two decades, fleets of crop-dusting planes, often operated by U.S. contractors, had regularly sprayed glyphosate herbicide over illegal coca crops as a central counter-narcotics tactic. By the mid-2010s, however, mounting health and legal concerns put this practice under scrutiny, and the World Health Organization had classified glyphosate as a probable carcinogen. This led President Juan Manuel Santos to ground the spray planes in 2015 and end the longstanding fumigation strategy. With the planes grounded, a major deterrent to large-scale coca planting disappeared overnight. The United Nations recorded a 39% surge in Colombia's coca cultivation in 2015 compared to the previous year. The government vowed to replace aerial spraying with manual eradication brigades, but those on-the-ground efforts proved too limited to stem the rebound.

A second upheaval followed with Colombia's historic peace accord with the FARC in late 2016, which formally ended a 52-year insurgency. Over 13,000 FARC fighters demobilized, and the guerrilla organization ceased to exist as an armed force. The peace deal was rightly celebrated for reducing violence: conflict-related killings plummeted in many areas after FARC units laid down their arms. However, the transition also upended the established order in Colombia's remote coca-growing zones, leading to unintended consequences for the drug trade. For years, the FARC had imposed its own kind of control in these rural territories: it decided who could grow coca and how much, taxed the trade, and kept out rival traffickers. When the FARC withdrew, a power vacuum opened across vast swaths of the countryside. Other actors quickly moved in. FARC dissidents who rejected the peace, the ELN guerrilla group, former paramilitary crime networks (i.e., the BACRIM), and even Mexican cartels rushed into the void and seized control of coca fields and trafficking routes. The result was a "gold rush" of new coca planting in

areas once tightly managed by the FARC. With the rebels gone and state authority still thin on the ground, many farmers turned to coca as the most lucrative crop, often spurred or coerced by the emerging armed groups.

The peace accord also reshaped the government's approach to coca growers. As part of the accord's rural reforms, the Colombian government agreed to treat coca cultivation more as a livelihood issue than a crime. It launched a National Program for the Substitution of Illicit Crops (PNIS), promising tens of thousands of farming families cash stipends and development assistance if they voluntarily uprooted their coca bushes. However, this well-intentioned program created perverse incentives: only those cultivating illicit crops stood to benefit from the subsidies. Anticipating compensation, many farmers began planting new coca or expanding their plots in 2016–2017 to qualify for the payouts. Subsequent studies confirmed this response. By 2017 Colombia's coca crop surged to over 171,000 hectares, which at that time was a record high.

Coca's resurgence. By 2017–2018, all these factors combined into a perfect storm for coca's comeback. The end of aerial spraying, the post-conflict power vacuum, and the new subsidy incentives collectively propelled Colombia into a full-fledged coca boom. This trend continued into the 2020s. After a brief plateau in 2018–2019, coca cultivation reached new historic highs during the COVID-19 pandemic and its aftermath. A UNODC survey in 2022 found Colombia's coca fields spanned an unprecedented 230,000 hectares which was the largest area ever recorded. This accounts for roughly two-thirds of the entire world's coca supply. Cocaine production soared as well: the UN estimated Colombia's cocaine output at 1,738 tons in 2022, another all-time high. Cultivation remains heavily concentrated in a few traditional hotspots. The border region of Catatumbo in Norte de Santander and the southern departments of Nariño and Putumayo together account for about 65% of the country's coca acreage.

Policy debates. The coca boom since 2015 has led to intense policy debate on both sides of the Colombia–United States partnership. President Juan Manuel Santos (in office 2010–2018) doubled down on voluntary eradication programs and struck development pacts with coca-growing communities. His administration argued that coercive tactics alone would not solve the problem, especially if crackdowns alienated rural farmers who already felt abandoned by the state. Indeed, the 2016 peace accord reflected this philosophy by treating coca farmers as partners to be helped out of poverty rather than as enemies, marking a significant shift in approach. Santos

even scaled back forced eradication efforts during the FARC peace negotiations (2012–2016) to build trust. His team maintained that the root causes of coca cultivation—poverty, lack of economic alternatives, and decades of neglect—had to be addressed for any lasting solution, and it urged the U.S. to invest in long-term rural development over short-term fumigation campaigns.

In Washington, however, many policymakers viewed Colombia's post-2015 approach as too lenient. Critics argued that Bogotá had been too soft on coca growers in the name of peace, allowing cultivation to spiral. Tensions between the two countries spiked as cocaine output hit record levels. In September 2017, U.S. President Donald Trump threatened to decertify Colombia as a partner in the drug war, a formal sanction implying failure to meet counter-narcotics obligations, which can trigger aid cuts. The White House noted that Santos had ended the aerial spraying program, described as "the backbone of almost two decades and $10 billion of U.S. counter-narcotics work in Colombia", and that Colombia's eradication efforts had been "significantly curtailed" in 2013 during the peace talks. In an unusual public rebuttal, the Colombian government insisted that no country had paid a higher price in blood and sacrifice fighting the drug trade than Colombia, and it pressed the United States to curb its own domestic demand. Santos's office pointed out that Colombia was interdicting 44 tons of cocaine for every 1 ton seized at the U.S. border, emphasizing Colombia's heavy lifting in the fight.

Debate within Colombia is also polarized. Opponents of the FARC peace deal, led by former President Álvaro Uribe, blamed the accord for the coca surge. They argued it rewarded criminals and eroded the fear of enforcement in rural areas. Uribe's protégé Iván Duque won the presidency in 2018 on a promise to get tough on coca. Once in office, President Duque (2018–2022) intensified forced eradication and deployed the military and manual eradicators to destroy record amounts of coca. In 2019 alone, Colombian forces manually uprooted roughly 100,000 hectares of coca and seized 428 tons of cocaine. By the end of Duque's term, coca cultivation had plateaued but at a historically high level, and cocaine production was still climbing. This outcome suggested that eradication alone could not reverse the tide, as new criminal groups kept replanting crops and adapting to enforcement.

Colombia's most recent shift in drug policy came with the election of President Gustavo Petro in August 2022. Petro, a former urban guerrilla, campaigned on a "Total Peace" platform and vowed to fundamentally change the country's anti-drug strategy. He has been openly critical

of the traditional war on drugs, even denouncing it as a "genocidal" failure that left a million Latin Americans dead while drug consumption continued unabated. Once in office, Petro halted the practice of forced coca eradication by the military, especially against small farmers, arguing that it only punishes poor peasants trapped in a cycle of survival. Instead, his administration is focusing on interdiction—going after cartels, traffickers, and money launderers—along with voluntary crop substitution. Petro has offered generous economic support for farmers who agree to replace coca with legal crops. He is also pushing to fully implement the rural development programs in the 2016 peace accord, such as land titling, local infrastructure projects, and the reintegration of ex-combatants, as a long-term solution to eliminate coca cultivation. Petro's approach marks a dramatic policy shift, framing Colombia's coca problem primarily as an issue of rural poverty and weak governance rather than a battlefield to be won by force.

2.2 Data

Colombia coca cultivation. We obtain data on coca cultivation in Colombia from the United Nations Office on Drugs and Crime (UNODC), which compiles annual metrics on illicit coca crop production. This data is based on surveys and official reports from coca-growing countries, which provides estimates of the area under coca cultivation (in hectares) between 2001-2020. In addition, we draw on data from the White House Office of National Drug Control Policy (ONDCP), which reports potential production of coca leaf (in metric tons) for 2010-2021. Using these sources, we construct annual series of the total cultivated coca area and estimated coca leaf output in Colombia.

U.S. state-level drug use. To measure drug consumption in the United States, we use data from the National Survey on Drug Use and Health (NSDUH), an annual nationally representative household survey of substance use prevalence and incidence. We extract state-by-year measures of cocaine use – specifically, the share of the population reporting cocaine use (or initiation) in the past year – as well as analogous measures for other substances (e.g. alcohol, tobacco) for context.

We supplement NSDUH data with the National Forensic Laboratory Information System (NFLIS), a DEA-managed database that aggregates results from forensic drug laboratories

nationwide. This administrative system records drug reports – instances where a seized substance is chemically identified – from state and local crime labs across the country. We use NFLIS data to obtain the number of cocaine drug reports in each state by year.

U.S. state-level drug seizure. To complement drug use data with more detail on drug supply characteristics, we use the DEA's Laboratory Information Management System (LIMS). LIMS is an internal database of forensic analyses conducted by DEA labs, recording attributes of drug evidence such as weight, purity, and estimated price of samples tested. These data are available by drug type, reported at the state and month level, which we aggregate to annual levels for analysis. From LIMS, we construct state-year indicators of cocaine supply quality – for example, the average net weight of cocaine seized in a state, the purity of cocaine samples, and price-related metrics. Together, these variables provide insight into the nature of cocaine being trafficked (e.g., typical shipment sizes and purity) and help us detect changes in the cocaine market following changes in coca production abroad.

U.S. county-level drug-related crime. Data on drug-related crime in the U.S. come from the FBI's National Incident-Based Reporting System (NIBRS), an administrative dataset of detailed police incident reports. NIBRS records each reported crime incident along with attributes such as the type of offense and any property or contraband seized. We focus on drug possession and trafficking offenses and specifically identify incidents where cocaine was reported as a seized substance. Using the incident-level microdata, we aggregate counts of cocaine-related offenses at the county-year year level between 2010-2014. In particular, we construct variables for the number of drug offense incidents per county and the subset of those involving cocaine, which serve as indicators of local cocaine involvement in crime. These NIBRS-derived measures help characterize the distribution of cocaine demand and enforcement encounters within states, and they feed into our county-level exposure index (described below) that links local areas to the Colombian cocaine supply.

U.S. county-level demographics. We incorporate demographic controls and community characteristics from the U.S. Census Bureau's American Community Survey (ACS), an ongoing nationwide survey that provides fresh data every year on social and economic traits of the population. For each county and year, we extract total population figures (used in rate calculations and as a size control) and information on residents' country of birth. In particular,

we use the ACS to determine the number of county residents who were born in Colombia, from which we compute the Colombian-born population share in the county from 2010-2014. This variable serves as a proxy for local ties to Colombian networks (for example, through immigration or trade links).

U.S. county-level overdose deaths. We use mortality data from the National Vital Statistics System (NVSS) from 2001-2020, which compiles official death records for the entire United States. NVSS mortality microdata include every death certificate, and we observe the date and county location of death, decedent characteristics, and the cause(s) of death as certified by medical authorities.

Our primary outcome is the *cocaine-related* overdose death rate per 100,000 residents in each county-year. We classify a death as cocaine-related if the underlying cause of death falls into any of the following ICD-10 categories: F14.0–F14.9 (mental and behavioral disorders due to cocaine use), T40.5 (poisoning by cocaine), R78.2 (cocaine found in blood), X42 and X62 (accidental or intentional self-poisoning by narcotics and psychodysleptics), and Y12 (poisoning by narcotics and psychodysleptics of undetermined intent). We then compute the county-year mortality rate as the number of cocaine-related overdose deaths divided by the county's population in that year.

Death certificates do not always specify the substances involved in an overdose, so our definition of cocaine-related overdoses main contain errors (CDC, 2025). As a robustness exercise, we use the subset of deaths that do report specific drugs in the multiple–cause-of-death (MCOD) section, where substances are coded using ICD-10 T-codes (e.g., T40.5 for cocaine; T40.1–T40.4 for heroin, natural opioids, methadone, and synthetic opioids such as fentanyl). Using these MCOD indicators, we construct *cocaine-specific* (and other drug-specific) overdose mortality rates for robustness checks.

U.S. county-level drug control measures. We count the number of substance-abuse treatment facilities at the county level using data from the U.S. Census Bureau's County Business Patterns (CBP). The CBP reports the annual number of substance-abuse treatment clinics by county for both outpatient and residential facilities. For our analysis, we extract county-level facility counts for 2001–2020.

We also use data from the High Intensity Drug Trafficking Areas (HIDTA) program, administered by the Office of National Drug Control Policy (ONDCP), which designates U.S. counties with high levels of drug trafficking and related criminal activity. HIDTA identifies counties that function as centers of illegal drug production, manufacturing, importation, or distribution. We use this data as a geographic indicator of enforcement intensity and trafficking risk.

3. Evidence

3.1 Empirical Framework

We use the surge in Colombian coca cultivation after 2015 as an exogenous shock to cocaine supply. This coca boom was driven by policy changes and conflict dynamics within Colombia and was largely unrelated to local conditions in the United States. Few, if any, U.S. policymakers or communities could have anticipated or influenced Colombia's decision to halt aerial coca eradication or to sign the 2016 peace accord with FARC. Consequently, Colombia's supply shock is plausibly independent of U.S. county-level trends, except through the channel of increased cocaine availability. Our aim is to isolate the causal impact of this foreign supply shock on U.S. drug overdose mortality.

We implement a difference-in-differences research design to link the Colombian shock to U.S. outcomes. In this framework, the "first difference" is the sharp post-2015 increase in Colombia's coca production, which represents a large overall rise in cocaine supply. The "second difference" is each U.S. county's baseline exposure to the cocaine market, which determines how strongly the supply shock "lands" in that county. We construct a predicted shock variable by multiplying these two components: the total coca cultivated in Colombia in a given year and each county's pre-2015 cocaine exposure share. This predicted shock varies by year and by county. We then estimate its effect on county-level overdose mortality by regressing the cocaine-related overdose death rate on the predicted shock, controlling for other factors.

Specifically, we construct a predicted shock variable as the product of these two components: Colombia's coca cultivation in year t × county i's baseline 2010-2014 exposure share. This measure varies over time and across counties. We then regress county-level drug mortality

rates on this predicted shock measure, controlling for other factors, to estimate the causal effect. Formally, we estimate the following regression model:

$$\text{Cocaine overdose mortality}_{it} = \beta \cdot \text{Coca}_t \times \text{Exposure}_i + \alpha_i + \alpha_t + \varepsilon_{it} \quad (1)$$

and we specify our cocaine exposure measure to be:

$$\text{Exposure}_i = \underbrace{\overbrace{\frac{\text{Cocaine use}_s}{\text{Population}_s}}^{\text{State cocaine use prevelance}} \times \overbrace{\frac{\text{DrugCrime}_i}{\text{DrugCrime}_s}}^{\text{County drug crime prevelance}}}_{\text{Proxy for county cocaine use prevelance}} \times \overbrace{\frac{\text{ColombianPopulation}_i}{\text{Population}_i}}^{\text{County Colombian connection}}$$

$$\text{Proxy for county cocaine use attributed to Colombian imports}$$

The dependent variable in the regression is the cocaine-related overdose mortality rate as defined in Section 2.2. The regression specification includes county fixed effects α_i to account for any time-invariant differences between counties, such as poverty or baseline drug environment, and year fixed effects α_t to account for nationwide trends affecting all counties, such as the overall opioid epidemic or economic changes. Regressions are weighted using county-year level population.[3] Standard errors are clustered at the county level.

Our key independent variable is the interaction of Colombia's coca supply and the county's baseline cocaine exposure. To measure a county's exposure share, we start with state-level cocaine use prevalence (the share of the population using cocaine) and apportion it to counties based on local drug activity. In practice, because cocaine use data are only available at the state level, we multiply each state's cocaine use rate by each county's share of drug-related crimes in that state to proxy the county-level cocaine prevalence. We consider several alternative exposure measures for robustness. One variant uses self-reported cocaine use rates from the National Survey on Drug Use and Health (NSDUH) for 2010–2014 at the county level. Another uses data from the National Forensic Laboratory Information System (NFLIS), specifically the fraction of drug samples from each county that tested positive for cocaine before 2015. Yet another measure draws on the National Incident-Based Reporting System (NIBRS), using the rate of cocaine-related offenses in the county. All of these serve as proxies for how heavily the county was involved in cocaine markets prior to the shock.

[3] The weighting scheme makes the estimated coefficient representative of the national-level impact of the coca shock. As we show below, unweighted results, which do not account for cross-county population differences, remain qualitatively similar.

Importantly, we verify that our results are not driven by spurious correlations by constructing placebo exposure measures. For example, we replace the cocaine prevalence data with the prevalence of other drugs, or we substitute a county's Colombian-born population share for its cocaine exposure share. Reassuringly, when we use these "fake" exposure variables, we find no effect of the coca shock on overdose deaths. In other words, counties do not experience a mortality increase when they are defined as "exposed" based on unrelated characteristics (such as high usage of other drugs or a large immigrant population). This supports the interpretation that our exposure measure is capturing something specific about cocaine.

We also experiment with alternative definitions of the Colombian supply shock. Instead of using the hectares of coca cultivation, one specification uses Colombia's estimated cocaine production volume (in metric tons) as the shock indicator. Another uses a simple dummy variable for the post-2015 period, treating all years from 2015 onward as "after the shock". For comparability, we standardize our main treatment variable to have mean zero and standard deviation one. This way, the coefficient β can be interpreted as the change in the cocaine overdose mortality rate associated with a one standard deviation increase in the Colombian supply shock. We will later translate this effect into more concrete units (such as the number of U.S. overdose deaths per additional hectare of coca) to illustrate its practical magnitude.

3.2 Threats to Identification

Our identification strategy relies on the assumption that, absent Colombia's coca boom, U.S. counties with higher exposure and those with lower exposure would have followed similar overdose mortality trends. In other words, any divergence in outcomes after 2015 should be attributable to the supply shock rather than to pre-existing differences. We present several pieces of evidence to support this parallel-trends assumption and to rule out alternative explanations.

Parallel pre-trends. We first conduct a visual check for parallel trends. Figure 2, panel B divides U.S. counties into four groups: those with zero cocaine exposure and, among the exposed counties, the bottom, middle, and top terciles of exposure. We then plot the cocaine-related overdose death rate for each group over time. Prior to 2015, the overdose trends for the low-, medium-, and high-exposure counties track each other closely. They even have similar levels.

After 2015, however, the high-exposure counties exhibit a much steeper increase in cocaine overdose mortality. By 2020, the overdose death rate in the top-exposure tercile is roughly 20% higher than in the middle- or low-exposure groups. Notably, even counties with no exposure (which serve as a baseline) begin to see a small uptick around 2013, but the post-2015 surge is far more pronounced in the counties that were heavily exposed to cocaine trafficking.

We also perform a formal event-study analysis to test for any pre-shock differences in trends. We augment our main regression equation (1) with a full set of year-specific shock variables, as described in equation (2) below.

$$\text{Cocaine overdose mortality}_{it} = \sum_{\tau \in [-5,4]} \beta_\tau \cdot 1(t = \tau)_t \times \text{Exposure}_i + \alpha_i + \alpha_t + \varepsilon_{it} \quad (2)$$

where $1(t = \tau)_t$ is event year dummy that equals 1 if year t is the τ-th year since 2015 (i.e., event year 0 is fiscal year 2015). We omit the event year dummy for $\tau = -1$ from the regression.[4] That is, we use 2014 (the year immediately preceding the onset of the coca boom) as the reference year. The β_τ coefficients trace the evolution of the relationship between cocaine-related overdose mortality and county-level coca exposure over time. If the parallel-trends assumption holds, the β_τ coefficients on the exposure–year interactions should be near zero in the years before the shock, and then turn positive once the shock occurs.

Falsification tests with placebo exposures. We next check whether some unobserved factor might be driving our results. One concern is that high-exposure counties could share other characteristics (for example, being large urban centers) that experienced their own shocks unrelated to Colombian coca. To assess this, we construct "fake" exposure measures that have no direct connection to Colombian cocaine. For example, we use each county's pre-2015 share of non-cocaine drug offenses, or the county's share of non-Colombian population, as alternative exposure variables. We then re-run our analysis using these placebo exposure definitions. If our original result were driven by a spurious correlation (say, if high-exposure counties were simply big cities hit by a different drug epidemic), we would expect to see a false "effect" with these fake exposures as well.

[4] Equation (2) does not have the main effect terms for the event year dummies as they are absorbed by the year fixed effects α_t.

Falsification tests with permutation. We further test the robustness of our result using a permutation approach. Essentially, this is a more generalized version of our falsification tests above with manually-defined placebo exposures: here, we *randomly* shuffle the assignment of the exposure share variable Exposure_i across counties within each state and re-estimate the model 1,000 times. This generates a distribution of "placebo" estimates that would arise if the geographic pattern of exposure were effectively random. If the actual estimate lies far out in the upper tail of this null distribution, then this exercise would confirm that our result is unlikely to have emerged by chance or due to generic within-state trends, broadly diffused policies, or other spatial patterns that are not accounted for by our fixed effects. The permutation test is especially powerful because it preserves any state-level factors (each shuffle keeps the overall exposure totals in each state the same) while breaking the specific county-by-county alignment between exposure and outcomes.

Concurrent drug epidemics. Finally, we consider whether the rise of other drugs—most notably fentanyl—could be confounding our results. The mid-2010s saw a nationwide surge in fentanyl and other synthetic opioids, which might have independently raised overdose mortality. However, fentanyl's spread was rapid and pervasive across the entire country, with no reason to expect it would concentrate in cocaine-exposed counties. In fact, opioid abuse was often higher in rural areas that had low cocaine exposure, the opposite pattern to cocaine. We conduct several checks to verify that the cocaine supply shock is driving our findings, rather than coincident opioid trends. First, we re-estimate equation (1) using the overdose death rate *excluding* cocaine-related deaths as the outcome to see if we would find effect on this non-cocaine overdose mortality measure. Second, we use a more stringent definition of cocaine overdose deaths based only on cases where the death certificate explicitly names cocaine (see Section 2.2 for details). This allows us to estimate the impact of the coca supply shock on overdose deaths explicitly attributed to fentanyl and other non-cocaine drugs. Finally, we augment equation (1) with placebo difference-in-differences terms that interact the coca boom with county's fentanyl exposure share. If fentanyl were driving the results, this additional term would also predict higher overdose deaths when interacted with the shock, and it should reduce the coefficient on the cocaine-shock interaction.

3.3 Results

Main effect. The surge in cocaine supply from Colombia led to a pronounced increase in U.S. cocaine-related overdose deaths. Table 1 presents our core regression results estimating equation (1). In Panel A, column 1, the coefficient indicates that a one standard deviation increase in a county's exposure to the Colombian supply boom raised the cocaine overdose mortality rate by approximately 0.387 (per 100,000 population per year). This is about a 6% increase relative to the sample's mean cocaine-related mortality rate of roughly 6.3 per 100,000. The effect is precisely estimated and statistically significant at the 1% level.

In columns 2–4 of Panel A, we test the robustness of this result to alternative exposure measures. In column 2, we use a more targeted proxy for pre-shock cocaine prevalence (cocaine-specific offense rates, rather than overall drug offenses, derived from NSDUH data). In columns 3 and 4, we use the NFLIS drug lab data for exposure, which cover a different set of counties, including many rural areas underrepresented in NSDUH. Across all these variations, the estimated effect remains positive, statistically significant, and of similar magnitude to the baseline in column 1. This consistency suggests that our findings are not sensitive to the exact way we measure a county's pre-2015 cocaine exposure.

Panels B and C of Table 1 report results using different definitions of the Colombian supply shock. Panel B uses Colombia's estimated cocaine production (in tons) instead of coca cultivation area as the shock metric, while Panel C uses a simple indicator (dummy) for years after 2015, i.e., treating the post-2015 period as the "treatment" years uniformly. The results are again qualitatively similar: higher exposure counties experienced a significant rise in overdose deaths after the shock. The magnitude in Panel B is nearly identical to Panel A, and in Panel C it is somewhat attenuated where the coefficient is roughly half as large as in Panel A, likely because a coarse post-2015 dummy captures the timing of the shock less precisely. All specifications confirm that the Colombian coca boom had a meaningful effect on U.S. cocaine mortality.

Temporal pattern and lag. We next examine timing of the effects. As discussed earlier, Figure 2 provides a visual comparison of raw trends of cocaine-related overdose in high- vs. low-exposure counties. We formalize the parallel trend test in Figure 3 with an event-study analysis outlined in equation (2). Here, we repeat the estimation underlying Table 1, panel C, column 1, but instead of a single post-2015 indicator, we include indicators for each year before and after

2015 (with year 2014 serving as the reference). Figure 3, panel A plots the coefficients for each year using raw overdose death counts as the outcome, and Figure 3, panel B does the same using overdose mortality rates (per 100,000 people, population-weighted). The pattern is clear in both: the estimated exposure effect in years prior to 2015 exhibits insignificant variation around zero, indicating no pre-trend. Starting in 2016, the coefficients become positive and statistically significant. The impact grows for a few years, peaking around 3–4 years after the shock (i.e., 2018–2019), and then plateaus.

These temporal patterns serve as strong parallel trend tests suggesting a lack of substantial difference between trends in overdose deaths in high versus low exposure counties until the coca boom happens in 2015. These patterns also shed light on how quickly did the impact materialize after the supply shock: the mortality effects appeared with only a short lag, within a year of the coca surge. The main policy-relevant point is that the spillover was not delayed by decades or highly attenuated – it was a near-term effect that would be noticeable within policy horizons.

Demographic groups. We examine whether the cocaine supply shock's impact on mortality was concentrated in certain demographic groups. Appendix Table 1, Panel A shows that the increase in overdose mortality is concentrated among individuals aged 15–44. Panel B indicates larger effects among Black and male populations, both in absolute terms and relative to each group's baseline mortality rate.

Specificity to cocaine-related mortality. We next ask whether Colombia's coca boom had spillover effects on drug deaths beyond those involving cocaine. If the shock mainly increased cocaine availability, we would expect the excess deaths to be concentrated in cocaine overdoses, rather than in fatalities from other substances or unrelated causes. The evidence bears this out. We detect essentially no change in non-cocaine drug overdose mortality in high-exposure counties relative to low-exposure counties. Appendix Table 2 confirms that the estimated coefficients for overdose deaths *not* involving cocaine are near zero and not statistically significant. We also consider broader categories of mortality that might be indirectly affected by drug abuse or despair. For example, Appendix Table 3 examines "deaths of despair" (suicides, alcohol-related deaths, and drug overdoses) excluding any cocaine overdoses, following the definitions

in Ruhm (2018) and Case and Deaton (2021).[5] Again, we find no evidence of an increase; if anything, some estimates are slightly negative. These null results reinforce that the Colombian shock's impact was quite specific to cocaine-related fatalities. The most plausible mechanism is a rise in cocaine consumption due to greater supply: for example, more people using cocaine, or users consuming larger quantities because the drug was more available and affordable.

Appendix Table 4 examines "drug-specific" overdose mortality rates, which we construct using the subset of death certificates that explicitly list the drugs involved, as described in Section 2.2. Because this restrictive approach captures fewer total deaths, the baseline mean for cocaine-specific mortality is much lower in this exercise than in our main analysis. We estimate separate regressions for cocaine, fentanyl, heroin, methadone, and other natural or semi-synthetic opioids. Consistent with all earlier findings, the coca shock leads to a rise in cocaine-specific overdose deaths, but we detect no change in deaths involving any other drug category.

Robustness and falsification checks. In the Online Appendix, we report a variety of additional checks showing that our results are robust. First, we show that the main findings are virtually unchanged if we do not weight the regressions by population (Appendix Table 5). Second, the result is similar or stronger when we restrict the sample to only those counties that had *some* baseline cocaine exposure (i.e. dropping the zero-exposure counties). Appendix Table 6 presents this test: the estimated effect is larger when zero-exposure counties are excluded, albeit less precisely estimated. This pattern is consistent with a small attenuation bias from including many counties that were never "at risk" of cocaine inflows. Third, we conduct falsification tests by altering how the exposure share is constructed (Appendix Table 7). In one variant, we use non-drug-related offenses as the basis for the county's exposure proxy, and in another we use the county's non-Colombian population share. In both cases we again find no effect, reinforcing that an unrelated exposure proxy does not produce a spurious result.

Appendix Figure 2 reports a more generalized falsification check. It shows spatial permutation test results as we randomly reshuffle county exposure values within state. We find

[5] The ICD-10 codes we use to define "deaths of despair" include suicide (X60-X80, Y87.0), drug and alcohol poisoning (X40-X45, Y10-Y15, Y45, Y47, Y49), and alcoholic liver disease and cirrhosis (K70, K73, K74). We then subtract non-cocaine related deaths drop cocaine related mortality from this variable to form the outcome variable of the analysis.

that the true effect size lies way outside of the permutation distribution, suggesting again the impact is specific to genuine geography of cocaine exposure prior to the coca boom.

Appendix Table 8 examines more directly whether fentanyl exposure could confound the relationship between Colombian supply shocks and cocaine-related overdose mortality. As fentanyl overdoses have gone up sharply in the past decade, it is important to assess whether counties with higher fentanyl exposure might mechanically generate patterns that resemble cocaine-driven responses. To address this, we estimate a joint specification that includes two interaction terms: the Colombian coca supply shock interacted with the county's cocaine exposure share, and the same supply shock interacted with the county's fentanyl exposure share. Across all three definitions of the $Coca_t$ variable (cultivation-based, production-based, and a post-2015 indicator) the results consistently show a strong and statistically significant effect for the $Coca_t$ × *Cocaine Exposure* interaction. In contrast, the $Coca_t$ × *Fentanyl Exposure* interaction is either negative and insignificant or much smaller in magnitude. Importantly, the inclusion of fentanyl exposure does not meaningfully change the magnitude or significance of the cocaine-exposure effect.

Effectiveness of demand-side mitigation. Our study provides an opportunity to contribute to the ongoing debate about the demand and supply of drugs and their health impacts. Specifically, we examine the role of demand-side regulations, such as counterdrug enforcement and the availability of drug treatment facilities, in the face of an exogenous increase in drug supply. To test this, in Table 2, columns 1 and 2, we estimate heterogeneous exposure effects based on counties' HIDTA (High Intensity Drug Trafficking Area) designation. If demand-side efforts dampened the supply shock's impact, one might expect smaller effects in HIDTA counties. Instead, we find the opposite: HIDTA-designated counties experience greater, not lesser, exposure effects. Column 3 presents a full interaction regression, where we interact the exposure effect term with the HIDTA indicator, and the results remain consistent. In column 4, we use the number of drug treatment facilities in the county as a second measure of demand-side regulatory effort. Again, we find no statistically significant evidence that this measure mitigates the exposure effect. These results should be interpreted with caution since they are correlational (counties with HIDTA status or more clinics may differ in many ways). However, it appears that existing demand-side measures did not meaningfully buffer the mortality impact of the foreign supply

shock. Even areas with substantial drug enforcement presence or treatment availability saw pronounced increases in cocaine-related deaths when Colombian supply surged.

Magnitude of effect. Finally, we assess the aggregate size of the effect in more concrete terms. Using our preferred estimate from Table 1 Panel A, column 1, we can approximate how many additional overdose deaths in the United States were attributable to Colombia's coca expansion. By applying the estimated exposure effect nationally, we calculate that in 2022 (when Colombia's coca cultivation reached roughly 230,000 hectares) the cocaine supply shock led to about 1,483 excess U.S. drug overdose deaths in that year alone. In 2015, before the surge, Colombian cultivation was much lower; our estimates imply that the Colombian supply at that time would have been associated with on the order of 620 U.S. overdose deaths annually. Summing over 2016–2022, the coca boom in Colombia likely resulted in several thousand additional American deaths in total. Put differently, each extra hectare of coca cultivated in Colombia eventually translated into approximately 0.0063 additional overdose deaths per year in the United States.

We can also express this externality in monetary terms. Based on the U.S. Environmental Protection Agency's standard Value of a Statistical Life (about $7.4 million in 2025 dollars), the loss of life from one hectare of coca cultivation corresponds to roughly $45,000 in damages per year. In other words, every hectare of Colombian coca imposes an annual cost of about $45,000 on U.S. society through increased overdose fatalities. For perspective, a Colombian farmer's annual profit from one hectare of coca is only a few thousand dollars, which is far below the $45,000 per-hectare cost imposed on the U.S. With roughly 230,000 hectares now under cultivation, that translates into on the order of $10 billion per year in U.S. overdose mortality costs. This calculation highlights the enormous health and economic stakes of international drug supply shocks. We turn to the policy implications of these findings in the next section.

4. Policy Implications and Conclusion

Our empirical findings carry several policy implications. First, our findings show that enforcement gaps caused by failures in diplomatic coordination can lead to large cross-border health spillovers. In our context, the abrupt halt of aerial coca eradication alongside the 2016 peace

accord that ended Colombia's internal conflict unintentionally spurred a resurgence in coca cultivation. While any major policy shift can have unintended consequences, the key issue here is that these changes produced externalities beyond Colombia's borders. Colombia's experience illustrates that transnational drug enforcement challenges are complex and often not anticipated or addressed proactively. Too often, responses come only after spillovers materialize, even when those spillovers entail significant public health consequences.

Second, has foreign aid to Colombia directly benefited the U.S.? The evidence indicates that it has. U.S. support for Colombian counter-narcotics efforts – notably *Plan Colombia*, which provided billions of dollars in aid starting in 1999 – helped drastically shrink Colombia's coca crop. Our analysis suggests that such aid yielded concrete benefits for the United States. By inference, the aggressive crop suppression of the 2000s likely prevented large number of U.S. drug deaths annually that would have occurred had cocaine supply remained unchecked.

Third, our analysis provides a quantification of how much is at steak going forward. By translating the spillover deaths into monetary terms, we can grasp the scale of harm and the value of intervention. Each additional hectare of coca cultivated in Colombia eventually inflicts an economic cost on the United States of roughly $45,000 per year, measured in the value of lives lost. In practical terms, the current coca cultivation (about 230,000 ha in 2022) is imposing on the order of $10 billion per year in U.S. costs via overdose fatalities. A full cost-benefit analysis is out of scope of this paper, but there is likely a strong cost-benefit case for investing heavily in coca reduction.

Finally, we speak to the effect of drug supply changes. International debate on drug control has long been revolving around whether the drug supply or the demand side is to be blame. Our new empirical findings show that supply reductions abroad save lives, even when underlying demand factors remain.

This paper shows that Colombia's post-2015 coca surge caused a measurable rise in U.S. cocaine overdose deaths. We link the foreign supply shock to larger increases in mortality in U.S. counties that were more exposed before the shock. The timing is tight: effects appear within a year of the surge and persist. Our preferred estimates imply roughly 1,400 excess U.S. overdose deaths per year in the late 2010s and early 2020s attributable to the boom. These results are robust

across alternative exposure measures, alternative ways to define the shock, and placebo tests, and they are specific to cocaine-related mortality.

The findings carry clear policy lessons. Cross-border coordination matters: gaps in enforcement during peace transitions can quickly spill over and raise deaths abroad. We also document sizable domestic benefits from past supply-side aid. Each additional hectare of coca cultivated in Colombia is associated with about $45,000 in annual mortality costs in the United States; at recent cultivation levels (about 230,000 ha), this amounts to roughly $10 billion per year. These magnitudes suggest that investments that reduce coca cultivation—or that prevent large enforcement gaps—can yield substantial health benefits for the U.S.

References

Acemoglu, Daron, James A. Robinson, and Rafael J. Santos. "The monopoly of violence: Evidence from Colombia." Journal of the European Economic Association 11, no. suppl_1 (2013): 5-44.

Alpert, Abby, William N. Evans, Ethan MJ Lieber, and David Powell. "Origins of the opioid crisis and its enduring impacts." The Quarterly Journal of Economics 137, no. 2 (2022): 1139-1179.

Alpert, Abby, David Powell, and Rosalie Liccardo Pacula. "Supply-side drug policy in the presence of substitutes: Evidence from the introduction of abuse-deterrent opioids." American Economic Journal: Economic Policy 10, no. 4 (2018): 1-35.

Angrist, Joshua D., and Adriana D. Kugler. "Rural windfall or a new resource curse? Coca, income, and civil conflict in Colombia." The Review of Economics and Statistics 90, no. 2 (2008): 191-215.

Balestra, Simone, Helge Liebert, Nicole Maestas, and Tisamarie B. Sherry. Behavioral responses to supply-side drug policy during the opioid epidemic. No. w29596. National Bureau of Economic Research, 2021.

Bellégo, Christophe, and Joeffrey Drouard. "Fighting Crime in Lawless Areas: Evidence from Slums in Rio de Janeiro." American Economic Journal: Economic Policy 16, no. 1 (2024): 124-159.

Camacho, Adriana, and Daniel Mejía. "The health consequences of aerial spraying illicit crops: The case of Colombia." Journal of Health Economics 54 (2017): 147-160.

Case, Anne, and Angus Deaton. "Deaths of Despair and the Future of Capitalism." (2021): 1-336.

Castillo, Juan Camilo, Daniel Mejía, and Pascual Restrepo. "Scarcity without leviathan: The violent effects of cocaine supply shortages in the mexican drug war." Review of Economics and Statistics 102, no. 2 (2020): 269-286.

Centers for Disease Control and Prevention (CDC). (n.d.). Provisional Drug Overdose Death Counts. National Center for Health Statistics. Retrieved December 1, 2025, from https://www.cdc.gov/nchs/nvss/vsrr/drug-overdose-data.htm

Chimeli, Ariaster B., and Rodrigo R. Soares. "The use of violence in illegal markets: Evidence from mahogany trade in the Brazilian Amazon." American Economic Journal: Applied Economics 9, no. 4 (2017): 30-57.

Cornaggia, Kimberly, John Hund, Giang Nguyen, and Zihan Ye. "Opioid crisis effects on municipal finance." The Review of Financial Studies 35, no. 4 (2022): 2019-2066.

Csete, Joanne, Adeeba Kamarulzaman, Michel Kazatchkine, Frederick Altice, Marek Balicki, Julia Buxton, Javier Cepeda et al. "Public health and international drug policy." The Lancet 387, no. 10026 (2016): 1427-1480.

Dávalos, Liliana M., Adriana C. Bejarano, Mark A. Hall, H. Leonardo Correa, Angelique Corthals, and Oscar J. Espejo. "Forests and drugs: Coca-driven deforestation in tropical biodiversity hotspots." Environmental Science & Technology 45, no. 4 (2011): 1219-1227.

Dell, Melissa. "Trafficking networks and the Mexican drug war." American Economic Review 105, no. 6 (2015): 1738-1779.

Dion, Michelle L., and Catherine Russler. "Eradication efforts, the state, displacement and poverty: Explaining coca cultivation in Colombia during Plan Colombia." Journal of Latin American Studies 40, no. 3 (2008): 399-421.

Dobkin, Carlos, and Nancy Nicosia. "The war on drugs: methamphetamine, public health, and crime." American Economic Review 99, no. 1 (2009): 324-349.

Donahoe, J. Travis, and Adam Soliman. "Drug Potency Shocks and Overdose Mortality: Evidence from Geographically Segmented Heroin Markets." SSRN, January 28, 2025.

Dube, Oeindrila, Omar García-Ponce, and Kevin Thom. "From maize to haze: Agricultural shocks and the growth of the mexican drug sector." Journal of the European Economic Association 14, no. 5 (2016): 1181-1224.

Dube, Oeindrila, and Suresh Naidu. "Bases, bullets, and ballots: The effect of US military aid on political conflict in Colombia." The Journal of Politics 77, no. 1 (2015): 249-267.

Eichmeyer, Sarah, and Jonathan Zhang. "Pathways into opioid dependence: Evidence from practice variation in emergency departments." American Economic Journal: Applied Economics 14, no. 4 (2022): 271-300.

Evans, Mary F., Matthew C. Harris, and Lawrence M. Kessler. "The hazards of unwinding the prescription opioid epidemic: Implications for child maltreatment." American Economic Journal: Economic Policy 14, no. 4 (2022): 192-231.

Evans, William N., Craig Garthwaite, and Timothy J. Moore. "The white/black educational gap, stalled progress, and the long-term consequences of the emergence of crack cocaine markets." Review of Economics and Statistics 98, no. 5 (2016): 832-847.

Evans, William N., Ethan MJ Lieber, and Patrick Power. "How the reformulation of OxyContin ignited the heroin epidemic." Review of Economics and Statistics 101, no. 1 (2019): 1-15.

Fisman, Raymond, and Shang-Jin Wei. "The smuggling of art, and the art of smuggling: Uncovering the illicit trade in cultural property and antiques." American Economic Journal: Applied Economics 1, no. 3 (2009): 82-96.

Galenianos, Manolis, and Alessandro Gavazza. "A structural model of the retail market for illicit drugs." American Economic Review 107, no. 3 (2017): 858-896.

Gelvez, Juan D., and Matilde Angarita Serrano. "Incentives war: the consequences of announcing a substitution policy on coca cultivation in Colombia." Journal of Illicit Economies and Development (JIED) 5, no. 1 (2023): 47-57.

Glenn, Ralph. Prepared Statement before the House Foreign Affairs Subcommittee on the Western Hemisphere. "Combatting Transnational Criminal Threats in the Western Hemisphere" (May 23, 2018).

Jalal, Hawre, Jeanine M. Buchanich, Mark S. Roberts, Lauren C. Balmert, Kun Zhang, and Donald S. Burke. "Changing dynamics of the drug overdose epidemic in the United States from 1979 through 2016." Science 361, no. 6408 (2018): eaau1184.

Mejía, Daniel. "Plan Colombia: an analysis of effectiveness and costs." Foreign Policy at Brookings 17 (2016).

Mejía, Daniel, and Pascual Restrepo. "The war on illegal drug production and trafficking: An economic evaluation of Plan Colombia." Centro de Estudios sobre Desarrollo Económico (CEDE), 2008.

Mejía, Daniel, and Pascual Restrepo. "Bushes and bullets: Illegal cocaine markets and violence in Colombia." Documento CEDE 2013-53 (2013).

Mejía, Daniel, and Pascual Restrepo. "The economics of the war on illegal drug production and trafficking." Journal of Economic Behavior & Organization 126 (2016): 255-275.

Mejía, Daniel, Pascual Restrepo, and Sandra V. Rozo. "On the effects of enforcement on illegal markets: evidence from a quasi-experiment in Colombia." The World Bank Economic Review 31, no. 2 (2017): 570-594.

Mejía, Daniel, and Carlos Esteban Posada. *Cocaine Production and Trafficking: What do we know?*. World Bank, 2008.

Miroff, Nick. "A side effect of peace in Colombia? A cocaine boom in the US." The Washington Post 8 (2017).

Miron, Jeffrey A., and Jeffrey Zwiebel. "The economic case against drug prohibition." Journal of Economic Perspectives 9, no. 4 (1995): 175-192.

Moore, Timothy J., William W. Olney, and Benjamin Hansen. Importing the Opioid Crisis? International Trade and Fentanyl Overdoses. No. w31885. National Bureau of Economic Research, 2023.

Moreno-Sanchez, Rocio, David S. Kraybill, and Stanley R. Thompson. "An econometric analysis of coca eradication policy in Colombia." World Development 31, no. 2 (2003): 375-383.

Negret, Pablo Jose, Laura Sonter, James EM Watson, Hugh P. Possingham, Kendall R. Jones, Cesar Suarez, Jose Manuel Ochoa-Quintero, and Martine Maron. "Emerging evidence that armed

conflict and coca cultivation influence deforestation patterns." Biological Conservation 239 (2019): 108176.

Office of National Drug Control Policy. "Survey Shows Significant Drop in Cocaine Production in Colombia." The White House, July 30, 2012. https://obamawhitehouse.archives.gov/ondcp/news-releases-remarks/survey-shows-significant-drop-in-cocaine-production-in-colombia

Prem, Mounu, Juan F. Vargas, and Daniel Mejía. "The rise and persistence of illegal crops: Evidence from a naive policy announcement." Review of Economics and Statistics 105, no. 2 (2023): 344-358.

Rincón-Ruiz, Alexander, Hyarold Leonardo Correa, Daniel Oswaldo León, and Stewart Williams. "Coca cultivation and crop eradication in Colombia: The challenges of integrating rural reality into effective anti-drug policy." International Journal of Drug Policy 33 (2016): 56-65.

Rozo, Sandra V. "On the unintended consequences of enforcement on illegal drug producing countries." UCLA CCPR Population Working Papers (2014).

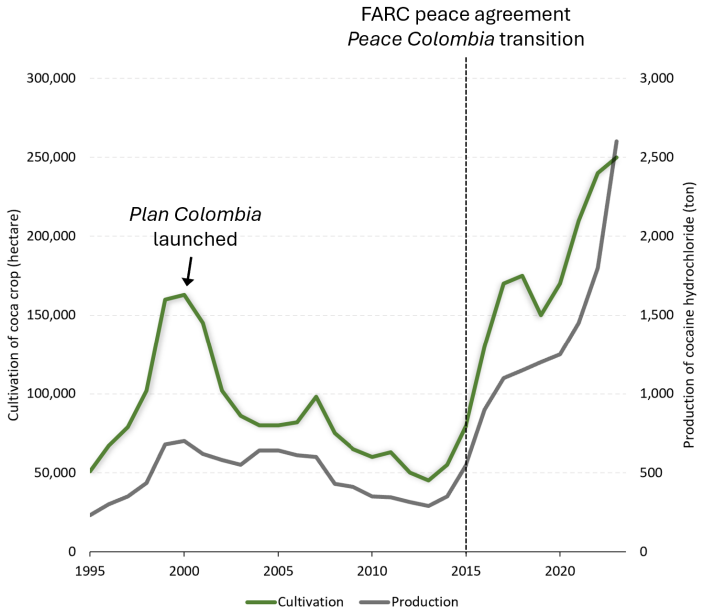
Ruhm, Christopher J. Deaths of despair or drug problems?. No. w24188. National Bureau of Economic Research, 2018.

United Nations Office on Drugs and Crime. World Drug Report 2010: Statistical Annex 4.1 Production. Vienna: United Nations Office on Drugs and Crime, 2010.

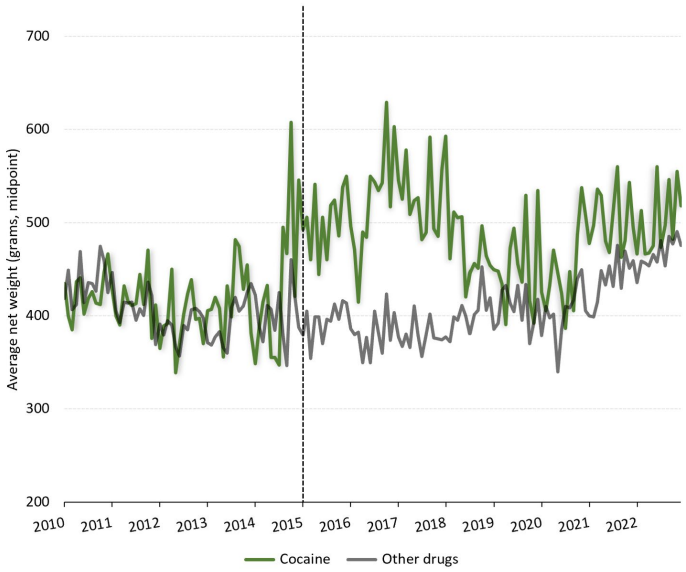
Figures and Tables

Figure 1. Trends in Colombia's Coca Cultivation and U.S. Cocaine Seizure

A. Coca Cultivation and Potential Production in Colombia



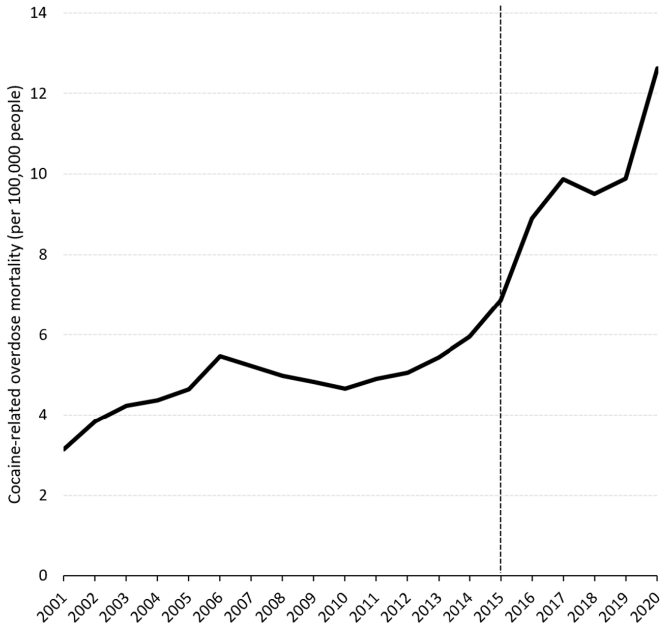
B. Average Net Weight of Cocaine and Other Drug Seizures in the United States



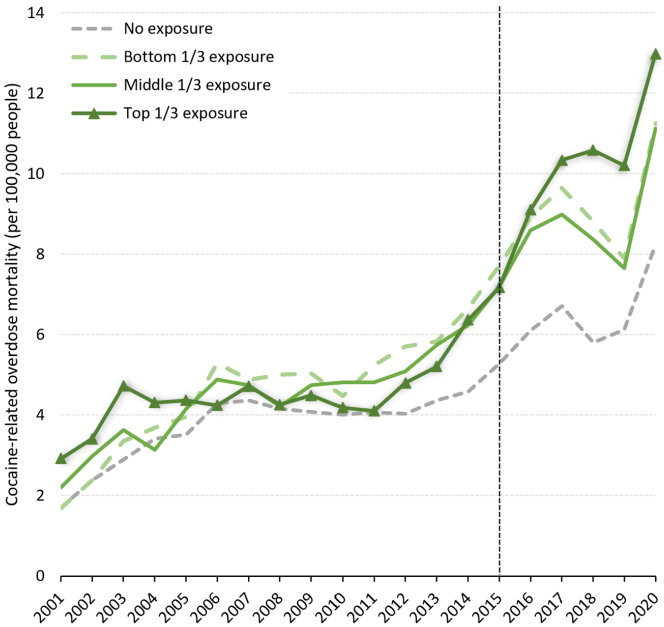
Notes: Panel A plots total coca cultivation area (in hectares, left axis) and potential coca production (in metric tons, right axis) in Colombia from 2005–2022, based on United Nations Office on Drugs and Crime (UNODC) annual estimates. Panel B plots monthly average net weight (grams, midpoint of DEA purity brackets) of drug seizures reported in the DEA Laboratory Information Management System (LIMS). The green line shows cocaine samples; the gray line shows all other drug types. The vertical dashed line in both panels marks the start of year 2015.

Figure 2. Trends in U.S. Cocaine-Related Overdose Mortality and Cross-County Differences

A. National Cocaine-Involved Overdose Mortality



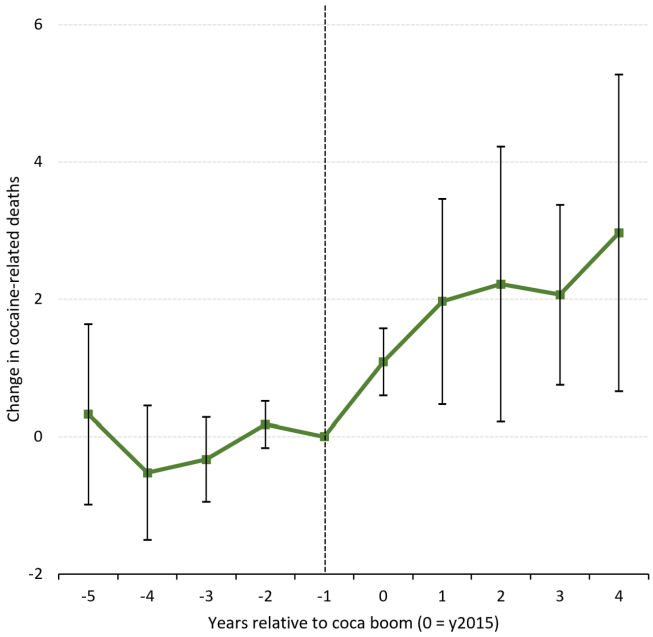
B. Overdose Mortality in High- versus Low-Exposure Counties



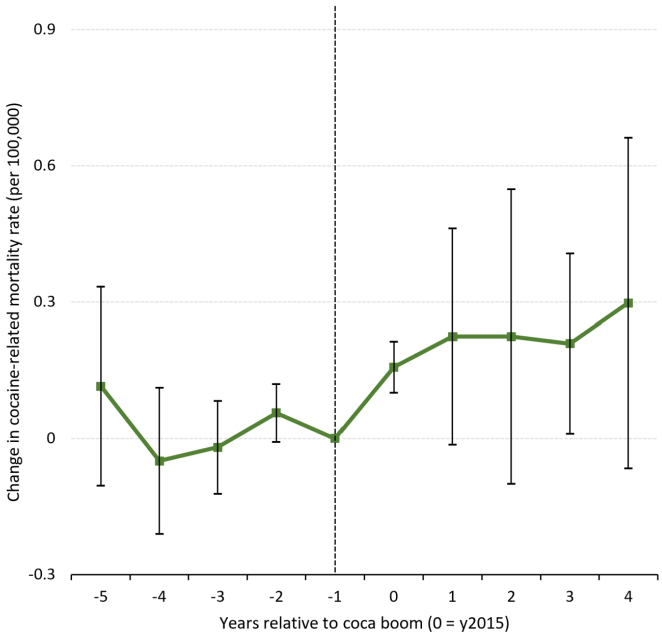
Notes: Panel A plots the national rate of cocaine-involved overdose deaths (per 100,000 people) in the United States. Panel B separates counties by their pre-2015 exposure to Colombian cocaine, corresponding to the top, middle, and bottom terciles of the Cocaine Exposure Index, with counties recording zero exposure shown separately.

Figure 3. Event Study Estimates of the Cocaine Supply Shock on U.S. Cocaine Overdose Mortality

A. Raw Death Counts



B. Cocaine-Related Overdose Mortality Rate



Notes: Each panel plots coefficients from an event-study regression estimating the dynamic effects of exposure to Colombia'scoca boom on U.S. cocaine-involved overdose outcomes. The horizontal axis shows event time centered on 2015 (defined as event year 0). The vertical dashed line marks one year prior to the onset of the supply shock. Bars show 95 percent confidence intervals.

Table 1. The Effect of the Cocaine Supply Shock on U.S. Cocaine-Related Overdose Mortality

	A. Cultivation area as $Coca_t$			
	Mortality rate (#deaths per 100,000)			
$Coca_t \times Exposure_i$ (std)	0.38725***	0.35126**	0.47212***	0.43480**
	(0.13124)	(0.13650)	(0.10438)	(0.17682)
Observations	59096	59096	59096	59096
R-square	0.575	0.575	0.576	0.575
Y-mean	6.320	6.320	6.320	6.320
Y-sd	6.441	6.441	6.441	6.441
	B. Production as $Coca_t$			
	Mortality rate (#deaths per 100,000)			
$Coca_t \times Exposure_i$ (std)	0.40183***	0.36629**	0.49456***	0.45977**
	(0.15034)	(0.15718)	(0.12436)	(0.20859)
Observations	29561	29561	29561	29561
R-square	0.689	0.689	0.690	0.689
Y-mean	7.946	7.946	7.946	7.946
Y-sd	7.812	7.812	7.812	7.812
	C. Post 2015 as $Coca_t$			
	Mortality rate (#deaths per 100,000)			
$Coca_t \times Exposure_i$ (std)	0.16967***	0.15695***	0.20430***	0.19132**
	(0.05564)	(0.05912)	(0.04719)	(0.07934)
Observations	59096	59096	59096	59096
R-square	0.575	0.575	0.576	0.575
Y-mean	6.320	6.320	6.320	6.320
Y-sd	6.441	6.441	6.441	6.441
County, Year FEs	Y	Y	Y	Y
Drug use	NSDUH	NSDUH	NFLIS	NFLIS
Crime	Drug offense	Cocaine property	Drug offense	Cocaine property

Notes: Each panel reports estimates from county-by-year regressions of cocaine-related overdose mortality on exposure to Colombia's coca expansion. The key variable, $Coca_t \times Exposure_i$, is the interaction between Colombia's coca shock (measured variously as cultivation area, potential production, or a post-2015 indicator) and each county's pre-2015 exposure to Colombian cocaine. Exposure is proxied using pre-shock measures from the National Survey on Drug Use and Health (NSDUH) and the DEA's National Forensic Laboratory Information System (NFLIS), based on drug-offense or cocaine-specific property crime shares. The dependent variable is the cocaine-related overdose death rate per 1,000 population. All models include county and year fixed effects; standard errors (in parentheses) are clustered at the county level. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

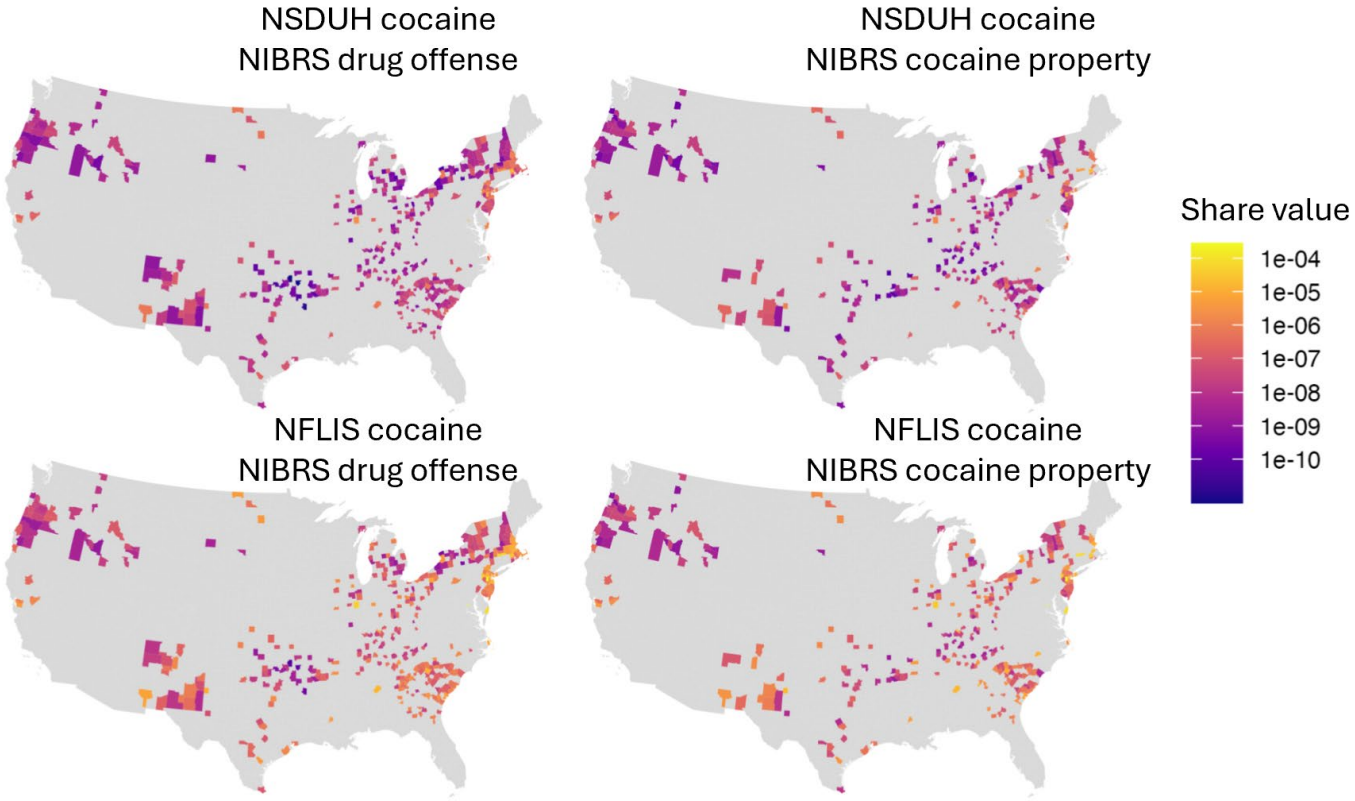
Table 2. Heterogeneity of Exposure Effects by Demand-Side Regulation

	Mortality rate (#deaths per 100,000)			
	HIDTA	non-HIDTA		
$Coca_t \times Exposure_i$ (std)	0.40483***	0.22184***	0.19532***	0.33352***
	(0.15245)	(0.06967)	(0.05935)	(0.11823)
$Coca_t \times Exposure_i$ (std) × HIDTA			0.21906	
			(0.16142)	
$Coca_t \times Exposure_i$ (std) × #Facilities (100)				0.08005
				(0.17928)
#Facilities (100)				-1.70539***
				(0.65050)
Observations	12830	46266	59096	59096
R-square	0.594	0.543	0.575	0.578
Y-mean	6.622	5.627	6.320	6.320
Y-sd	6.015	7.275	6.441	6.441
County, Year FEs	Y	Y	Y	Y
Drug use	NSDUH	NSDUH	NSDUH	NSDUH
Crime	Drug offense	Drug offense	Drug offense	Drug offense

Notes: Columns 1–2 split counties by their HIDTA (High Intensity Drug Trafficking Area) designation. Columns 3–4 test for heterogeneity by the number of drug treatment facilities per 100,000 people. $Coca_t \times Exposure_i$, is the interaction between Colombia's coca shock (measured variously as cultivation area, potential production, or a post-2015 indicator) and each county's pre-2015 exposure to Colombian cocaine. All regressions include county and year fixed effects. Standard errors (in parentheses) are clustered at the county level. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

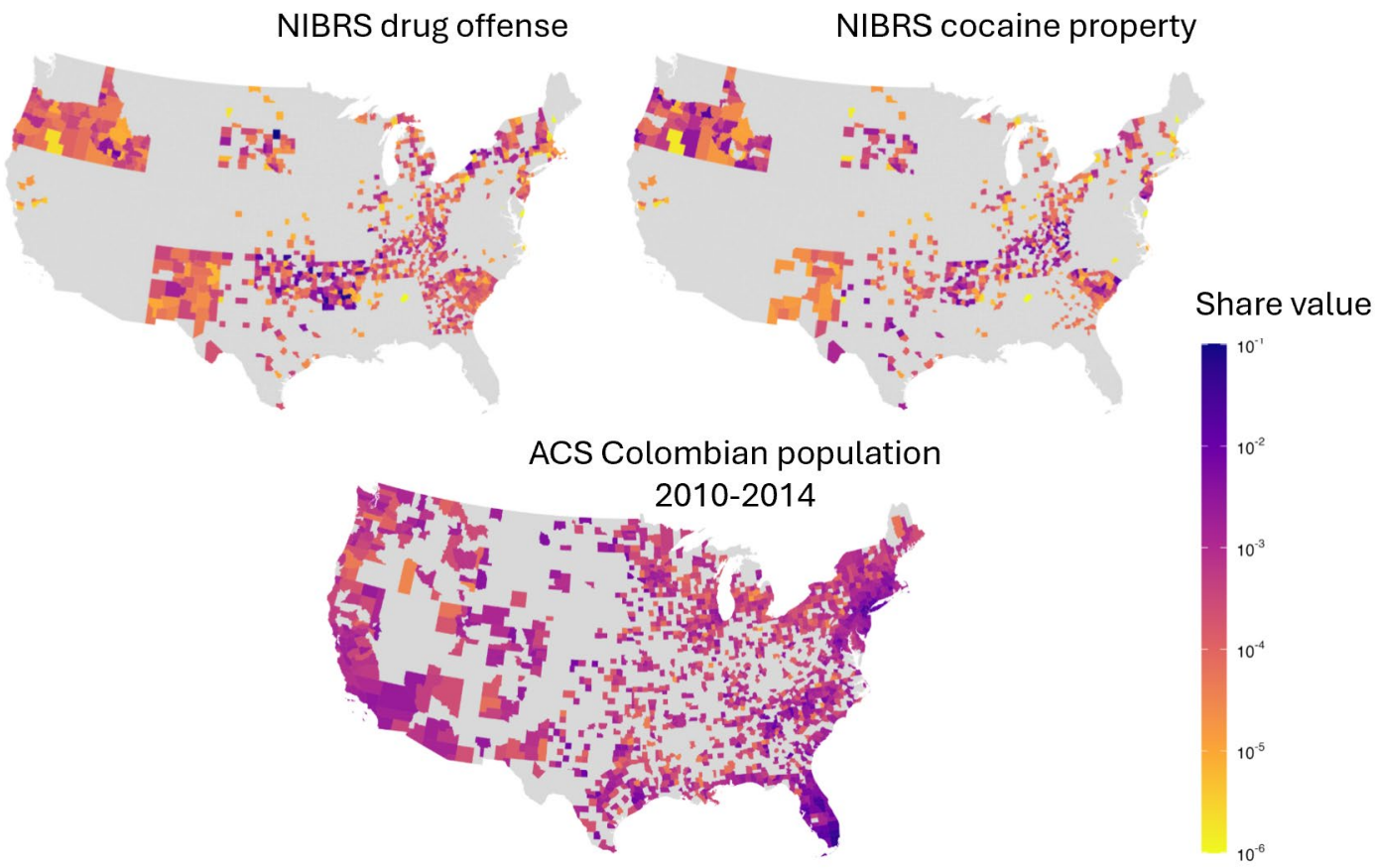
Appendix Figures and Tables

Appendix Figure 1. Geographic Distribution of County-Level Cocaine Exposure Measures



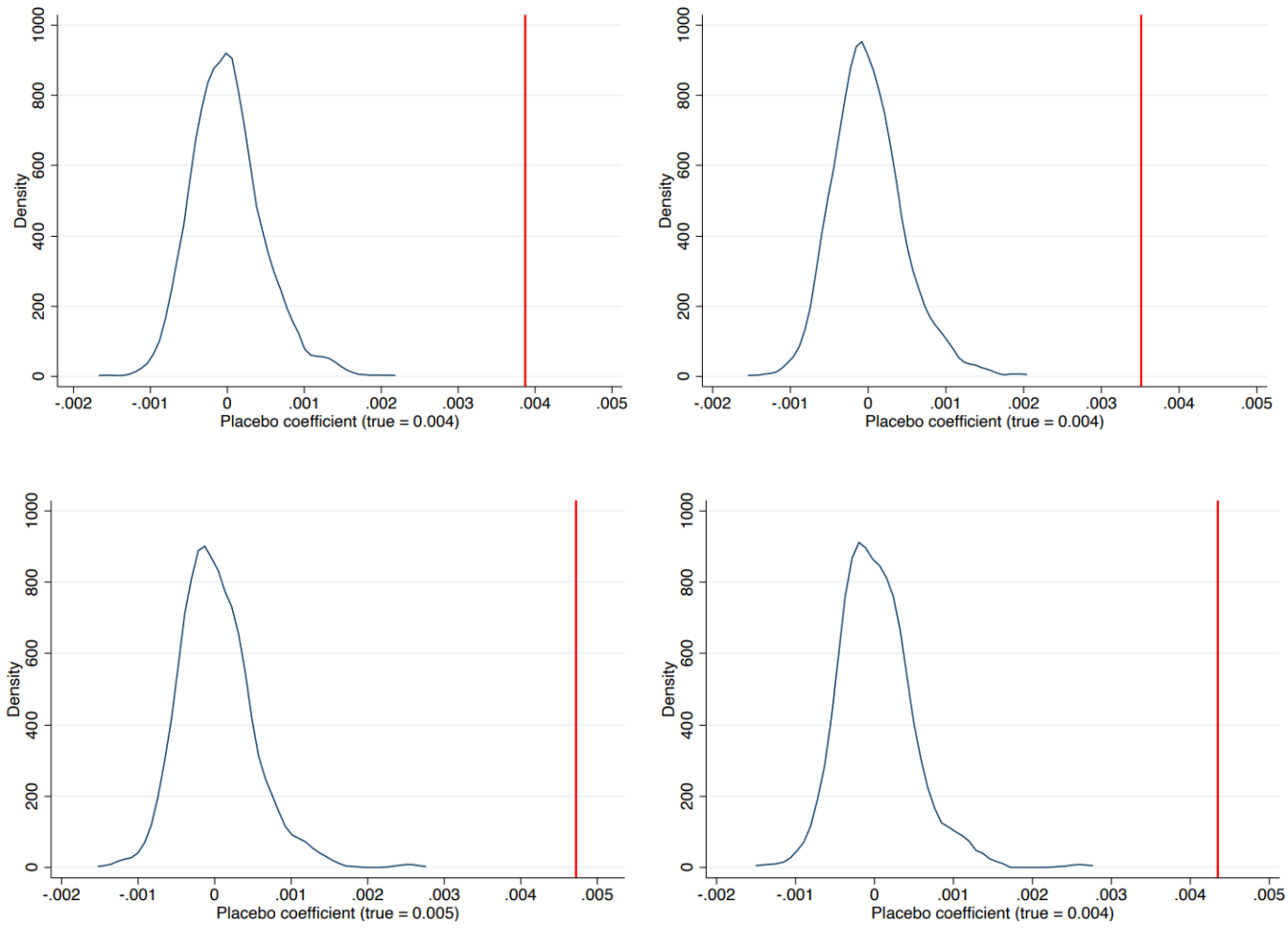
Notes: This figure maps alternative county-level exposure measures ($Exposure_i$) used in constructing the exposure variable. Each panel shows one variant of the pre-2015 exposure proxy, derived from different data sources: cocaine-related drug offenses, total drug offenses, cocaine property crimes, or cocaine lab reports from the National Forensic Laboratory Information System (NFLIS). Colors indicate the relative intensity of cocaine prevalence within a state (higher values in yellow, lower in purple). Darker shades represent counties more historically involved in cocaine markets, which are expected to experience stronger effects from Colombia's post-2015 coca boom. Grey areas indicate counties with missing or zero exposure observations.

Appendix Figure 1 (Cont.) Geographic Distribution of County-Level Cocaine Exposure Measures



Notes: This figure maps alternative county-level exposure measures ($Exposure_i$) used in constructing the exposure variable. Each panel shows one variant of the pre-2015 exposure proxy, derived from different data sources: cocaine-related drug offenses, total drug offenses, cocaine property crimes, or cocaine lab reports from the National Forensic Laboratory Information System (NFLIS). Colors indicate the relative intensity of cocaine prevalence within a state (higher values in yellow, lower in purple). Darker shades represent counties more historically involved in cocaine markets, which are expected to experience stronger effects from Colombia's post-2015 coca boom. Grey areas indicate counties with missing or zero exposure observations.

Appendix Figure 2. Spatial Permutation Tests for the Cocaine Exposure Effect



Notes: Each panel shows the distribution of placebo coefficients from 1,000 spatial permutation tests in which the pre-2015 county exposure index ($Exposure_i$) is randomly reassigned among counties within the same state. The blue curve shows the density of estimated coefficients under these placebo reassignments; the red vertical line marks the true estimated coefficient from the actual exposure geography (≈0.004).

Appendix Table 1. Heterogeneity of Exposure Effects by Demographic Groups

A. By Age

	Mortality rate (#deaths per 100,000)			
	≤14	15-44	45-64	65+
$Coca_t \times Exposure_i$ (std)	0.00031	0.25114***	0.90412*	0.47858
	(0.00438)	(0.09003)	(0.51250)	(0.37863)
Observations	10475	56909	54649	31755
R-square	0.048	0.513	0.532	0.264
Y-mean	0.127	8.919	9.618	1.764
Y-sd	0.818	9.952	11.546	3.610
County, Year FEs	Y	Y	Y	Y
Drug use	NSDUH	NSDUH	NSDUH	NSDUH
Crime	Drug offense	Drug offense	Drug offense	Drug offense

B. By Race and Gender

	Mortality rate (#deaths per 100,000)				
	White	Black	Other race	Male	Female
$Coca_t \times Exposure_i$ (std)	0.26530***	0.84278**	0.07373	0.62958***	0.16537***
	(0.08001)	(0.36806)	(0.04807)	(0.21640)	(0.05971)
Observations	46904	46899	46904	46904	46904
R-square	0.528	0.539	0.174	0.561	0.422
Y-mean	6.746	8.404	1.578	9.677	3.621
Y-sd	6.413	11.322	5.961	9.866	4.044
County, Year FEs	Y	Y	Y	Y	Y
Drug use	NSDUH	NSDUH	NSDUH	NSDUH	NSDUH
Crime	Drug offense	Drug offense	Drug offense	Drug offense	Drug offense

Notes: This table estimates the heterogeneous effects of Colombia's coca expansion on U.S. cocaine-involved overdose mortality by demographic group. The dependent variable is the cocaine-involved overdose death rate (per 100,000 population). Panel A disaggregates the analysis by age group (<15, 15–44, 45–64, and 65+), while Panel B separates results by race and gender. The key regressor, $Coca_t \times Exposure_i$, interacts Colombia's coca cultivation with each county's pre-2015 cocaine exposure share (proxied by NSDUH drug-offense data). All specifications include county and year fixed effects; standard errors (in parentheses) are clustered at the county level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 2. Effects on Non-Cocaine-Related Overdose Mortality

	Cultivation area as $Coca_t$			
	Mortality rate (#deaths per 100,000)			
$Coca_t \times Exposure_i$ (std)	0.02898	0.01808	0.10625	0.09507
	(0.08526)	(0.07955)	(0.07155)	(0.09195)
Observations	59096	59096	59096	59096
R-square	0.630	0.630	0.630	0.630
Y-mean	8.196	8.196	8.196	8.196
Y-sd	6.553	6.553	6.553	6.553
	Production as $Coca_t$			
$Coca_t \times Exposure_i$ (std)	0.00550	-0.00590	0.08898	0.07929
	(0.09885)	(0.09105)	(0.09557)	(0.11391)
Observations	29561	29561	29561	29561
R-square	0.681	0.681	0.681	0.681
Y-mean	10.372	10.372	10.372	10.372
Y-sd	7.178	7.178	7.178	7.178
	Post 2015 as $Coca_t$			
$Coca_t \times Exposure_i$ (std)	0.00704	0.00463	0.03399	0.03134
	(0.03819)	(0.03509)	(0.04098)	(0.04709)
Observations	59096	59096	59096	59096
R-square	0.630	0.630	0.630	0.630
Y-mean	8.196	8.196	8.196	8.196
Y-sd	6.553	6.553	6.553	6.553
County, Year FEs	Y	Y	Y	Y
Drug use	NSDUH	NSDUH	NFLIS	NFLIS
Crime	Drug offense	Cocaine property	Drug offense	Cocaine property

Notes: Each panel reports estimates from county-by-year regressions of non-cocaine-related overdose mortality on exposure to Colombia's coca expansion. The key variable, $Coca_t \times Exposure_i$, is the interaction between Colombia's coca shock (measured variously as cultivation area, potential production, or a post-2015 indicator) and each county's pre-2015 exposure to Colombian cocaine. Exposure is proxied using pre-shock measures from the National Survey on Drug Use and Health (NSDUH) and the DEA's National Forensic Laboratory Information System (NFLIS), based on drug-offense or cocaine-specific property crime shares. The dependent variable is the cocaine-related overdose death rate per 100,000 population. All models include county and year fixed effects; standard errors (in parentheses) are clustered at the county level. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Appendix Table 3. Effects on Non-Cocaine-Related "Deaths of Despair"

	Cultivation area as $Coca_t$			
	Deaton per 100,000			
$Coca_t \times Exposure_i$ (std)	-0.10087	-0.10254	-0.01615	-0.01833
	(0.07861)	(0.06635)	(0.08232)	(0.08096)
Observations	59096	59096	59096	59096
R-square	0.723	0.723	0.723	0.723
Y-mean	24.821	24.821	24.821	24.821
Y-sd	11.986	11.986	11.986	11.986
	Production as $Coca_t$			
$Coca_t \times Exposure_i$ (std)	-0.13435	-0.13868*	-0.03752	-0.04094
	(0.09398)	(0.07978)	(0.10583)	(0.10412)
Observations	29561	29561	29561	29561
R-square	0.758	0.758	0.758	0.758
Y-mean	29.063	29.063	29.063	29.063
Y-sd	12.683	12.683	12.683	12.683
	Post 2015 as $Coca_t$			
$Coca_t \times Exposure_i$ (std)	-0.07196**	-0.06606**	-0.05394	-0.04901
	(0.03525)	(0.02800)	(0.04301)	(0.03368)
Observations	59096	59096	59096	59096
R-square	0.723	0.723	0.723	0.723
Y-mean	24.821	24.821	24.821	24.821
Y-sd	11.986	11.986	11.986	11.986
County, Year FEs	Y	Y	Y	Y
Drug use	NSDUH	NSDUH	NFLIS	NFLIS
Crime	Drug offense	Cocaine property	Drug offense	Cocaine property

Notes: Each panel reports estimates from county-by-year regressions of non-cocaine-related "deaths of despair" mortality on exposure to Colombia's coca expansion. The key variable, $Coca_t \times Exposure_i$, is the interaction between Colombia's coca shock (measured variously as cultivation area, potential production, or a post-2015 indicator) and each county's pre-2015 exposure to Colombian cocaine. Exposure is proxied using pre-shock measures from the National Survey on Drug Use and Health (NSDUH) and the DEA's National Forensic Laboratory Information System (NFLIS), based on drug-offense or cocaine-specific property crime shares. The dependent variable is the cocaine-related overdose death rate per 100,000 population. All models include county and year fixed effects; standard errors (in parentheses) are clustered at the county level. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Appendix Table 4. Effects on Drug-Specific Overdose Mortality

	Mortality rate (#deaths per 100,000)				
	Cocaine	Fentanyl	Heroin	Nat./semi-synth	Methadone
$Coca_t \times Exposure_i$ (std)	0.01858**	-0.00072	-0.00120	-0.00018	0.00002
	(0.00735)	(0.00051)	(0.00142)	(0.00161)	(0.00113)
Observations	50436	50436	50436	50436	50436
R-square	0.479	0.248	0.341	0.413	0.283
Y-mean	0.138	0.037	0.063	0.129	0.063
Y-sd	0.661	0.262	0.371	0.672	0.423
County, Year FEs	Y	Y	Y	Y	Y
Drug use	NSDUH	NSDUH	NSDUH	NSDUH	NSDUH
Crime	Drug offense	Drug offense	Drug offense	Drug offense	Drug offense

Notes: Each panel reports estimates from county-by-year regressions of drug-specific overdose mortality on exposure to Colombia's coca expansion. The key variable, $Coca_t \times Exposure_i$, is the interaction between Colombia's coca shock (measured as cultivation area) and each county's pre-2015 exposure to Colombian cocaine. Exposure is proxied using pre-shock measures from the National Survey on Drug Use and Health (NSDUH) based on drug-offense. The dependent variable is drug-specific overdose death rate per 100,000 population. All models include county and year fixed effects; standard errors (in parentheses) are clustered at the county level. ***, **, * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Appendix Table 5. Robustness: Unweight Regressions

	Cultivation area as $Coca_t$			
	Mortality rate (#deaths per 100,000)			
$Coca_t \times Exposure_i$ (std)	0.52316***	0.46244***	0.56883***	0.48324**
	(0.14185)	(0.14579)	(0.15326)	(0.20789)
Observations	59096	59096	59096	59096
R-square	0.312	0.312	0.312	0.312
Y-mean	4.688	4.688	4.688	4.688
Y-sd	6.778	6.778	6.778	6.778
	Production as $Coca_t$			
$Coca_t \times Exposure_i$ (std)	0.55023***	0.48712***	0.59886***	0.50960**
	(0.15864)	(0.16633)	(0.17353)	(0.23824)
Observations	29561	29561	29561	29561
R-square	0.424	0.424	0.424	0.424
Y-mean	5.824	5.824	5.824	5.824
Y-sd	7.838	7.838	7.838	7.838
	Post 2015 as $Coca_t$			
$Coca_t \times Exposure_i$ (std)	0.23540***	0.21004***	0.24997***	0.21381**
	(0.06206)	(0.06532)	(0.06839)	(0.09333)
Observations	59096	59096	59096	59096
R-square	0.312	0.312	0.312	0.312
Y-mean	4.688	4.688	4.688	4.688
Y-sd	6.778	6.778	6.778	6.778
County, Year FEs	Y	Y	Y	Y
Drug use	NSDUH	NSDUH	NFLIS	NFLIS
Crime	Drug offense	Cocaine property	Drug offense	Cocaine property

Notes: This table replicates the main specification from Table 1 but estimates all regressions without population weighting. The dependent variable is the cocaine-related overdose death rate per 1,000 population. The key regressor, $Coca_t \times Exposure_i$, interacts Colombia's coca cultivation or production (or a post-2015 indicator) with each county's pre-2015 cocaine exposure share. Exposure is proxied using the National Survey on Drug Use and Health (NSDUH) and the DEA's National Forensic Laboratory Information System (NFLIS), based on drug-offense or cocaine-property crime measures. All models include county and year fixed effects, and standard errors (in parentheses) are clustered at the county level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 6. Robustness: Counties with Positive Exposure Only

	Cultivation area as $Coca_t$			
	Mortality rate (#deaths per 100,000)			
$Coca_t \times Exposure_i$ (std)	0.76007**	0.81849**	0.99042***	1.08067**
	(0.33888)	(0.40168)	(0.28990)	(0.53371)
Observations	7860	5940	7860	5940
R-square	0.616	0.588	0.618	0.590
Y-mean	7.538	7.196	7.538	7.196
Y-sd	6.883	6.673	6.883	6.673
	Production as $Coca_t$			
$Coca_t \times Exposure_i$ (std)	0.84204**	0.90911*	1.09574***	1.20397*
	(0.40182)	(0.47518)	(0.35922)	(0.64382)
Observations	3930	2970	3930	2970
R-square	0.715	0.696	0.717	0.698
Y-mean	9.893	9.562	9.893	9.562
Y-sd	8.253	8.048	8.253	8.048
	Post 2015 as $Coca_t$			
$Coca_t \times Exposure_i$ (std)	0.32477**	0.35539**	0.41952***	0.46402*
	(0.14687)	(0.17531)	(0.13449)	(0.24019)
Observations	7860	5940	7860	5940
R-square	0.616	0.589	0.618	0.591
Y-mean	7.538	7.196	7.538	7.196
Y-sd	6.883	6.673	6.883	6.673
County, Year FEs	Y	Y	Y	Y
Drug use	NSDUH	NSDUH	NFLIS	NFLIS
Crime	Drug offense	Cocaine property	Drug offense	Cocaine property

Notes: This table reports robustness checks restricting the sample to U.S. counties with strictly positive pre-2015 cocaine exposure ($Exposure_i > 0$). The dependent variable is the cocaine-related overdose death rate per 1,000 population. The key regressor, $Coca_t \times Exposure_i$, interacts Colombia's coca cultivation or production (or a post-2015 indicator) with each county's pre-2015 exposure to Colombian cocaine. Exposure measures are based on pre-shock proxies from the National Survey on Drug Use and Health (NSDUH) and the DEA's National Forensic Laboratory Information System (NFLIS), using drug-offense or cocaine-property crime shares. All models include county and year fixed effects; standard errors (in parentheses) are clustered at the county level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 7. Falsification Checks: Regressions with Placebo Share

	Cultivation area as $Coca_t$	
	Mortality rate (#deaths per 100,000)	
	Non-cocaine drug	Non-Colombian
$Coca_t \times Exposure_i$ (std)	1.02486	0.37855
	(0.68666)	(0.49236)
Observations	59096	59096
R-square	0.574	0.573
	Production as $Coca_t$	
$Coca_t \times Exposure_i$ (std)	1.02189	0.44110
	(0.78453)	(0.54680)
Observations	29561	29561
R-square	0.688	0.687
	Post 2015 as $Coca_t$	
$Coca_t \times Exposure_i$ (std)	0.43645	0.14063
	(0.31643)	(0.23309)
Observations	59096	59096
R-square	0.574	0.573
County, Year FEs	Y	Y
Drug use	NFLIS	NFLIS
Crime	Drug offense	Drug offense

Notes: This table presents falsification tests using alternative, non-cocaine-related exposure measures. The dependent variable is the cocaine-related overdose death rate per 1,000 population. The key regressor, $Coca_t \times Exposure_i$, interacts Colombia's coca cultivation or production (or a post-2015 indicator) with two placebo versions of county exposure: (1) the county's pre-2015 share of non-cocaine drug offenses, and (2) the share of residents born outside Colombia ("Non-Colombian" exposure). Both placebo exposure variables are constructed from DEA's National Forensic Laboratory Information System (NFLIS) and U.S. Census data. All regressions include county and year fixed effects; standard errors (in parentheses) are clustered at the county level.

Appendix Table 8. Regressions with Both Cocaine and Fentanyl Exposure Share

	Mortality rate (#deaths per 100,000)			
	Cultivation area as $Coca_t$			
$Coca_t$ × Cocaine Exposure$_i$ (std)	0.51461***	0.50819**	0.43628***	0.39612**
	(0.12891)	(0.22110)	(0.10737)	(0.18548)
$Coca_t$ × Fentanyl Exposure$_i$ (std)	-0.15316	-0.17717	0.13930***	0.12060***
	(0.11973)	(0.17172)	(0.04525)	(0.03583)
Observations	59096	59096	59096	59096
Y-mean	6.320	6.320	6.320	6.320
Y-sd	6.441	6.441	6.441	6.441
	Production as $Coca_t$			
$Coca_t$ × Cocaine Exposure$_i$ (std)	0.55981***	0.54960**	0.46107***	0.42265*
	(0.16341)	(0.26974)	(0.13084)	(0.21904)
$Coca_t$ × Fentanyl Exposure$_i$ (std)	-0.19030	-0.20727	0.13042***	0.11596***
	(0.13602)	(0.20517)	(0.04055)	(0.04003)
Observations	29561	29561	29561	29561
Y-mean	7.946	7.946	7.946	7.946
Y-sd	7.812	7.812	7.812	7.812
	Post 2015 as $Coca_t$			
$Coca_t$ × Cocaine Exposure$_i$ (std)	0.21330***	0.21358**	0.18696***	0.17213**
	(0.06464)	(0.10162)	(0.04870)	(0.08306)
$Coca_t$ × Fentanyl Exposure$_i$ (std)	-0.05246	-0.06393	0.06748***	0.05992***
	(0.05897)	(0.08029)	(0.02213)	(0.01809)
Observations	59096	59096	59096	59096
Y-mean	6.320	6.320	6.320	6.320
Y-sd	6.441	6.441	6.441	6.441
County, Year FEs	Y	Y	Y	Y
Cocaine drug use	NSDUH	NSDUH	NFLIS	NFLIS
Fentanyl drug use	NFLIS	NFLIS	NFLIS	NFLIS
Crime	Drug offense	Cocaine property	Drug offense	Cocaine property

Notes: This table reports regressions that include both cocaine exposure and fentanyl exposure in the same specification. The dependent variable in all columns is the cocaine-related overdose death rate per 1,000 population. Each panel uses a different definition of $Coca_t$: (1) Colombia's coca cultivation share, (2) Colombia's cocaine production share, and (3) a post-2015 indicator capturing the period when synthetic opioids expanded rapidly in the United States. In each specification, $Coca_t$ × *Cocaine Exposure* is the main interaction of interest, and $Coca_t$ × *Fentanyl Exposure* serves as a placebo interaction testing whether fentanyl exposure can account for the observed effects. All regressions include county and year fixed effects, and standard errors are clustered at the county level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.