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ABSTRACT

Landing on Water: Air Interdiction, Drug-Trafficking Displacement, and Violence in the Brazilian Amazon*

We study a Force-down/Shoot-down intervention in Brazil that led cocaine traffickers to shift from air to river routes. Using data on cocaine production, homicides, and the network of rivers in the Amazon, we provide evidence that violence increased in municipalities along river routes originating from Andean producing countries after the policy. We also show that, during the same period, violence in these municipalities became more responsive to cocaine production in origin countries. We document an instance of crime displacement over the three-dimensional space, involving sophisticated adaptations from criminals regarding transportation technologies, with dramatic side-effects for local populations.

JEL Classification: K42, O54, Q34

Keywords: cocaine, illegal markets, crime displacement, violence, Brazil, Amazon

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1 Introduction

Violence in the Brazilian Amazon has increased sharply in the last decades, in contrast to the trends observed for the rest of the country. From 2000 to 2019, the homicide rate in the region almost doubled. This pattern has emerged amidst growing concerns about the capacity of the state to enforce the rule of law in a region that, in addition to containing the world's main tropical forest, is larger than the European Union and, for the most part, very sparsely populated. The dominant view is that land conflicts and environmental crimes historically associated with the Amazon—such as illegal logging and mining—are the main drivers of the local dynamics of violence (Chimeli and Soares, 2017; Fetzer and Marden, 2017; Pereira and Pucci, 2022). Yet, this recent trend points to major increases in violence in areas where these illegal activities have not been traditionally prevalent (Soares et al., 2021). At the same time, anecdotal evidence suggests that the Amazon basin has become an increasingly important drug-trafficking route for cocaine coming out of the Andean region and heading to Southern Brazil and Europe (Phillips and Collyns, 2022; UNODC, 2023).

This paper explores the possibility that the displacement of cocaine trafficking from aerial routes to waterways partly accounts for the recent increase in violence in the more remote areas of the Brazilian Amazon. In the early 2000s, the Brazilian government started the implementation of a major monitoring system for the Amazon airspace, which led to the adoption of an interdiction policy against suspicious airplanes. We present evidence that this air-interdiction policy, introduced in the end of 2004, displaced cocaine trafficking routes to the Amazon river network, generating as collateral damage violence on the ground. Our empirical strategy explores the timing of adoption of the policy and an exogenous measure of local exposure to cocaine trafficking routes. This measure of exposure combines heterogeneity in cocaine production over time and across Andean countries with the location of municipalities along river routes. We document that violence in municipalities exposed to river trafficking routes became responsive to cocaine production in origin countries only after the implementation of the air-interdiction policy.

These results are in line with recent research on crime suggesting that stronger enforcement in one location may displace crime to relatively less monitored areas (Weisburd et al., 2006; Dell, 2015; Chalfin and McCrary, 2017; Banerjee et al., 2019; Blattman et al., 2021; Collazos et al., 2021). Nonetheless, while most of the literature focuses on locale-based interventions and crime displacement on a two-dimensional plane—usually an urban grid or a highway network—we document a natural experiment affecting a very large area and leading to crime reallocation over the three-dimensional space. This displacement response is noteworthy in that it shows how responsive criminal groups can be. Faced with stricter enforcement, they may adapt to new technologies, exploring alternative transportation modes, with very different social implications. A systemic view of crime enforcement, taking into account these responses and their broader socioeconomic consequences, is therefore essential for the optimal design of public security policies.

Our argument relies on the following logic. The air interdiction policy increased the probability of detecting and intercepting aerial cocaine trafficking. With high enough enforcement, air transportation should become relatively costlier and shift at least part of cocaine trafficking to the ground. For most of the Amazon, this means shifting the transportation mode to boats (Marin, 2004). Unlike airplanes, boats cross many cities and take a substantial amount of time before reaching their final destination, requiring support along the way for fuel, food, and protection, among others. This exposes many more local communities to drug-trafficking organizations and drugs, leading to more involvement of local populations in the business. Given what is known about the relationship between illegal markets and violence, such displacement to ground-level drug trade should therefore generate more violence. This is particularly true because, during most of the period we analyze, drug-trafficking activity in the region was highly fragmented, involving multiple small criminal groups as well as local populations, with no hegemonic presence of large and organized criminal cartels (see Appendix A for anecdotal evidence on the landscape of drug-trafficking in the Amazon during this time).

We present supporting evidence related to the main steps involved in the argument above. First, there is an increase in expenditures with new military aircraft by the Brazilian Air Force following the implementation of the policy, as part of an effort to increase enforcement capacity. Second, there are several reports in the media about airplane interceptions after 2004 (R. and Werneck, 2007). Third, there is a large reduction in fuel consumption by small airplanes in the western portion of the Amazon, which connects the region to the Andean countries. And, fourth, there are increases in cocaine seizures in this same region, as well as increased deaths by overdose in affected municipalities, after the adoption of the policy. So the evidence indicates that the policy indeed discouraged aerial drug trafficking and seems to have moved at least part of it to the ground, in closer proximity to local communities.

Our main analysis focuses on municipalities located in the western portion of the Amazon. This area is closer to the Andean border and constitutes a natural river pathway for moving cocaine from producing countries to Manaus, the only major international transportation hub in the upper Amazon basin. In addition, West Amazon is distant from large urban centers and highways, being historically somewhat protected from traditional environmental crimes and property rights disputes associated with deforestation and violence in the East Amazon. Finally, we focus on municipalities with less than 100,000 inhabitants in order to clean our sample from the idiosyncratic nature of violence in large urban centers. This allows us to study smaller and more remote municipalities while still keeping a relatively large sample. Out of the 277 municipalities in the West Amazon, only 8 have more than 100,000 inhabitants.[1]

To assess the effects of the air-interdiction policy on local violence, we rely on the timing of implementation and on our measure of municipalities' exposure to trafficking routes. We estimate a panel regression model to compare—before and after the policy—the effect of cocaine production in an Andean region on violence (and other outcomes) in municipalities located in river routes originating from that region. Identification stems first from the fact that the air interdiction, imposed at the national level, does not endogenously correlate with municipalities' location relative to cocaine river routes or with local dynamics of violence. Second, our measure of exposure to cocaine production allows us to leverage variation, over time and in the cross section, across exposed and non-exposed municipalities and also among exposed municipalities along different river routes.

We find that violence increased in exposed municipalities due to the displacement of cocaine trafficking to river routes after the air-interdiction policy. In particular, the responsiveness of local homicides along river routes to cocaine production in Andean regions increased significantly after the adoption of the policy. Our preferred estimate implies that approximately 1430 homicides that occurred between 2005 and 2020 can be attributed to the displacement of cocaine trafficking caused by the air-interdiction policy. This corresponds to 27% of the total number of homicides in municipalities in river routes during the same period. Alternatively, the increase in homicide rates was roughly 13 per 100,000 larger in treated municipalities when compared to controls. 41% of this difference (or 5.4 per 100,000) can be accounted for as side effects of the policy.

These results are robust to the inclusion of state-year fixed effects, as well as to the interaction of year fixed effects with time-invariant municipal characteristics in 2000 (such as population, income, average years of schooling, and share of urban population, among others). Most of the effect on homicides comes from male victims aged 20 years or older and, among these, by homicides outside of home and caused by firearms. Additionally, as mentioned before, we document an increased responsiveness of overdose deaths in municipalities along river routes to cocaine production in Andean countries, suggesting that there is more cocaine flowing locally. This lends further support to the idea that the drug trade was displaced from aerial routes to waterways. Finally, our results do not seem to come from changes in local income or other

[1] The median population of these 8 large urban centers is 235,000 and Manaus is the biggest city with 1.4 million inhabitants. Our main results remain unchanged if we include all municipalities in the analysis.

socioeconomic conditions. There are no significant effects of the policy on local GDP per capita or on death due to common diseases, suicide, and traffic accidents.

More broadly, our paper contributes to the literature on violence in contestable and illegal markets (Angrist and Kugler, 2008; Dube and Vargas, 2013; Idrobo et al., 2014; Chimeli and Soares, 2017; Fetzer and Marden, 2017; Pereira and Pucci, 2022). We document that changes in cocaine trafficking strategies had an important role in explaining the recent surge in violence in the West Amazon. This should raise awareness among policymakers, since recent anecdotal evidence suggests an increased presence of international drug-trafficking organizations in the region (Gagne, 2017; Fórum de Segurança Pública, 2022; Reid, 2022; The Economist, 2022).

Our work is also related to the literature on the unintended consequences of the War on Drugs (Keefer et al., 2010; García-Jimeno, 2016; Castillo et al., 2020; Sviatschi, 2022). Prohibition with imperfect enforcement may increase violence by creating rents from scarcity with undefined property rights. This side effect on general violence is particularly problematic when the illegal activity takes place closer to, and involves, local communities. In our context, it is not drug prohibition per se that increases violence, but rather the intensification of law enforcement along one specific route and the shift of illegal activity to an initially unmonitored alternative that involves closer contact with local populations.

In this sense, our findings speak more directly to the literature on crime displacement, which is primarily concerned with spillover effects of locale-based policy interventions. Empirical work in this field usually evaluates 'hot-spot' police interventions, providing mixed evidence on their side effects (Hesseling, 1994; Telep et al., 2014). For instance, di Tella and Schargrodsky (2004), Weisburd et al. (2006), and Draca et al. (2010), find no sign of crime displacement, whereas Yang (2008), Dell (2015), Vollaard (2017), Banerjee et al. (2019), Blattman et al. (2021), Maheshri and Mastrobuoni (2021), and Collazos et al. (2021) provide evidence on the opposite direction (for a review of the literature on crime displacement, see Chalfin and McCrary, 2017).

We add to this body of evidence by studying a natural experiment affecting a much larger area inside the Brazilian Amazon, instead of looking at a hyper-local hot-spot intervention. In particular, our paper relates to Dell (2015) and Banerjee et al. (2019), who document that criminals can learn from and strategically adapt to law enforcement policies. We provide novel evidence that criminal groups react to stronger law enforcement not only by moving to less monitored places, but also by devising new technologies to bypass increased policing efforts. In our case, this response leads to crime displacement across very distinct modes of transportation, moving cocaine trafficking from the air to waterways, with dramatically different social side effects.

The remainder of the paper is structured as follows. Section 2 discusses institutional details of cocaine trafficking in the Amazon and the air interdiction policy. Section 3 presents the data and explains our measure of exposure to cocaine trafficking. Section 4 describes our empirical strategy. Section 5 presents the main results and robustness checks. Finally, section 6 concludes the paper.

2 Institutional Background

2.1 The Amazon in the International Cocaine Trade

Brazil does not produce coca, but shares long international borders with Bolivia, Colombia, and Peru. These three Andean nations produce almost all of the cocaine consumed in the world. Combined, they have approximately 8,000 kilometers of international borders with Brazil, or roughly 2.5 times the length of the US-Mexican border (United States Central Intelligence Agency, 2021).

This border runs primarily through the vast and sparsely populated Amazon. The Brazilian Amazon is roughly the same size of the entire European Union, but almost 20 times less densely populated (5.6 inhabitants per square kilometer, compared to 109, according to Santos et al., 2021 and Eurostat). State presence is similarly rare. An Amazon municipality spans typically 6,500 square kilometers, over 130 times larger than the average municipality in the European Union.

Although Brazil and, in particular, the Amazon region have recently gained prominence in the global cocaine trade, they have not historically played a significant role in this market. The UNODC World Drug Reports from the 2000s, for example, make no mention of the Amazon as a cocaine trafficking route (UNODC, 2000, 2004, 2006). At that time, cocaine went from the Andean Countries to North America and Europe mainly through a direct route or via Central America, Mexico and the Caribbean. Cocaine trafficking coming through the Amazon was typically destined to the domestic market. In the early 2000s, Brazil ranked tenth worldwide in terms of seized cocaine volume (UNODC, 2006). Similarly, between 2006 and 2008, only 10% of cocaine seizures in European ports were linked to Brazil (UNODC, 2011). To put it in perspective, today Brazil ranks third worldwide in seized cocaine volume, behind only the US and Colombia (UNODC, 2021), and 43% of cocaine apprehended in European ports originates from Brazil (EMCDDA; Europol, 2022; UNODC, 2022).

During the earlier period, drug-trafficking activities in the region were highly decentralized.

The main Brazilian criminal organizations were still in their infancy, particularly in terms of international presence, and did not have any substantial or continued presence in the Amazon. According to Manso and Dias (2018), for example, the establishment of 'Família do Norte,' now one of the region's largest criminal factions, traces back to 2006. Similarly, 'Comando Vermelho' and 'Primeiro Comando da Capital,' the two main organized groups from the Southern part of the country, had no substantial presence in the area. Additionally, there is no evidence suggesting that Bolivian, Colombian, or Peruvian cartels exerted any control over Brazilian territory (O Estado de São Paulo, 2000, 2008; Fórum de Segurança Pública, 2022).

In Appendix A, we provide specific pieces of anecdotal evidence to further support the view that, until quite recently, drug-trafficking in the Brazilian Amazon was very fragmented, based on small groups, and without the presence of hegemonic actors.

2.2 Transportation Networks in the Amazon

The Brazilian Amazon is crossed by a network of numerous rivers running down from the Andean mountains to the Amazon River, which has more than one thousand tributaries and drains into the Atlantic Ocean (Crist et al., 2022). Historically, the network created by these rivers was crucial for the development of and communication between cities in the region (Marin, 2004).

Five of the largest tributaries originate in the Andes and provide a direct path of navigable waterways connecting cocaine-producing regions to the municipality of Manaus. This city is the 7^{th} largest in Brazil and, despite being in the middle of the forest, has an international airport and also a port that provides transcontinental cargo transportation (most seaworthy ships can make the 1,600 kilometers river trip separating Manaus from the Atlantic Ocean; see Crist et al., 2022). Manaus is the main transportation hub in the entire region, making it a key element in the trafficking of cocaine to other parts of the country and the world (Polícia Federal, 2016).

Except for the waterway network formed by large rivers, the Brazilian Amazon has notoriously poor transportation infrastructure on the ground. According to Araujo et al. (2022), market access in the region is much lower than in the rest of the country, which is largely explained by the low quality of infrastructure. This is especially true in the western portion of the region, which includes the states of Acre, Amazonas, Rondônia, and Roraima, and where paved roads and railroads are very rare. For instance, the trip from Tefé (in the state of Amazonas) to the state capital Manaus, located 520 kilometers away in a straight line, can range from fourteen to thirty-six hours because the Amazon River is the only available route. In contrast, in other parts of Brazil, the same distance could be covered in just about five hours by car. In Europe, the same distance from Paris to Amsterdam on a high-speed train would take roughly three and a half hours.

The only alternative for moving cargo across the western Amazon is air travel. Although expensive, this transportation mode can be economically feasible for products with high value added per weight. One example is raw gold, which is exploited both legally and illegally in remote sites within the forest and then transported via small airplanes to buyers in urban areas (Wanderley, 2015; Ministério Público Federal, 2020; Pereira and Pucci, 2022).

Cocaine is another obvious example of high-valued cargo that can be transported by air (Couto and Oliveira, 2017). In fact, the use of airplanes to transport drugs through the Amazon is not new. Illegal airstrips were and still are common in the region (O Estado de São Paulo, 2000). According to an investigation by The New York Times, there are more than 1,200 unregistered airstrips in the Amazon today (Andreoni et al., 2022).

Drug traffickers have also historically used the river network, since it provides relatively unmonitored routes across the Brazilian border (Couto and Oliveira, 2017). But, before 2002, the Brazilian government had very little control over the Amazon's airspace, which allowed flights from Andean countries to move freely. Given the relative travel times and the dangers associated with river travel, this made air transportation the dominant choice for those bringing cocaine into the country (Guedes da Costa, 2001; Feitosa and Pinheiro, 2012).

2.3 The Air Interdiction Policy

Between 2002 and 2005, the Brazilian government invested in two main initiatives to increase airspace control: the Amazon Surveillance and Protection Systems (SIVAM-SIPAM) and the Integrated Air Defense and Air Traffic Control Center (CINDACTA IV). They were designed to improve the capacity to detect irregular flights and thus tighten border control. These initiatives reflected the Brazilian government's concern with the ascension of revolutionary groups and drug cartels in neighboring countries, specifically in the Andean region (O Estado de São Paulo, 2000; Jansen and Marques, 2001; O Estado de São Paulo, 2003). In practice, these initiatives built new air control centers and installed several stationary and moving radar systems to improve aircraft identification (Wittkoff, 2003).

Following, in 2004, taking advantage of the new monitoring infrastructure, Brazil implemented an air interdiction policy to combat drug trafficking from neighboring countries (Feitosa and Pinheiro, 2012). The government regulated and established procedures allowing the Air Force to intercept and force or shoot down suspicious aircraft inside the Brazilian airspace.[2]

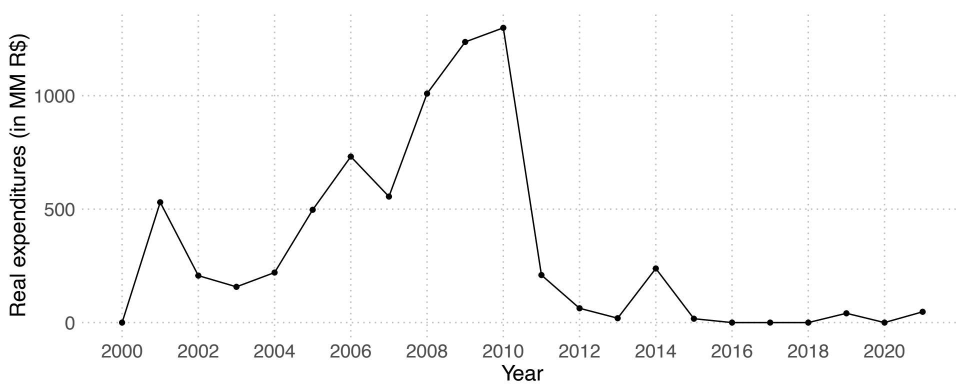
[2]The original law was approved in 1998 (Law 9.614/98). However, it only came into effect after 2004, when procedures for forcing or shooting down aircraft were regulated.

This Force-down/Shoot-down policy against suspicious aircraft is still in effect today.

Anecdotal and descriptive evidence suggests that the implementation of the policy indeed caused a major disruption for irregular flights moving over the Amazon. According to Air Force official statements, the program caused an immediate reduction of 32% in the number of irregular flights in the first few months following implementation (Força Aerea Brasileira, 2004). Specific data on interceptions and seizures by the Brazilian Air Force are unfortunately unavailable since they are classified, but we provide below several pieces of indirect evidence that reinforce this view.

First, Figure 1 shows that expenditures on military aircraft increased substantially after 2004, following the implementation of the air interdiction policy. This suggests that the government was committed to providing the necessary equipment for the Air Force to perform Force-down/Shoot-down operations.

Figure 1: Aircraft Expenses Incurred by Ministry of Defense, in Real Terms



At the same time, there is a reduction in the use of small airplanes, which are the default choice of drug traffickers. Figure 3 shows that the consumption of fuel by small airplanes decreased after 2004 in West Amazon states, which are much closer to cocaine-producing regions in the Andes than other parts of Brazil.

Furthermore, in Figure 3, we see a sharp increase in the amount of cocaine seized in the West Amazon as opposed to the East Amazon. Such change is consistent both with increased seizure of airplanes and with the displacement of cocaine trafficking to river routes.[3] Interestingly, there is no differential increase in marijuana seizures across West and East Amazon after the

[3] It is unclear from Figure 3 where the increased cocaine seizures are happening. On the one hand, airborne drug transportation became more vulnerable, which could lead to more cocaine seizures. On the other hand, displacing cocaine trafficking to rivers also increases, to some extent, exposure to monitoring by local police. Unfortunately, we do not have specific data on the type of seizure.

Figure 2: Airplane Fuel Sales in West Amazon, East Amazon, and Rest of Brazil

(i) Decree 5.144/04 in effect after Oct. 16th, 2004.

first years of the interdiction policy.[4] This patterns suggests that the higher amount of cocaine seizures immediately after implementation is indeed associated with cocaine trafficking coming into the country through the West Amazon, and with increased enforcement capacity after the policy.

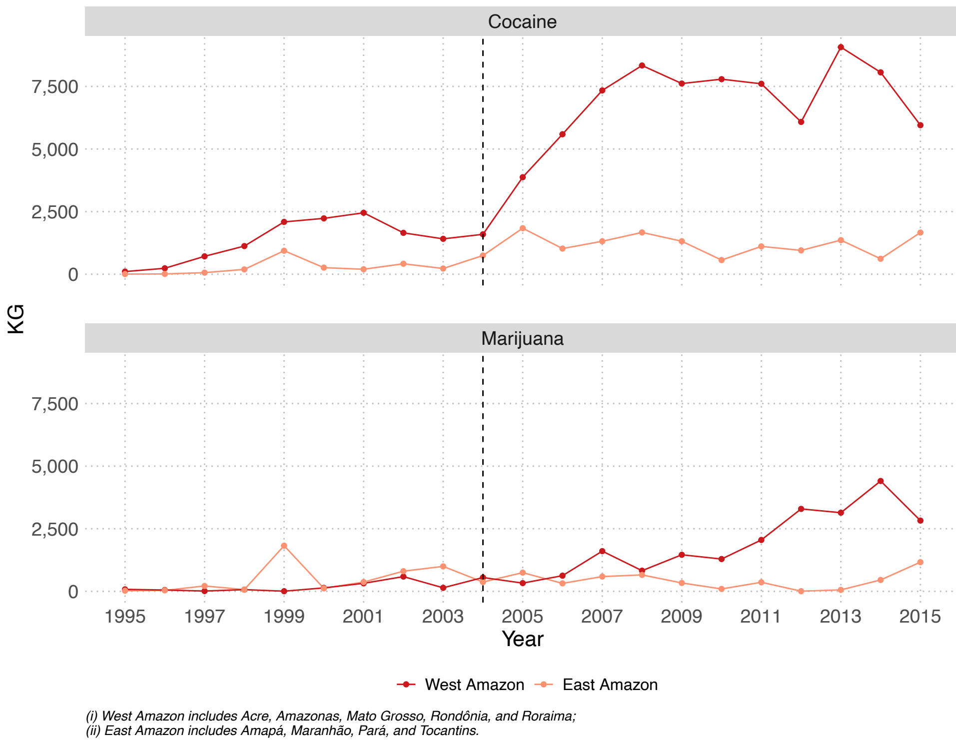
Newspaper articles from "O Estado de São Paulo" and "O Globo," two of the main news outlets in the country, seem to indicate a marked shift to river trafficking precisely around the time of the adoption of the new policy. Searching through historical records from 2001 to 2010, we found 30 news pieces with keywords related to cocaine trafficking in the Amazon.[5] Between 2001 and 2004, 10 out of 16 articles (63%) mentioned airborne trafficking, and only 2 (13%) were about rivers. From 2005 to 2010, the proportion of pieces about river drug trafficking increased to 64%. Moreover, some of the articles claimed explicitly that the Force Down/Shoot Down policy led to a reduction in airborne trafficking and to the migration of the cocaine trade to waterways, ultimately leading to a surge in drug seizures in some rivers (R. and Werneck, 2007; O Estado de São Paulo, 2008). It is also worth mentioning that, as discussed before, the Amazon region was not an important international cocaine trafficking route in the early 2000s. Hence, one should not expect the air interdiction policy to have sizeable impacts on international cocaine markets.

Finally, a recent report from the Federal Police shows that cocaine is now extensively transported in Amazon waterways (Polícia Federal, 2016). Together, the pieces of evidence presented

[4]Most of the marijuana consumed in Brazil comes either from the country's Northeastern region or from Paraguay (UNODC, 2003; Gemelli, 2013; Fett et al., 2020; Ministério da Justiça and UNODC, 2022).

[5]We read and classified all the newspaper articles containing the words 'Amazon', 'Cocaine' and 'Trafficking.'

Figure 3: Cocaine and Marijuana Seizures by Federal Police in West and East Amazon Regions



here point to a change in the default transportation mode for cocaine after the air interdiction of 2004.

2.4 Violence and Cocaine Trafficking in the Amazon

In this paper, we study a potential side effect of the shift of cocaine trafficking from aerial to river routes. As opposed to airplanes, boats take a long time and cross many cities and villages before reaching their final destination. As a result, local communities that were likely isolated become suddenly exposed to drug trafficking. Given what is known about the relationship between illegal markets and violence, one should expect this change in transportation mode to affect the level of violence in local communities (Dube and Vargas, 2013; Chimeli and Soares, 2017). There are a few alternative, non-exclusive, channels that could lead to this result.

First, trafficking of cocaine by rivers creates fragmented demand for several services along the way, including transportation, storage, protection, feeding, and accommodations. Local populations are likely to become involved in these markets, bringing children and young adults closer to illegality, which may translate into long-term criminal involvement (Araújo, 2001).

This has been documented, for example, in the case of illegal coca crops in Peru (Sviatschi, 2022). In addition, profits generated in these new routes, with the lack of property rights inherent to illegal markets, can attract criminals and increase the violent dispute for rents, leading to what has been termed the *rapacity effect* (Keefer et al., 2010; Dube and Vargas, 2013). Depending on the size of the rents and number of groups involved, this fight for control can spiral into turf wars around key locations in the most valuable routes (Dell, 2015).

Appendix A presents some anecdotal evidence on how local communities get involved in the cocaine trade. In the following sections, we explain in detail how we test the hypothesis that the air-interdiction policy led to increased violence on the ground in the Brazilian Amazon.

3 Data and Construction of Exposure Variable

Our empirical strategy relies on three main sources of variation: the location of municipalities along rivers in the Amazon, the potential amount of cocaine going through these rivers, and the timing of implementation of the air-interdiction policy. The first two variables provide a measure of exposure to cocaine trafficking for each municipality, whereas the third is a shock shifting the equilibrium quantities of cocaine transported via air and water.

Our analysis focuses on the period between 1996 and 2020 and on the Brazilian states that are closer to the main cocaine producers, as they are the most exposed to the trafficking routes. These states include Acre, Amazonas, Rondônia, Roraima, and Mato Grosso. For simplicity, we refer to them as West Amazon throughout the paper.

Below, we describe the databases used to construct our variable measuring exposure to cocaine trafficking. Following, we explain how this variable is constructed and discuss the sources of variation used in our identification.

3.1 Data

We map all main rivers in the Amazon that are likely to be used as cocaine trafficking routes. We use geocoded data on waterways provided by the Brazilian Ministry of Infrastructure. These waterways constitute the main network of navigable rivers in the region, which are used for transportation of both passengers and cargo.

We use data on cocaine production from the International Narcotics Control Strategy Reports (INCSR), provided by the United States' State Department. These reports estimate yearly cocaine production in Bolivia, Colombia, and Peru based on the area of coca crops detected by satellite images. We also use coca crop area from the United Nations Office on Drugs and Crime

(UNODC) at the province level, which allows for within-country variation in drug production that is not available from the INCSR reports.

Our main dependent variable is the yearly municipal homicide rate based on mortality data from DataSUS, provided by the Brazilian Ministry of Health, and population data from the Brazilian Census Bureau (IBGE). Following previous work (Chimeli and Soares, 2017), we define homicides as deaths by assault according to the International Classification of Diseases (ICD-10).[6]

Finally, we construct some other outcome variables and controls using additional municipal-level data on common diseases from DataSUS, as well as socioeconomic indicators from the 2000 Brazilian Census (such as income per capita, share of urban population, average years of schooling, and population composition by age groups, among others).

Next, we describe in detail how we define the main river routes and the construction of the variable indicating exposure to cocaine trafficking.

3.2 River Routes

We identify potential cocaine-trafficking river routes relying on previous field research (Araújo, 2001; Couto and Oliveira, 2017). We use data on waterways to geocode rivers and identify those originating from one or more of the main cocaine-producing countries. Then, we follow these rivers until they reach the Amazon River and the city of Manaus. Although the Amazon River continues flowing to the Atlantic Ocean, Manaus is typically the endpoint of the trafficking routes coming from the West, since it is the key distribution center for both national and international markets (Polícia Federal, 2016).

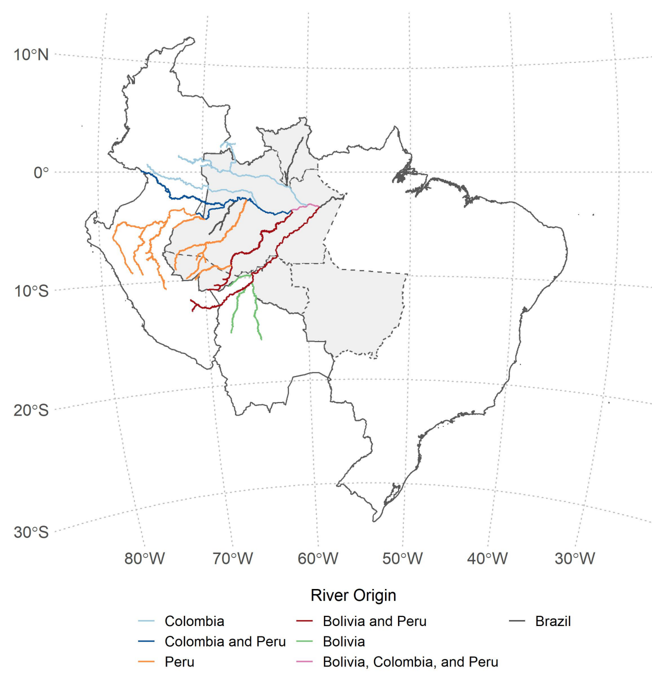
We categorize as 'off-route' all the rivers whose sources are not in one of the three cocaine-producing countries. We also consider as 'off-route' the non-tributaries to the Amazon River, because these rivers are mostly running through a different part of Brazil, where road infrastructure is much better and thus displacement of cocaine trafficking to rivers is less likely.

We are left with sixteen "cocaine rivers:" Abuna, Acre, Amazonas, Caquetá, Envira, Içá, Japurá, Javari, Juruá, Madeira, Mamoré, Negro, Purus, Tarauacá, Uaupés, and Xiê. Most of these rivers serve as economically viable routes for very large vessels to navigate throughout the year, according to the Brazilian Ministry of Infrastructure. While there are a few of them where navigability may be affected during dry periods, this is a concern primarily for large vessels. For smaller boats (e.g., speedboats), which would be the ones used for drug trafficking in this area, seasonality does not pose a relevant limitation.

[6] Deaths by assault correspond to ICD-10 codes X85 through Y09.

We then categorize the origin of each river according to which Andean countries they cross. If a river crosses multiple countries, all of them are considered for that route. This means that each river route has one of six different combinations of origin countries. Figure 4 presents a map of Brazil and cocaine-producing countries, highlighting the West Brazilian Amazon in grey and the river routes with different origins in different colors. Rivers in grey are 'off-route.' As explained later, these routes generate relevant heterogeneity in exposure to cocaine trade.

Figure 4: Cocaine Trafficking River Routes and Countries of Origin

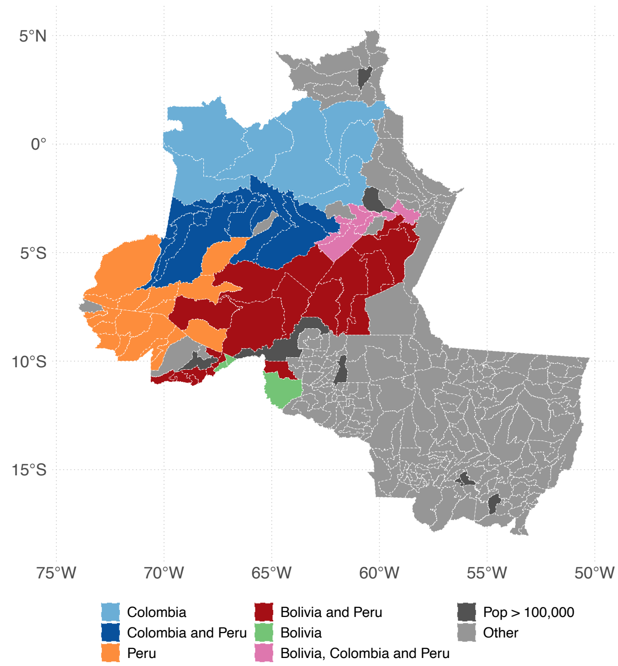


Notes: The grey area represents West Amazon, with dashed lines defining its federal states. The color of each river is associated with a different cocaine-trafficking route. Rivers in grey are 'off-route.' National borders are in solid black line, with Brazil on the right-hand side and, from top to bottom, Colombia, Peru, and Bolivia on the left-hand side.

After identifying the origin of each river, we categorize municipalities according to which route crosses their territory. If a municipality is reached by rivers running from multiple countries, we consider it to be exposed to cocaine trafficking from all of them. For instance, if Municipality A is crossed by one river originating from Peru and another from Colombia, it will be categorized as being in the Colombia-Peru route.

Figure 5 shows municipalities in the West Amazon according to their exposure to origin countries. The map includes municipalities that are not crossed by cocaine trafficking river routes in light grey. It also identifies municipalities with more than 100,000 inhabitants, which are excluded from our final sample. This last restriction is meant to reduce the influence of urban violence in large cities on our estimates.[7]

Figure 5: Municipalities Categorized According to River Routes Crossing their Territory



3.3 Exposure to Cocaine Trafficking

We calculate the level of exposure of each municipality to cocaine trafficking based on production in Andean countries and the origin of each river route. The more a country produces, the larger the potential for cocaine trafficking in a river originating from that country.

Formally, for each municipality i and year t, exposure is given by Equation 1.

$$CocaExposure_{it} = \begin{cases} ln(\sum_{r \in R} D_{ir} * CocaProd_{rt}), & \text{if } r \in R \\ 0, & \text{if } r \notin R \end{cases} \tag{1}$$

such that the set $R = \{Bolivia, Colombia, Peru\}$ comprises the origin countries and r identifies each route origin. D_{ir} is a dummy indicating whether municipality i is in route originating in r and $CocaProd_{rt}$ is cocaine production in year t in route origin r. We apply the natural logarithm to the sum of total production. For municipalities that are **not** exposed to cocaine trafficking

[7]This sample selection only removes 8 municipalities out of 277. In the Appendix, we provide robustness exercises that include larger municipalities.

routes ($r \notin R$), $CocaExposure_{it} = 0$ for every t.

As an illustration, in our previous example, Municipality A was crossed by rivers coming from both Colombia and Peru and, therefore, was in the Colombia-Peru route. Its exposure to cocaine trafficking in a given year would then be the natural logarithm of the sum of cocaine production from these two countries in that same year.

4 Empirical Strategy

4.1 Sources of Variation

We start this section by exploring descriptively the three sources of variation driving our results: exposure of municipalities to cocaine-trafficking river routes; potential volume of cocaine going through each of these routes; and the timing of the air-interdiction policy.

Figure 6a compares municipalities located in cocaine-trafficking river routes to the rest of West Amazon. After the air interdiction in 2004, homicide rates in municipalities in trafficking routes increased substantially, whereas the same did not happen in municipalities outside these routes. This is consistent with the partial displacement of cocaine trade caused by stronger monitoring of aerial routes. This figure highlights the pattern behind the first source of variation mentioned before, coupled with the timing of policy change: the comparison of municipalities on the main trafficking routes to municipalities outside of these routes, before and after the 2004 implementation of the air interdiction.

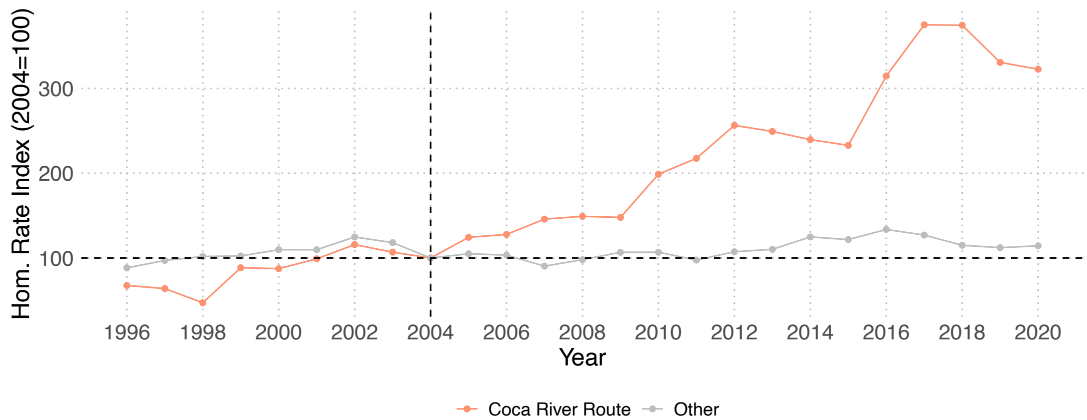
Figure 6b, in turn, illustrates the second source of variation by plotting the responsiveness of violence along river routes to the production of cocaine in origin countries, before and after the policy change. Violence in municipalities along trafficking routes was not responsive to cocaine production in origin countries prior to the air interdiction (gray dots), but it became so afterwards (red dots). The relationship between cocaine production in Andean countries and violence in municipalities along river routes changed significantly after the air interdiction. This suggests that the amount of cocaine produced in origin countries is also relevant. Routes connected to regions producing relatively more cocaine should be busier, increasing the exposure of downstream municipalities.

4.2 Empirical Specification

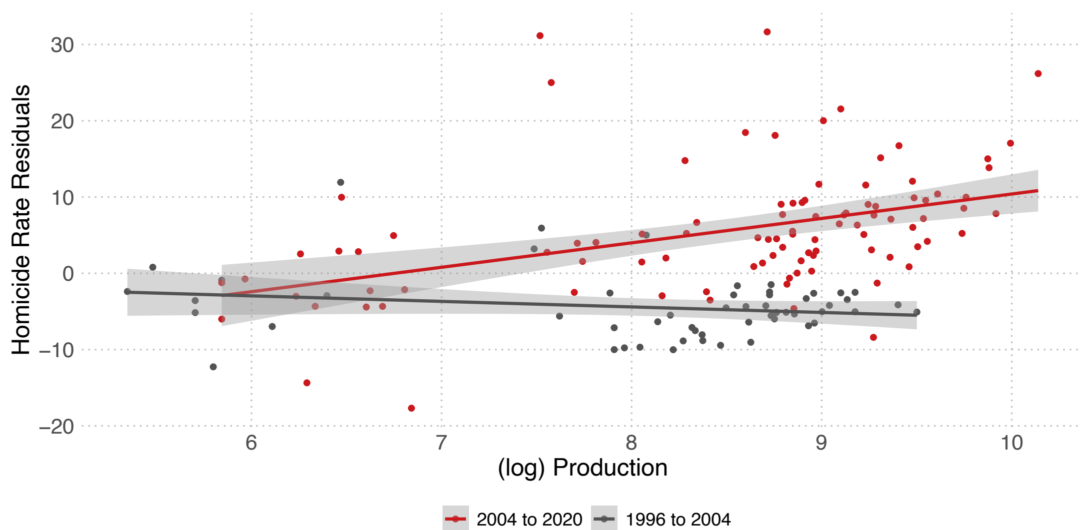
We analyze whether violence along river routes originating from the Andes became more responsive to cocaine production in origin countries after the Force-down/Shoot-down policy.

Figure 6: Homicide Rate and Cocaine Exposure in West Amazon

(a) Homicide Rate in Cocaine River Routes



(b) Correlation of Homicide Rate Residuals and Cocaine Production in each Route-Year



Notes: Each point in the plot 6b corresponds to a year-and-route combination of homicide rate residuals and cocaine production. Grey dots present combinations up to 2004, while red dots indicate years after 2004. To create the plot, we first run a regression at the municipality-year level of the homicide rate on state and year fixed effects. Next, we calculate the average homicide rate residuals for each year and route. Cocaine production is simply the yearly average cocaine in the country of origin of that route.

Therefore, we estimate a panel regression model where violence in each municipality can respond differently to the variable measuring exposure to cocaine trafficking before and after the air interdiction.

Identification stems from a combination of factors. First, the air interdiction was imposed at the national level and its implementation is not endogenously correlated with the location of municipalities along cocaine-trafficking river routes and local determinants of violence. Second, since the Amazon was not relevant for the global cocaine trade in the 2000s, the policy should not have any major impact on international cocaine supply or prices. Third, the air interdiction is also unlikely to be endogenously correlated with our municipal-level measure of exposure, since this depends both on the location of municipalities across multiple routes and the changes in supply in cocaine-producing countries.

Therefore, we assume that the interaction between the timing of the policy and our measure of exposure should produce plausibly exogenous variation in local cocaine trafficking, which allows us to isolate the effect of the displacement of trafficking to river routes on violence on the ground.

We estimate the following regression model:

$$\begin{aligned} HomRate_{it} = \beta_0 CocaExposure_{it} + \beta_1 CocaExposure_{it} * I_{t \geq 2005} + \\ + \theta_i + \lambda_{st} + \delta_t \times X_i + \mu_{it}, \end{aligned} \tag{2}$$

where $HomRate_{it}$ is the homicide rate in municipality i in year t, $CocaExposure_{it}$ is given by Equation 1; θ_i represents municipality fixed effects; λ_{st} represents state-year fixed effects; and $\delta_t \times X_i$ are year fixed effects interacted with time-invariant municipal characteristics in 2000 (including population, income, average years of schooling, urbanization rate, poverty rate, proportion of population between ages 20 and 39, forest coverage, and the distribution of jobs across agriculture, extractive industries, and the public sector). Following previous literature, our preferred specification also uses analytical population weights, since the variance of homicide rates in very small municipalities can be very large, even when the number of homicides varies little in absolute terms (Chimeli and Soares, 2017).

We are interested in coefficient β_1, which gives the increased effect of exposure to cocaine trafficking after the implementation of the air interdiction. We expect this coefficient to be positive, i.e., drug trafficking should be more strongly associated with violence after the policy.

Nonetheless, we are also interested in β_0, which is the effect of exposure to cocaine trafficking before the air interdiction. Since drug traffickers used primarily air routes before 2004, we do not expect β_0 to be significant. This does not mean that cocaine trafficking via river was nonexistent prior to 2004, but rather that it was too small to significantly affect local violence.

Table 1 provides a brief description of variables in vector X_i according to municipalities' location in each river route.

Overall, mean values do not differ substantially across columns. However, municipalities on

Table 1: Descriptive Statistics for Western Amazon Municipalities with less than 100,000 people in each River Route

	Origin Country of River Routes						
	Bolivia	Colombia	Peru	Bolivia Peru	Colombia Peru	Bolivia Colombia Peru	Off Route
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Avg. School Years	4.30	3.60	2.46	3.34	2.99	3.66	4.51
	(1.15)	(0.85)	(0.75)	(0.70)	(0.79)	(0.67)	(0.66)
(log) Income p.c.	6.02	5.92	5.63	5.79	5.74	5.76	6.14
	(0.24)	(0.31)	(0.23)	(0.17)	(0.19)	(0.15)	(0.34)
(log) Population	9.72	9.63	9.45	9.69	9.97	9.93	9.26
	(0.79)	(0.45)	(0.84)	(0.62)	(0.70)	(0.90)	(0.81)
(%) Jobs Agriculture	0.38	0.40	0.48	0.49	0.46	0.47	0.44
	(0.23)	(0.13)	(0.15)	(0.12)	(0.11)	(0.17)	(0.16)
(%) Jobs Mining	0.00	0.00	0.00	0.00	0.00	0.00	0.01
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.03)
(%) Jobs Pub. Sector.	0.11	0.10	0.08	0.08	0.07	0.06	0.06
	(0.04)	(0.06)	(0.04)	(0.04)	(0.04)	(0.02)	(0.04)
(%) Forest Cover	0.70	0.93	0.97	0.85	0.95	0.82	0.48
	(0.21)	(0.07)	(0.02)	(0.15)	(0.02)	(0.09)	(0.30)
(%) Low Income	0.51	0.68	0.78	0.68	0.77	0.68	0.41
	(0.09)	(0.12)	(0.10)	(0.12)	(0.09)	(0.05)	(0.15)
(%) Aged 20-39	0.30	0.29	0.26	0.28	0.27	0.27	0.32
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)
(%) Urban Pop.	0.59	0.44	0.42	0.48	0.47	0.42	0.55
	(0.24)	(0.16)	(0.16)	(0.14)	(0.17)	(0.21)	(0.21)
Observations	3	7	17	18	14	8	202

Notes: Columns summarize means and standard deviations (in parenthesis) for municipalities in each river route.

river routes seem to have more forest cover, higher poverty, and lower education when compared to those off route. Such differences may be related to the fact that many exposed municipalities are in the same state. Out of 67 exposed units, 45 are in the state of Amazonas. At the same time, out of 202 'off route' municipalities, only 16 are in this state.

This imbalance could pose problems, because municipalities in Amazonas may not be comparable to municipalities in other states. However, our strategy should account for this not only because we include state-year fixed effects, but also because we use route-specific cocaine production as a source of variation. This means that our model incorporates within-state variation across exposed municipalities.

In Appendix B, we provide an additional approach to deal with this potential problem. We run an exercise with Inverse Probability Weighting (IPW) and restrict our sample to a more balanced group of exposed and non-exposed municipalities. There, we follow Hirano et al. (2003), Busso et al. (2014), and Cunningham (2021) to estimate, based on observable characteristics, the probability that a municipality is exposed to river routes. We then use the estimated propensity score $\hat{p}$ to weigh observations and re-balance the sample. This approach has limitations in our setting, however, because the common support assumption requires us to drop a large number of observations in both groups. Despite this limitation, we still find similar results as in our main specification when using propensity score weighting.

In the following sections, we investigate the effect of the air-interdiction policy on homicide rates and homicide characteristics. In addition, we shed light on specific mechanisms by looking at a proxy for local availability of drugs and by conducting some robustness and placebo exercises.

5 Results

5.1 Main Results

Table 2 presents estimates based on Equation 2. In all specifications, we control for initial conditions in each municipality and aggregate yearly shocks by adding municipality fixed effects and year or state-year fixed effects.

The first row (*Exposure*) presents the effect of cocaine trafficking on local violence **before the air interdiction**. As expected, this coefficient is not significant after adding covariate-specific trends or state-year fixed effects. This suggests that municipalities in river routes were mildly exposed to cocaine trafficking before the Force-down/Shoot-down policy.

The second row ($Exposure \times I(Year \geq 2005)$) provides the estimated **additional** effect of cocaine trafficking on violence **after the air interdiction**. These estimates are positive and significant regardless of the specification. This corroborates the hypothesis that the partial displacement of cocaine trade from air to river routes after the Force-down/Shoot-down policy affected the level of violence in exposed municipalities.

From now on, we focus on the specification in Column (4) of Table 2 and on the coefficient on the interaction $Exposure \times I(Year \geq 2005)$. For the interested reader, we also estimate a classical Difference-in-Differences specification in Appendix Table C.1. We define the post-treatment period based on the timing of the air interdiction and the treated group based on exposure to any river route. Despite exploring less variation in this case, we still find results that are

Table 2: Exposure to Cocaine Trafficking in River Routes and Force-Down/Shoot-Down Policy, from 1996 to 2020

	Homicide Rate				
Model:	(1)	(2)	(3)	(4)	(5)
Exposure	6.2***	2.4	-0.71	-0.21	-2.6
	(1.9)	(2.3)	(1.8)	(2.1)	(2.1)
Exposure $\times$ $I(Year \geq 2005)$	1.4***	1.4***	0.88***	0.96**	1.1***
	(0.22)	(0.41)	(0.25)	(0.39)	(0.37)
Munic FE (269)	Yes	Yes	Yes	Yes	Yes
Year FE (25)	Yes	Yes			
State-Year FE (125)			Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	
Covariates*Year		Yes		Yes	Yes
Observations	6,697	6,697	6,697	6,697	6,697
R^2	0.47	0.50	0.50	0.54	0.42
Within R^2	0.04	0.10	0.002	0.07	0.06

Notes: Western Amazon municipalities with less than 100,000 people. All errors are clustered at the municipality level. *p<.1; **p<.05; ***p<.01.

qualitatively similar to those in Table 2. This corroborates our finding that the air interdiction seems to have played an important role in displacing cocaine trafficking and increasing violence in exposed municipalities.

5.2 Homicides Characterization

We decompose the estimated effect by age groups in Columns (2) through (5) in Panel (A) of Table 3.[8] As expected, the effect is mainly driven by victims aged 20 to 49 years (Column 4). However, there is a large share of homicides against children younger than one year old (Column 2). This rather abnormal behavior is likely caused by infanticides among indigenous people, as documented in Scotti (2017).[9]

[8] The denominator for all estimates is always the total population. However, estimates in Columns (2) through (5) do not add up to Column (1) due to homicides of undetermined age.

[9] The Brazilian Senate discussed passing a law criminalizing indigenous infanticides https://bit.ly/3ED6oar. This was also discussed in some news pieces: https://bit.ly/2FX4bHZ and http://glo.bo/3Z58PuV.

Table 3: Age Group Decomposition of Homicide Rate, Exposure to Cocaine Trafficking in River Routes, and Force-Down/Shoot-Down Policy, from 1996 to 2020

(A) Entire Sample	Hom. Rate (1)	<1 (2)	$1-19$ (3)	$20-49$ (4)	>50 (5)	>1 (6)
Exposure $\times$ $I(Year \geq 2005)$	0.96**	0.18	0.07	0.58**	0.12	0.76**
	(0.39)	(0.20)	(0.08)	(0.28)	(0.08)	(0.37)
Observations	6,697	6,697	6,697	6,697	6,697	6,697
R^2	0.54	0.46	0.29	0.49	0.25	0.52
Within R^2	0.07	0.04	0.06	0.06	0.04	0.07
(B) Removing Outliers						
Exposure $\times$ $I(Year \geq 2005)$	0.84**	-0.002	0.09	0.60**	0.11	0.80**
	(0.39)	(0.02)	(0.08)	(0.29)	(0.09)	(0.37)
Observations	6,597	6,597	6,597	6,597	6,597	6,597
R^2	0.53	0.24	0.28	0.49	0.24	0.52
Within R^2	0.07	0.03	0.06	0.06	0.04	0.07

Notes: All specifications include individual fixed effects, state-year fixed effects, pre-treatment covariates interacted with year fixed effects, and population weights. *p<.1; **p<.05; ***p<.01. All errors are clustered at the municipality level. Panel A considers all Western Amazon municipalities with less than 100,000 people. Panel B excludes the following municipalities with high infanticide rates: Caracaraí (RR), Alto Alegre (RR), Santa Isabel do Rio Negro (AM), and Barcelos (AM). Coefficients of specific age groups do not add up to the total due to homicides with age undetermined.

To further investigate this issue, we exclude from the sample four small municipalities with indigenous communities that have incredibly high infanticide rates: Caracaraí (RR), Alto Alegre (RR), Santa Isabel do Rio Negro (AM), and Barcelos (AM). Panel (B) of Table 3 shows results for this new sample. The abnormal effect on infanticides (Column 2) vanishes, while the other age-specific estimates remain mostly unchanged, or increase slightly in magnitude.

Although a relevant issue in and of itself, there is little reason to believe that these high infanticide rates in a very small number of municipalities are related with cocaine trafficking. Therefore, to avoid contamination in our estimates, we restrict our dependent variable to account only for homicides against individuals older than one year. The estimated coefficient for this specification is presented in Column (6) of Panel (A) in Table 3 and it is still positive and significant, albeit slightly smaller than in Column (1). For the sake of completeness, Appendix Table C.2 repeats the same specifications from the previous Table 2 for the dependent variable defined above age 1. Qualitative results remain unchanged. Henceforth, Column (6) of Panel (A) in Table 3 is our benchmark specification. For the interested reader, we also present all of our results using an alternative sample that excludes those four outlier municipalities (see Appendix D).

Table 4 presents results decomposing homicides based on gender, location, and use of weapon. As shown in Columns (1) through (5), the estimated effect comes predominantly from violence against men, outside of the household, and using weapons (firearm or knife). Moreover, estimates in Column (6) suggest that these homicides do not seem to be motivated by land conflict. In this exercise, the outcome variable is the likelihood of a land-conflict-related murder, based on data from *Comissão Pastoral da Terra*, which monitors land conflicts in Brazil. We also do not find any evidence that homicides are driven by police interventions following stronger enforcement against drug trafficking. Columns 7 and 8 point to no effect on killings by the police or violent deaths of undetermined intent.

Table 4: Decomposition of Homicides, Exposure to Cocaine Trafficking in River Routes, and Force-Down/Shoot-Down Policy, from 1996 to 2020

	>1	Men 20+				Other Homicides		
	Baseline	Men 20+	Home	Out of Home	Firearm or Knife	CPT	Police	Undet.
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure $\times$ $I(Year \geq 2005)$	0.76**	0.59*	0.10	0.49*	0.50*	-0.007**	0.010	0.04
	(0.37)	(0.31)	(0.07)	(0.27)	(0.27)	(0.003)	(0.007)	(0.10)
Observations	6,697	6,697	6,697	6,697	6,697	6,428	6,697	6,697
R^2	0.52	0.50	0.26	0.48	0.49	0.22	0.11	0.29
Within R^2	0.07	0.07	0.04	0.06	0.07	0.06	0.02	0.05

Notes: All specifications include individual fixed effects, state-year fixed effects, pre-treatment covariates interacted with year fixed effects, and population weights. *p<.1; **p<.05; ***p<.01. All errors are clustered at the municipality level. Western Amazon municipalities with less than 100,000 people. CPT is an indicator variable equal to one when there are deaths in the countryside due to land conflicts according to the Comissão Pastoral da Terra. Police and Undet. are homicide rates committed by the police or by an undetermined actor.

Additionally, we analyze homicides recorded according to the victim's city of residence, as opposed to the city of death in our benchmark specification. In this case, point-wise estimates are slightly smaller, as presented in Appendix Table C.3. This may indicate that some people from outside the exposed municipalities are suffering from the effects of the air interdiction, which is consistent with a larger presence of drug traffickers coming from other cities and just passing by the affected locations.[10]

5.3 Statistical Inference

One may be worried about the fact that exposed municipalities are geographically clustered and that most of the variation comes from only six combinations of origin countries. This may raise concerns about potential issues in the estimation of standard errors. We address this question by estimating our models using various inference methods that are robust to spatial and serial correlation, including a specification that allows for arbitrary correlation in the error term across municipalities within the same drainage basin. Details and results are presented in Appendix C.4. For all inference methods adopted, our benchmark result remains statistically significant.

5.4 Timing of the Effect

Another potential concern is the possibility of something analogous to pre-trends driving our results. Maybe there was an increased responsiveness of violence in municipalities in river routes to Andean cocaine production pre-dating the adoption of the air-interdiction policy. If this were the case, it would indicate that the effect we are estimating would be unlikely to be causally related to the 2004 implementation of the policy.

Although we cannot run the same type of pre-trend analysis as seen in Difference-in-Differences estimations, we conduct a similar exercise. Figure 7 shows the dynamic estimate of β_1, the coefficient for the interaction $CocaExposure_{it} * I_{t\geq 2005}$. We present this for every two years in order to have more statistical power and use 2003-2004 as the baseline.

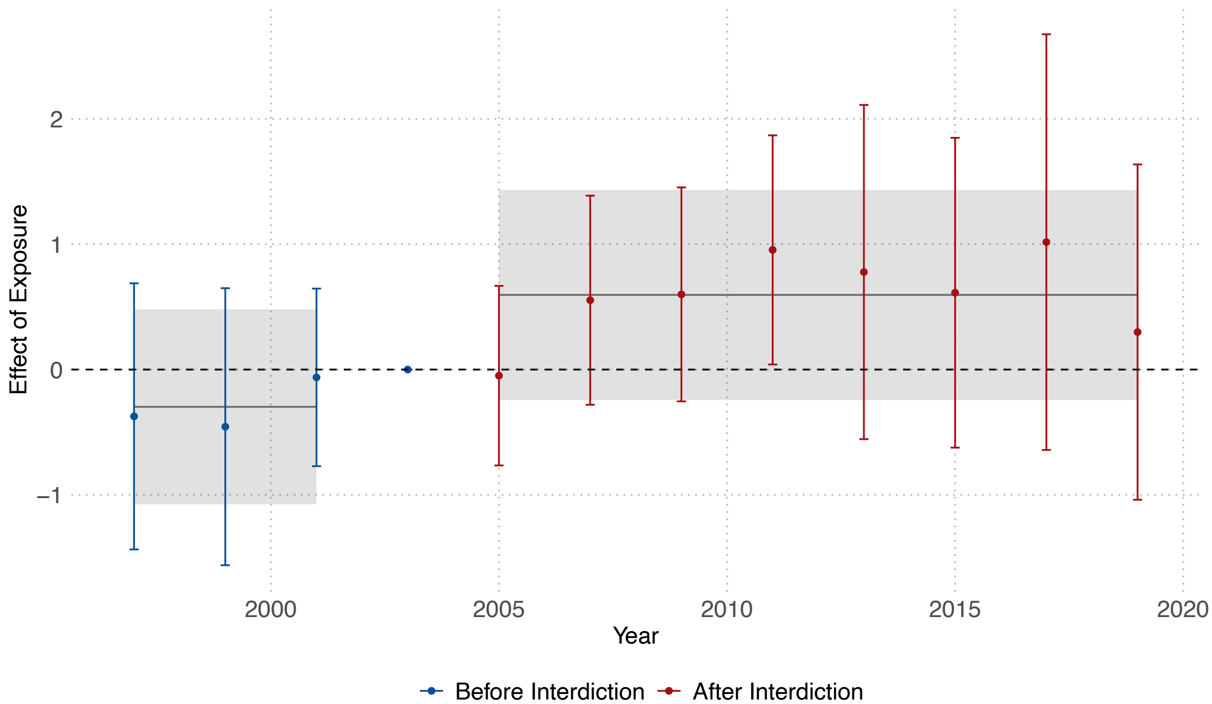
Analogously to Equation 2, we estimate the following model, where p is a given two-year period and P is the set that comprises all two-year periods in our sample, except for 2003-2004:

$$\begin{aligned} HomRate_{it} = \beta_0 CocaExposure_{it} + \sum_{p\in P} \beta_p CocaExposure_{it} * I_{t\in p} + \\ + \theta_i + \lambda_{st} + \delta_p \times X_i + \mu_{it}. \end{aligned} \tag{3}$$

We find no evidence of changes in the relationship between exposure to cocaine trafficking and violence before 2004. Moreover, although coefficients are not individually significant for the period following the Force-down/Shoot-down policy, point-wise estimates are all positive

[10]There is a caveat in this argument, though. There are more missing observations in homicides by municipality of residence when compared to homicides by municipality of occurrence. Throughout our sample period, an average of 2.3% of homicides lack records regarding victims' residence.

Figure 7: Dynamic Effect of Exposure to Cocaine Trafficking in River Routes and Force-Down/Shoot-Down Policy



Notes: Specification includes individual fixed effects, state-year fixed effects, pre-treatment covariates interacted with year fixed effects, and population weights (Column 4 of Table 2). The coefficient is estimated for every two years. The average effects before and after intervention are in dark grey, with the light grey area representing their 95% confidence intervals.

and indicate a change in level with respect to pre-intervention years. Also, the average difference in responsiveness of violence to cocaine trafficking between the post- and pre-intervention periods is statistically significant.

We also investigate whether the presence of international drug-trafficking organizations affects our results. As mentioned earlier, there is anecdotal evidence suggesting that these organizations have expanded their presence in the Amazon since 2016 (Fórum de Segurança Pública, 2022). Therefore, our findings could be influenced by violence in recent years, possibly linked to the growth of drug trade conducted by organized crime.

Figure 7 should alleviate part of this concern, since point-wise estimates are similar over most of the post-period. If results were driven by the expansion of organized crime after 2016, we should observe larger estimates closer to the end of the sample. Nonetheless, we also show in Appendix Table C.5 that our main results remain similar when we limit our sample to the period ending in 2015.

5.5 Mechanism

We provide an indirect test of our proposed mechanism, despite the challenge of directly measuring drug-trafficking activity at the local level. We argue that more drug trade should lead to a larger availability of drugs in exposed municipalities. As a consequence, locals could have increased their consumption of cocaine, becoming more susceptible to adverse consequences such as overdoses. Moreover, if some people involved in the drug trade are also users, this should lead to more overdose cases in exposed municipalities as well. To verify this hypothesis, we run the same regression as before, but now using *deaths by drug overdose* as dependent variable.[11]

Table 5 shows an increased responsiveness of drug overdose deaths to cocaine exposure after the air interdiction. This is consistent with more cocaine circulating in exposed municipalities after the partial displacement of drug trade from aerial to river routes.

Table 5: Deaths from Overdose, Exposure to Cocaine Trafficking in River Routes, and Force-Down/Shoot-Down Policy, from 1996 to 2020

	Overdose Death Rate				
Model:	(1)	(2)	(3)	(4)	(5)
Exposure $\times$ $I(Year \geq 2005)$	0.02**	0.04***	0.03**	0.04***	0.04**
	(0.010)	(0.01)	(0.01)	(0.01)	(0.02)
Munic FE (269)	Yes	Yes	Yes	Yes	Yes
Year FE (25)	Yes	Yes			
State-Year FE (125)			Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	
Covariates*Year		Yes		Yes	Yes
Observations	6,697	6,697	6,697	6,697	6,697
R^2	0.08	0.13	0.10	0.15	0.11
Within R^2	0.01	0.07	0.001	0.05	0.03

Notes: Estimates in Columns (1) to (4) include municipality and year fixed effects, and are weighted by population. Column (2) adds interaction between covariates in 2000 and year fixed effects; Column (3) adds state-year fixed effects; Column (4) adds both state-year fixed effects and interaction between covariates in 2000 and year fixed effects; Column (5) repeats column (4) except we do not include population weights; Western Amazon municipalities with less than 100,000 people. All errors are clustered at the municipality level. *p<.1; **p<.05; ***p<.01.

Alternatively, we could have used cocaine overdose deaths, instead of the broader category presented in Table 5. However, although this may seem more precise, under-reporting is a serious issue in this context. As a result, very few cases of cocaine abuse are actually accounted

[11] Deaths by overdose are classified by ICD-10 codes X40 to X44 and Y10 to Y14 and include both accidental deaths and deaths with undetermined intention.

for in hospital certificates. This issue is not limited to Brazilian data. In the United States, the quality of drug-specific data on overdose varies substantially across states. In some cases, less than 40% of death records contain the type of drug involved (Warner et al., 2013; Ahmad et al., 2023). Hence, although we test a specification with cocaine overdose as the dependent variable, we refrain from presenting it, since results are very small, imprecise, and subject to the limitations mentioned above.

Finally, we test similar specifications using hospital admissions resulting from drug or cocaine abuse, but do not find significant results. Again, this could be happening due to underreporting, which tends to be even more relevant when dealing with hospital admissions, since not all cases are properly informed. In addition, the availability of hospitals in small municipalities in the Amazon is quite limited, making it unlikely that most cases actually arrive at a health facility.

5.6 Placebo Tests

Our dynamic analysis shows that it seems unlikely that changes unrelated to the air-interdiction policy are driving our results. Still, it is possible that the causal effect that we estimate is not driven directly by the local presence of cocaine trafficking, but indirectly by the economic impacts that it may bring.

For example, it is possible that municipalities on cocaine-trafficking routes may experience growth in income and population due to increased local trafficking. Drug trade may increase local income, leading to more immigration and improved socioeconomic conditions. Although our dependent variable is normalized by population, these social processes may change mortality patterns due to changes in urbanization, diet, and local social norms. To address this point, we use our benchmark empirical specification to analyze the behavior of mortality rates related to the most common causes of death, which are not attributable to drug trafficking but which should respond to changes in local socioeconomic conditions.

Table 6 provides evidence that most common causes of death are not affected by increased exposure to cocaine trafficking. We look at death rates by infectious diseases, neoplasms, circulatory conditions, respiratory conditions, digestive diseases, and suicide. The lack of significant effects on the mortality rate from these causes of death suggests that changes in local socioeconomic conditions are not a key driving force behind the increase in violence observed in exposed municipalities.

Most of the point estimates are quite small, with the exception maybe of circulatory diseases. This could be driven by the association between cardiac arrests and cocaine consumption

Table 6: Other Death Rates and Cocaine Exposure in Waterway Trafficking Routes after the Force-Down/Shoot-Down Policy, from 1996 to 2020

Model:	Infect Parasite (1)	Neoplasm (2)	Circulatory (3)	Respiratory (4)	Digestive (5)	Suicide (6)
Exposure $\times$ $I(Year \geq 2005)$	0.28	0.04	0.40	0.12	0.11	0.19
	(0.19)	(0.37)	(0.53)	(0.19)	(0.18)	(0.16)
Observations	6,697	6,697	6,697	6,697	6,697	6,697
R^2	0.67	0.57	0.72	0.61	0.61	0.33
Within R^2	0.35	0.10	0.07	0.09	0.09	0.06

Notes: All specifications include individual fixed effects, state-year fixed effects, pre-treatment covariates interacted with year fixed effects, and population weights. *p<.1; **p<.05; ***p<.01. All errors are clustered at the municipality level. Western Amazon municipalities with less than 100,000 people.

(Mittleman et al., 1999). Running a specification exclusively with deaths from myocardial infarction, we do find that the estimated coefficient makes up for 65% of the effect in Column (3), but it is still not significant.

In Table 7, we look directly at some measures of local economic activity. The table shows that, during our sample period, there does not seem to be any major change in the functioning of the local legal economy. Exposed municipalities are not experiencing faster urbanization, measured by traffic accidents, or faster economic growth, measured by the municipal GDP per capita. Moreover, the correlation between GDP composition and cocaine trafficking after 2004 is also not significant, suggesting no relevant changes in sector participation.

5.7 Robustness

We made some choices when defining routes and constructing the variable measuring municipal exposure to cocaine trafficking. In Figure 8, we provide several robustness exercises that consider alternatives both in the number of potential origin areas used to define the routes and in the level of production attributed to each route.

In the figure, points represent estimates for our coefficient of interest under different alternative scenarios, while bars represent confidence intervals. Orange lines take into account within-country variation in cocaine production, whereas black lines do not. To incorporate within-country cocaine production in the estimation, we find the origin of each river route based on a map of cocaine-producing regions inside Bolivia, Colombia, and Peru, provided by UNODC.

Table 7: Economic Activity, Cocaine Exposure in Waterway Trafficking Routes, and the Force-Down/Shoot-Down Policy, from 1996 to 2020

Model:	Traffic Accident (1)	(log) GDP per Capita (2)	Share Agric. (3)	Share Manuf. (4)	Share Service (5)	Share Public (6)	Share Taxes (7)
Exposure $\times$ $I(Year \geq 2005)$	-0.05	0.0004	-0.003	0.002	0.0005	-0.002	0.002^{**}
	(0.40)	(0.009)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
Observations	4,842	4,842	4,842	4,842	4,842	4,842	4,842
R^2	0.43	0.96	0.88	0.78	0.93	0.94	0.84
Within R^2	0.08	0.08	0.11	0.07	0.09	0.06	0.05

Notes: All specifications include individual fixed effects, state-year fixed effects, and pre-treatment covariates interacted with year fixed effects. GDP estimates does not include include population weights, because GDP varies more smoothly than homicides. Traffic deaths are considered a proxy for economic activity and urbanization. *p<.1; **p<.05; ***p<.01. All errors are clustered at the municipality level. Western Amazon municipalities with less than 100,000 people.

Then, we attribute to each river route only the amount of cocaine produced in each of these regions, instead of using national production. Because INCSR does not estimate cocaine production at the regional level, we use the estimates of regional coca leaf production from UNODC as weights to calculate the share of cocaine production in each region.

The black line in **Baseline Route** represents our main estimate from Column (1) in Table 4, whereas the orange line uses exposure to regional cocaine production (within origin country variation). In **North, Middle and South**, we split municipalities in three groups. Municipalities crossed by northern tributaries of the Amazon River are exposed to Colombia's production (North); those crossed by southern tributaries receive production from Bolivia and Peru (South); and those crossed by the Amazon River receive production from Colombia and Peru (Middle).

In **North and South**, we redefine exposure based on the location of municipalities in river routes with respect to the Amazon River banks. Municipalities in river routes to the north are exposed to cocaine production from Colombia, whereas the others are exposed to cocaine production from Peru and Bolivia.

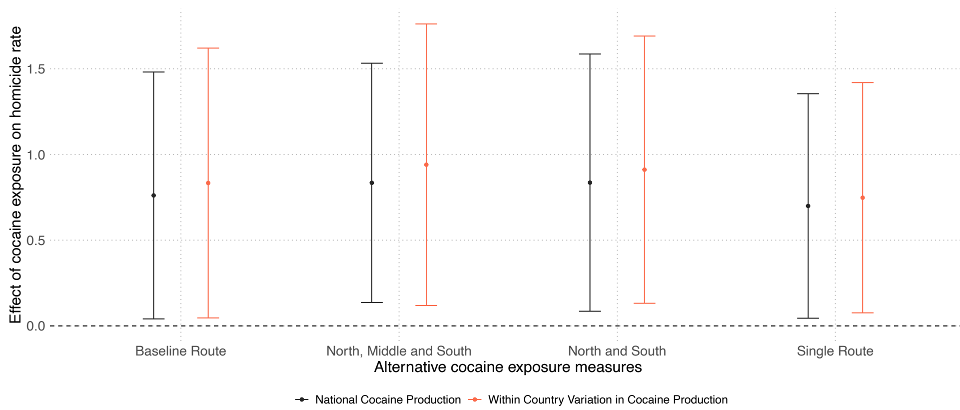
In **Single Route**, we assume that all municipalities in river routes are exposed to the entire cocaine production in the Andes, regardless of country origin. Again, black and orange lines refer to national versus regional allocation of cocaine production to rivers.[12]

[12] Because some regions in cocaine-producing countries are not crossed by rivers that reach Brazil, they are not included when we use within-country variation in production. This is why there are differences in estimates across the two vertical bars also in the Single Route case.

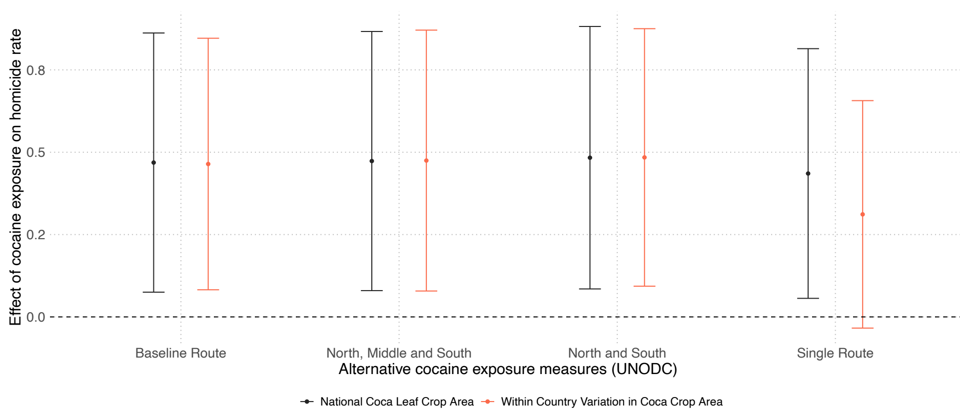
Furthermore, we address the fact that cocaine production from INCSR is not directly measured, but rather estimated from coca leaf production detected by satellite images. Because this requires assumptions about how many coca leaves are needed to produce one kilo of cocaine, measurement error could affect our estimates. In Figure 8b, we use directly the area of coca crops detected by satellite images (provided by UNODC) instead of INCSR cocaine production estimates. All else is exactly the same as before.

Figure 8: Effect of Force-down/Shoot-down Policy on Homicide Rate with Alternative Trafficking Routes and Cocaine Exposure

(a) Alternative Routes and Exposure to Cocaine Production



(b) Alternative Routes and Exposure to Coca Leaf Crop Area



Notes: All specifications include individual fixed effects, state-year fixed effects, pre-treatment covariates interacted with year fixed effects, and population weights (Column 1 of Table 4). **Baseline Route:** uses our preferred trafficking route definition. **North, Middle and South:** municipalities on North and South of Solimões river bank are considered middle routes and are exposed to Colombia's and Peru's production. **North and South:** municipalities located North of Solimões are exposed to Colombia's cocaine production, while others are exposed to both Peru's and Bolivia's production; **Single Route:** every municipality in a coca river is exposed to total Andean cocaine production.

Overall, results from Figures 8a and 8b are very similar to those from our benchmark specification. As expected, using the area of coca crops instead of cocaine production changes point estimates, since the scale of the variables is different. Nonetheless, conclusions are qualitatively the same: the partial displacement of cocaine trafficking from air to river routes seems to have increased the responsiveness of violence in exposed municipalities to cocaine production in origin countries. It is also interesting to notice that, in Figure 8a, point estimates that account for within-origin-country variation in cocaine production tend to be slightly larger (though more imprecisely estimated).

Finally, even though the West Amazon lacks road infrastructure, and transportation primarily occurs via rivers, one could argue that the few existing roads in the region affect our results. For instance, the federal highway BR-364, which connects the states of Acre, Rondônia, and Mato Grosso, could serve as an alternative route for cocaine originating from Peru or Bolivia.

Table 8: Exposure to Cocaine Trafficking in River Routes and Force-Down/Shoot-Down Policy, from 1996 to 2020 - West Amazon.

	Homicide Rate			
Model:	(1)	(2)	(3)	(4)
Exposure Rivers	0.90 (1.9)		0.72 (1.9)	0.76 (2.1)
Exposure Rivers × $I(Year \geq 2005)$	0.76** (0.37)		0.83** (0.35)	0.87** (0.35)
Exposure Roads		-0.005 (0.005)	-0.006 (0.005)	-0.007 (0.006)
Exposure Roads × $I(Year \geq 2005)$		0.005 (0.003)	0.006* (0.003)	0.007* (0.004)
Exposure Rivers × Exposure Roads				0.001 (0.001)
Exposure Rivers × Exposure Roads × $I(Year \geq 2005)$				-0.001 (0.0010)
Munic FE (269)	Yes	Yes	Yes	Yes
State-Year FE (125)	Yes	Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes
Covariates*Year	Yes	Yes	Yes	Yes
Observations	6,697	6,697	6,697	6,697
R^2	0.52	0.52	0.52	0.52
Within R^2	0.07	0.07	0.07	0.07

Notes: Western Amazon municipalities with less than 100,000 people. All errors are clustered at the municipality level. *p<.1; **p<.05; ***p<.01.

To assess this possibility, we propose an additional robustness exercise that incorporates exposure to roads that, in principle, could also be cocaine-trafficking routes. We select cocaine road routes based on Couto and Oliveira (2017), which was also the source for our cocaine river routes. Appendix C.6 shows municipalities in the Amazon along with their classification in terms of origin country, now based on both river and road routes.

Findings are presented in Table 8. Column (1) reproduces our baseline results. In Column (2), we investigate whether cocaine trafficking has shifted from air to road routes, ignoring river routes. Columns (3) and (4) explore the combined effects of exposure to both river and road routes. Overall, the results indicate that the displacement of cocaine trafficking has primarily occurred from air to rivers. While positive, the estimates for the interaction term $ExposureRoads \times I(Year \geq 2005)$ are very small. Furthermore, our coefficient of interest becomes slightly stronger once we account for the possibility of road-based exposure to cocaine trafficking. In Column (4), one can see that there seems to be no compounded effect of simultaneous exposure to river and road routes.

6 Final Remarks

In this paper, we study the violent consequences of crime displacement due to an air-interdiction policy in Brazil. We provide evidence that the implementation of a Force-down/Shoot-down policy in the Brazilian Amazon seems to have made drug traffickers substitute away from airborne trafficking and take advantage of an extensive river network connecting the Andes to the Atlantic Ocean.

We compare municipalities that are exposed to river routes originating from cocaine-producing countries to those that are not. The results show that, after the air interdiction, exposed municipalities experienced an increased responsiveness of local violence (homicides) to cocaine production in Andean countries. This corroborates the hypothesis that violence associated with cocaine trafficking increased in exposed municipalities after the intervention. We present additional evidence to support the idea that this effect is due specifically to traffickers shifting to using river routes more frequently.

Our findings provide further evidence on the complexity of enforcement in the illegal drugs market. Displacement caused by stricter enforcement not only happens across routes, but also across transportation modes. In our context, in order to evade improved airspace monitoring, criminals have proven to be quite resourceful in adapting relatively fast to a completely different transportation technology. Different modes of transportation, in turn, can have very different socioeconomic implications, because they entail different levels of contact with, and involvement of, local populations. This point is particularly important from a policy perspective, and seems to have been generally overlooked.

We do not conduct a cost-benefit analysis of the air-interdiction policy, since we cannot directly estimate its effects on cocaine volumes coming through Brazil and the associated social cost. Nevertheless, policy makers have to prepare for the possibility of major crime displacements, and for their potential socioeconomic implications, when conceiving major enforcement interventions such as the one we analyzed here.

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APPENDIX

A Appendix - Decentralized Crime in The Amazon

We present some anecdotal evidence on the decentralization of drug-related crime within the Amazon during the 2000's and early 2010's. Overall, our period of analysis was not marked by the presence of large criminal organizations, but rather by small groups or even individuals haphazardly involved in drug trafficking.

Criminals in the region were not typically affiliated with a single organized group. For example, the Federal Police's "Operation Ilhas" in 2011 arrested 32 individuals involved in cocaine trafficking in Amazon rivers who collaborated without a clear hierarchical structure. Instead, they formed a sort of "criminal consortium," pooling resources to transport drugs from multiple traffickers simultaneously and thereby reducing transportation costs (Procuradoria da República no Amazonas, 2011). This type of consortium was subject to recurrent fractures, leading to violence among members.

There were also pirate gangs operating along important river routes. In 2011, authorities apprehended 11 individuals implicated in piracy in the Solimões River (Melo, 2011). In one episode, pirates intercepted a speedboat carrying 300 kg of cocaine going from Peru to Manaus (Polícia Federal, 2014). The pirates shot five individuals transporting the illicit substance, three of which were arrested in the hospital after receiving medical care.[13]

Furthermore, there are many accounts of drug-related crime affecting communities. Some reports reveal drug traffickers trying to enlist locals to transport cocaine along the Amazon rivers (Couto and Oliveira, 2017). According to these reports, a boatman could earn between $1,000 and $1,600 working with drug trafficking. Other, more trivial, involvements of local populations with the drug business were also common. In Tabatinga, a city situated in the border of Brazil, Peru, and Colombia, for example, motorcycle taxi riders were involved in distributing coca paste, according to a news piece by Abbud (2011).

B Appendix - Propensity Score Matching

In this section, we repeat our main specification, except that we re-weigh observations according to an IPW procedure (Hirano et al., 2003; Busso et al., 2014; Cunningham, 2021).

[13] For more details, please refer to pages 379-385 of Polícia Federal (2014) report.

First, we specify a Probit model to estimate the probability $\hat{p}$ that each municipality is in cocaine trafficking river routes (treated group). In this estimation, we add the same explanatory variables included in vector X_i from Equation 2.

We run the Probit model detailed in Equation B.1, such that $\Phi(\cdot)$ is a standard cumulative Normal distribution and α is a vector of coefficients estimated by maximum likelihood.

$$Prob(Treated_i = 1|X_i) = \Phi(X_i\alpha) \tag{B.1}$$

The estimated coefficients are presented in Table B.1 for different population thresholds.

Table B.1: Probit Regression of Treatment Status on Pre-Intervention Cross-Sectional Municipal Characteristics for Different Thresholds of Population in 2000

	$\leq 50,000$	$\leq 100,000$	$\leq 200,000$
	(1)	(2)	(3)
(log) Population	0.91^{***} (0.34)	1.04^{***} (0.31)	1.01^{***} (0.30)
(log) Income p.c.	-0.68 (1.19)	-0.75 (1.19)	-0.77 (1.19)
Avg. School Years	-2.29^{***} (0.52)	-2.30^{***} (0.51)	-2.30^{***} (0.50)
(%) Low Income	2.16 (2.91)	2.15 (2.90)	2.18 (2.91)
(%) Urban Pop.	0.24 (1.56)	0.27 (1.56)	0.25 (1.56)
(%) Aged 20-39	13.56 (12.10)	12.46 (11.94)	12.32 (11.98)
(%) Forest Cover	2.99^{***} (1.13)	2.90^{***} (1.04)	2.92^{***} (1.05)
(%) Jobs Agriculture	-5.04^{**} (2.05)	-5.36^{**} (2.08)	-5.33^{**} (2.08)
(%) Jobs Mining	-22.84 (22.77)	-26.88 (23.33)	-26.03 (23.23)
(%) Jobs Pub. Sector.	17.52^{***} (6.74)	16.46^{***} (6.34)	16.50^{***} (6.36)
Constant	-2.60 (9.88)	-2.71 (9.86)	-2.29 (9.85)
Pseudo-R2	0.76	0.77	0.77
AIC	88.69	91.66	92.02
Observations	255	269	271

Notes: Only AC, AM, RO, RR, and MT. Population thresholds from Census 2000. *p<.1; **p<.05; ***p<.01

Then, we run our main model in Equation 2 using the estimated propensity scores $\hat{p}$ to re-weigh the regression (Hirano et al., 2003; Busso et al., 2014; Cunningham, 2021). We attribute weights $1/\hat{p}$ for treated units and $1/(1-\hat{p})$ for control units. Additionally, because very low or very high values of $\hat{p}$ can excessively over-weigh some observations, we only keep observations with $0.05 \leq \hat{p} \leq 0.95$.

By re-weighing and restricting our sample using IPW, we get more balanced treated and control groups on average. Table B.2 presents descriptive statistics for each observable characteristic included in X_i. The *Unmatched* columns describe our main sample, whereas the *Matched* columns present the re-weighed and restricted sample produced by the IPW procedure.

Table B.2: Propensity-Score Matching Balance Test for Municipalities with less than 100,000 people

	Unmatched			Matched		
	Treated (1)	Control (2)	Difference (3)	Treated (4)	Control (5)	Difference (6)
Avg. School Years	3.152	4.510	-1.358	3.900	3.827	0.073
			(0.102)			(0.144)
(log) Income p.c.	5.759	6.142	-0.383	5.929	5.901	0.028
			(0.045)			(0.056)
(log) Population	9.709	9.260	0.449	9.578	9.745	-0.167
			(0.112)			(0.166)
(%) Jobs Agriculture	0.461	0.441	0.021	0.505	0.479	0.027
			(0.022)			(0.039)
(%) Jobs Mining	0.002	0.010	-0.008	0.003	0.002	0.000
			(0.004)			(0.002)
(%) Jobs Pub. Sector.	0.080	0.058	0.022	0.071	0.076	-0.005
			(0.005)			(0.011)
(%) Forest Cover	0.902	0.481	0.420	0.812	0.807	0.005
			(0.038)			(0.052)
(%) Low Income	0.714	0.414	0.300	0.603	0.600	0.003
			(0.021)			(0.032)
(%) Aged 20-39	0.271	0.322	-0.051	0.292	0.286	0.005
			(0.004)			(0.007)
(%) Urban Pop.	0.455	0.553	-0.099	0.453	0.473	-0.020
			(0.029)			(0.046)
Observations	67	202	-	27	36	-

Notes: Columns (1) and (2) show the means of each variable conditional on treatment status. Columns (4) and (5) show the re-weighed means such that treated and control municipalities receive weights 1/p and 1(1-p) respectively. Columns (3) shows the estimated coefficient of an OLS regression of each variable on treatment. Columns (6) repeats the regression in Column (3), but re-weighing according to (4) and (5).

The IPW, however, comes at the cost of dropping many observations from the sample. Moreover, there is weak evidence of common support. Figure B.1 presents the distribution of estimated propensity scores ($\hat{p}$) for treated and control units after we eliminate extreme values.

Keeping in mind the aforementioned potential caveats, Table B.3 presents the new results, which can be directly compared with Table 2. Point-wise estimates are typically slightly larger, but qualitative implications are the same as in our benchmark specification.

Figure B.1: Density of Propensity Score Estimates according to Treatment Status and Population Threshold in 2000

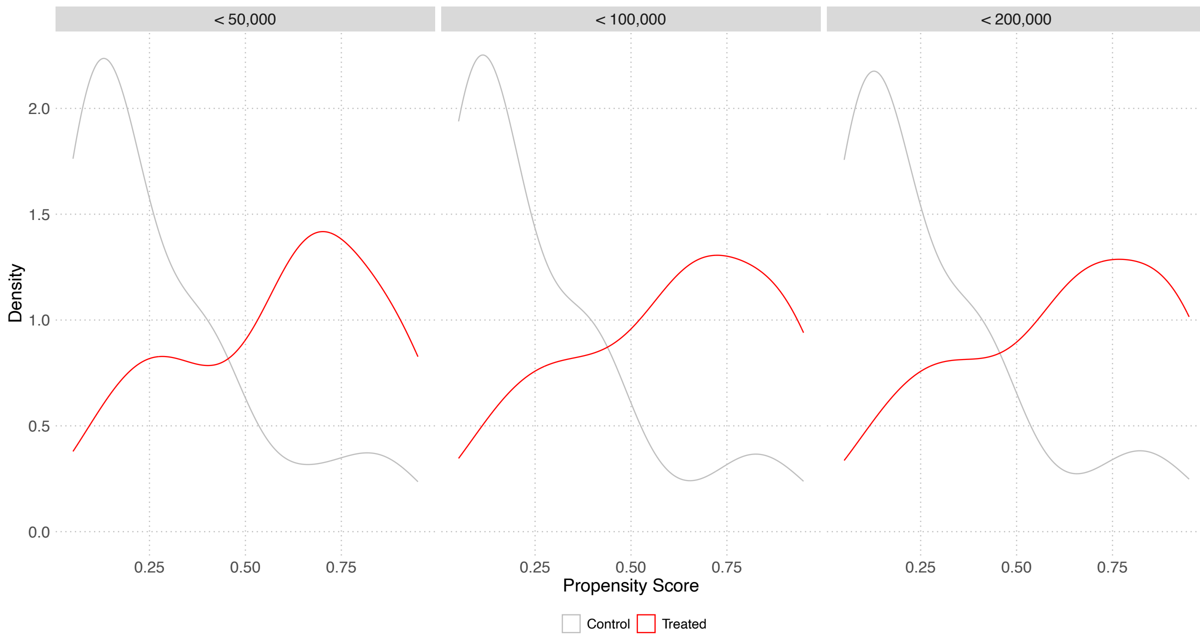


Table B.3: Exposure to Cocaine Trafficking in River Routes and Force-Down/Shoot-Down Policy, from 1996 to 2020

	Homicide Rate			
Model:	(1)	(2)	(3)	(4)
Exposure	-5.0	-3.4	-7.3**	-7.8**
	(3.8)	(3.0)	(3.1)	(3.5)
Exposure $\times$ $I(Year \geq 2005)$	0.83*	0.71*	0.92**	0.93**
	(0.47)	(0.39)	(0.41)	(0.38)
Munic FE (63)	Yes	Yes	Yes	Yes
Year FE (25)	Yes	Yes		
State-Year FE (125)			Yes	Yes
Covariates*Year		Yes		Yes
Yes		Yes		
IPW	Yes	Yes	Yes	Yes
Observations	1,569	1,569	1,569	1,569
R^2	0.48	0.62	0.59	0.70
Within R^2	0.005	0.26	0.008	0.28

Notes: All estimates include municipality and year fixed effects, as well as Inverse Probability Weights. Column (2) adds interaction between covariates in 2000 and year fixed effects; Column (3) adds state-year fixed effects; Column (4) adds both state-year fixed effects and interaction between covariates in 2000 and year fixed effects; Western Amazon municipalities with less than 100,000 people. All errors are clustered at the municipality level. *p<.1; **p<.05; ***p<.01.

C Appendix - Additional Results

C.1 Difference-in-Differences

Table C.1 presents the results for the pure Difference-in-Differences specification, using 2005 as the first year of treatment. Instead of a continuous exposure to cocaine production, as before, this model simply compares treated and control units, before and after the policy change. Variable *Coca River* indicates whether a municipality is treated, i.e., whether it is located on a cocaine-trafficking river route, regardless of how much cocaine is potentially being transported through it.

Table C.1: Exposure to Cocaine Trafficking in River Routes and Force-Down/Shoot-Down Policy, from 1996 to 2020

	Homicide Rate				
Model:	(1)	(2)	(3)	(4)	(5)
Coca River × $I(Year \geq 2005)$	11.7***	10.1***	5.2***	6.3**	6.4***
	(1.7)	(2.9)	(1.5)	(2.4)	(2.3)
Munic FE (269)	Yes	Yes	Yes	Yes	Yes
Year FE (25)	Yes	Yes			
State-Year FE (125)			Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	
Covariates*Year		Yes		Yes	Yes
Observations	6,697	6,697	6,697	6,697	6,697
R^2	0.46	0.50	0.50	0.54	0.42
Within R^2	0.03	0.10	0.002	0.07	0.06

Notes: Estimates in Columns (1) to (4) include municipality and year fixed effects, and are weighted by population. Column (2) adds interaction between covariates in 2000 and year fixed effects; Column (3) adds state-year fixed effects; Column (4) adds both state-year fixed effects and interaction between covariates in 2000 and year fixed effects; Column (5) repeats column (4) except we do not include population weights; Western Amazon municipalities with less than 100,000 people. All errors are clustered at the municipality level. *p<.1; **p<.05; ***p<.01.

C.2 Main Table Excluding Infanticides

Table C.2 simply repeats the specifications from Table 2, but with a redefined dependent variable that includes only homicides against people older than one year of age. The population in the denominator is the same as before.

Table C.2: Exposure to Cocaine Trafficking in River Routes and Force-Down/Shoot-Down Policy, from 1996 to 2020

	Homicide Rate for Age > 1				
Model:	(1)	(2)	(3)	(4)	(5)
Exposure	6.6***	3.8*	0.11	0.90	-1.0
	(1.8)	(2.1)	(1.7)	(1.9)	(1.7)
Exposure $\times$ $I(Year \geq 2005)$	1.3***	1.2***	0.69***	0.76**	0.72**
	(0.21)	(0.35)	(0.23)	(0.37)	(0.35)
Munic FE (269)	Yes	Yes	Yes	Yes	Yes
Year FE (25)	Yes	Yes			
State-Year FE (125)			Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	
Covariates*Year		Yes		Yes	Yes
Observations	6,697	6,697	6,697	6,697	6,697
R^2	0.46	0.49	0.49	0.52	0.40
Within R^2	0.04	0.10	0.002	0.07	0.06

Notes: Estimates in Columns (1) to (4) include municipality and year fixed effects, and are weighted by population. Column (2) adds interaction between covariates in 2000 and year fixed effects; Column (3) adds state-year fixed effects; Column (4) adds both state-year fixed effects and interaction between covariates in 2000 and year fixed effects; Column (5) repeats column (4) except we do not include population weights; Western Amazon municipalities with less than 100,000 people. All errors are clustered at the municipality level. *p<.1; **p<.05; ***p<.01.

C.3 Homicides in Place of Residence

Homicides in our main analysis are registered according to the municipality where they happened. In Table C.3, we use homicides registered according to the victim's municipality of residence.

Table C.3: Exposure to Cocaine Trafficking in River Routes and Force-Down/Shoot-Down Policy, from 1996 to 2020

	Homicide Rate - Place of Residence				
Model:	(1)	(2)	(3)	(4)	(5)
Exposure	6.9***	4.7**	0.84	1.7	-0.10
	(1.7)	(1.9)	(1.5)	(1.7)	(1.6)
Exposure $\times$ $I(Year \geq 2005)$	1.2***	1.1***	0.60***	0.69*	0.61*
	(0.19)	(0.35)	(0.23)	(0.35)	(0.34)
Munic FE (269)	Yes	Yes	Yes	Yes	Yes
Year FE (25)	Yes	Yes			
State-Year FE (125)			Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	
Covariates*Year		Yes		Yes	Yes
Observations	6,697	6,697	6,697	6,697	6,697
R^2	0.45	0.48	0.48	0.51	0.38
Within R^2	0.04	0.09	0.002	0.05	0.05

Notes: Western Amazon municipalities with less than 100,000 people. All errors are clustered at the municipality level. *p<.1; **p<.05; ***p<.01.

C.4 Spatial Correlation

We provide two alternative methods to model spatial correlation. Driscoll and Kraay (1998) propose a method robust to general cross-sectional and serial correlation, whereas Conley (1999) explicitly models spatial correlation based on maximum geographical distances between units.

Our results are robust to any of these alternative methods. Table C.4 provides our main estimate in the *baseline* column along with alternative specifications for standard error estimation in subsequent columns.

In *Driscoll-Kraay* (DK), we use two time lags to model cross-sectional correlation. In *Conley*, we provide three different distance thresholds to identify spatially correlated units: 100 km, 250 km, and 500 km. In all cases, our estimates are robust.

In *River Basins*, we cluster municipalities according to rivers and their tributaries. This should capture geographical correlation that operates through the river network. To do this, we use data on Ottobasins, which are organized in levels. A Level 1 Ottobasin is the most comprehensive one and corresponds to the Amazon River Basin and all its tributaries. As levels increase, basins become smaller. We use levels 3 and 4, which constitute 51 and 132 clusters respectively. To categorize municipalities across river basins, we consider the Ottobasin that covers the largest area in each municipality.

Table C.4: Spatial Correlation: Exposure to Cocaine Trafficking in River Routes and Force-Down/Shoot-Down Policy, from 1996 to 2020

	Homicide Rate						
	Baseline	DK		Conley		River Basins	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure $\times$ $I(Year \geq 2005)$	0.76**	0.76***	0.76**	0.76***	0.76***	0.76**	0.76**
	(0.37)	(0.20)	(0.36)	(0.27)	(0.28)	(0.38)	(0.30)
Standard-Errors	Munic FE	L=2	100km	200km	300km	Level 4	Level 3
Observations	6,697	6,697	6,697	6,697	6,697	6,697	6,697
R^2	0.52	0.52	0.52	0.52	0.52	0.52	0.52
Within R^2	0.07	0.07	0.07	0.07	0.07	0.07	0.07

Notes: All specifications include individual fixed effects, state-year fixed effects, pre-treatment covariates interacted with year fixed effects, and population weights*p<.1; **p<.05; ***p<.01. All errors are clustered at the municipality level. Western Amazon municipalities with less than 100,000 people. In River Basins, levels 3 and 4 correspond to Ottobasin definition in which the largest basin is level 1. Level 3 basins delimit 51 clusters whereas Level 4 basins delimit 132 clusters.

C.5 Shorter Period of Treatment

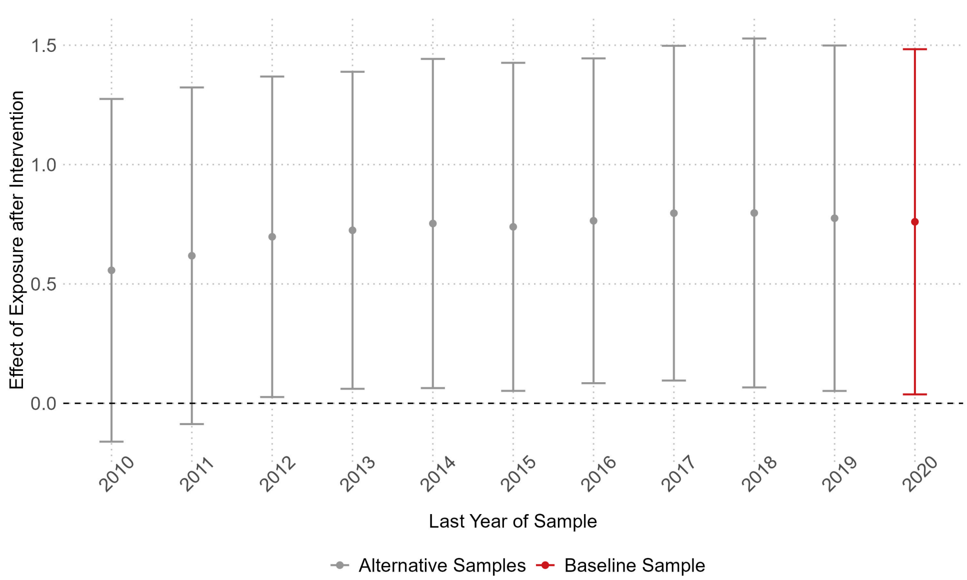
In Table C.5, the sample period ends in 2015 instead of 2020. Figure C.1 repeats this exercise, but instead changes the last year of the sample. Our main sample is in red.

Table C.5: Exposure to Cocaine Trafficking in River Routes and Force-Down/Shoot-Down Policy, from 1996 to 2015

	Homicide Rate				
Model:	(1)	(2)	(3)	(4)	(5)
Exposure	1.7	3.6**	-1.3	0.31	-1.1
	(1.3)	(1.5)	(1.5)	(1.6)	(1.5)
Exposure × $I(Year \geq 2005)$	1.2***	1.2***	0.66***	0.74**	0.75**
	(0.20)	(0.34)	(0.21)	(0.35)	(0.35)
Munic FE (269)	Yes	Yes	Yes	Yes	Yes
Year FE (20)	Yes	Yes			
State-Year FE (100)			Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	
Covariates*Year		Yes		Yes	Yes
Observations	5,352	5,352	5,352	5,352	5,352
R^2	0.51	0.54	0.52	0.55	0.42
Within R^2	0.02	0.08	0.002	0.06	0.05

Notes: Western Amazon municipalities with less than 100,000 people. All errors are clustered at the municipality level. *p<.1; **p<.05; ***p<.01.

Figure C.1: Alternative Samples with Shorter Post-Treatment Periods



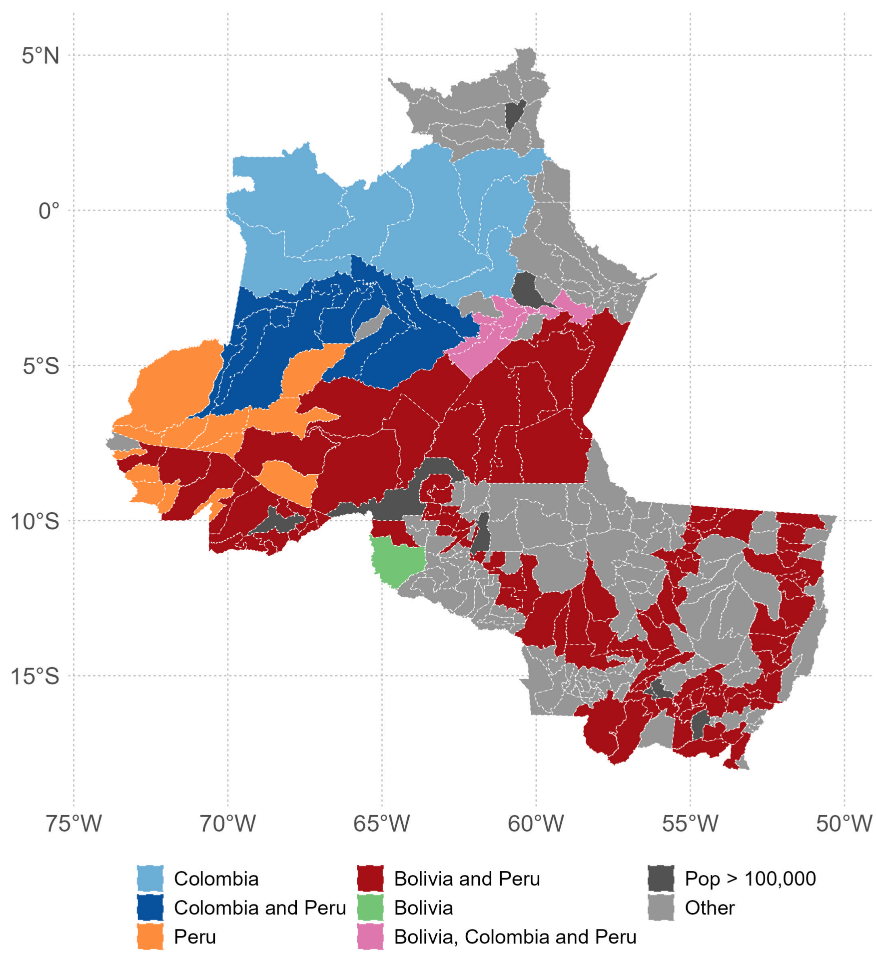
Notes: All specifications include individual fixed effects, state-year fixed effects, pre-treatment covariates interacted with year fixed effects, and population weights (Column 1 of Table 4). Each estimate is based on a sample starting in 1996 and ending in different years shown in the X-axis. All estimates are presented with a 95% confidence interval.

C.6 Municipalities Categorized According to River and Road Routes

Figure C.2 categorizes municipalities according to both river and road routes. We use the work of Couto and Oliveira (2017) to identify cocaine-trafficking road routes. In the database, we can observe municipalities that are exposed to river routes, road routes or both.

As before, the classification of routes is based on their countries of origin (Bolivia, Colombia or Peru). We then use this information to calculate the exposure to cocaine production.

Figure C.2: Municipalities Categorized According to River and Road Routes Crossing their Territory



D Appendix - Excluding Municipalities with High Infanticide Rates

This appendix presents the main results of the paper for a different sample, which excludes municipalities with abnormally high infanticide rates. These outliers are Caracaraí (RR), Alto Alegre (RR), Santa Isabel do Rio Negro (AM), and Barcelos (AM).

D.1 Main Table

Table D.1: Exposure to Cocaine Trafficking in River Routes and Force-Down/Shoot-Down Policy, from 1996 to 2020

	Homicide Rate				
Model:	(1)	(2)	(3)	(4)	(5)
Exposure	7.5***	5.3***	1.3	2.5	-0.13
	(1.8)	(2.0)	(1.5)	(1.7)	(1.7)
Exposure × $I(Year \geq 2005)$	1.3***	1.3***	0.75***	0.84**	0.89**
	(0.21)	(0.37)	(0.24)	(0.39)	(0.36)
Munic FE (265)	Yes	Yes	Yes	Yes	Yes
Year FE (25)	Yes	Yes			
State-Year FE (125)			Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	
Covariates*Year		Yes		Yes	Yes
Observations	6,597	6,597	6,597	6,597	6,597
R^2	0.47	0.50	0.49	0.53	0.40
Within R^2	0.04	0.11	0.003	0.07	0.06

Notes: Western Amazon municipalities with less than 100,000 people. All errors are clustered at the municipality level. *p<.1; **p<.05; ***p<.01.Excludes the following municipalities with high infanticide rates: Caracaraí (RR), Alto Alegre (RR), Santa Isabel do Rio Negro (AM), and Barcelos (AM).

D.2 Decomposition

Table D.2: Characterization of Homicides, Exposure to Cocaine Trafficking in River Routes, and Force-Down/Shoot-Down Policy, from 1996 to 2020

	>1	Men 20+				Other Homicides		
	Homicide Rate	Men 20+	Home	Out of Home	Firearm or Knife	CPT	Police	Undet.
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure × $I(Year \geq 2005)$	0.84**	0.61*	0.10	0.51*	0.53*	-0.007**	0.01*	0.06
	(0.39)	(0.33)	(0.07)	(0.28)	(0.28)	(0.003)	(0.007)	(0.11)
Observations	6,597	6,597	6,597	6,597	6,597	6,332	6,597	6,597
R^2	0.53	0.51	0.25	0.48	0.49	0.22	0.10	0.29
Within R^2	0.07	0.07	0.04	0.06	0.07	0.06	0.03	0.05

Notes: All specifications include individual fixed effects, state-year fixed effects, pre-treatment covariates interacted with year fixed effects, and population weights. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$. All errors are clustered at the municipality level. Western Amazon municipalities with less than 100,000 people. CPT is an indicator variable equal to one when there are deaths in the countryside due to land conflicts according to the Comissão Pastoral da Terra. Police and Undet. are homicide rates committed by the police or by an undetermined actor. Excludes the following municipalities with high infanticide rates: Caracaraí (RR), Alto Alegre (RR), Santa Isabel do Rio Negro (AM), and Barcelos (AM).

D.3 Mechanism

Table D.3: Deaths from Overdose, Exposure to Cocaine Trafficking in River Routes, and Force-Down/Shoot-Down Policy, from 1996 to 2020

	Overdose Death Rate				
Model:	(1)	(2)	(3)	(4)	(5)
Exposure $\times$ $I(Year \geq 2005)$	0.03***	0.05***	0.04***	0.04***	0.04***
	(0.009)	(0.01)	(0.01)	(0.01)	(0.02)
Munic FE (265)	Yes	Yes	Yes	Yes	Yes
Year FE (25)	Yes	Yes			
State-Year FE (125)			Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	
Covariates*Year		Yes		Yes	Yes
Observations	6,597	6,597	6,597	6,597	6,597
R^2	0.08	0.13	0.11	0.15	0.11
Within R^2	0.01	0.07	0.002	0.05	0.03

Notes: Western Amazon municipalities with less than 100,000 people. Excludes the following municipalities with high infanticide rates: Caracaraí (RR), Alto Alegre (RR), Santa Isabel do Rio Negro (AM), and Barcelos (AM). All errors are clustered at the municipality level. *p<.1; **p<.05; ***p<.01.

D.4 Placebo

Table D.4: Placebo: Other Death Rates and Cocaine Exposure in Waterway Trafficking Routes after the Force-Down/Shoot-Down Policy, from 1996 to 2020

	Infect Parasite	Neoplasm	Circulatory	Respiratory	Digestive	Suicide
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Exposure $\times$ $I(Year \geq 2005)$	0.31	0.09	0.55	0.17	0.13	0.27*
	(0.19)	(0.38)	(0.54)	(0.20)	(0.19)	(0.15)
Observations	6,597	6,597	6,597	6,597	6,597	6,597
R^2	0.67	0.57	0.72	0.61	0.60	0.33
Within R^2	0.36	0.10	0.07	0.09	0.09	0.06

Notes: All specifications include individual fixed effects, state-year fixed effects, pre-treatment covariates interacted with year fixed effects, and population weights. *p<.1; **p<.05; ***p<.01. All errors are clustered at the municipality level. Western Amazon municipalities with less than 100,000 people. Excludes the following municipalities with high infanticide rates: Caracaraí (RR), Alto Alegre (RR), Santa Isabel do Rio Negro (AM), and Barcelos (AM).

Table D.5: Placebo: GDP per Capita and GDP Composition, Cocaine Exposure in Waterway Trafficking Routes, and the Force-Down/Shoot-Down Policy, from 1996 to 2020

Model:	Traffic Accident (1)	(log) GDP per Capita (2)	Share Agric. (3)	Share Manuf. (4)	Share Service (5)	Share Public (6)	Share Taxes (7)
Exposure $\times$ $I(Year \geq 2005)$	0.08	0.002	-0.004	0.002	0.001	-0.002	0.002**
	(0.40)	(0.009)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
Observations	4,770	4,770	4,770	4,770	4,770	4,770	4,770
R^2	0.43	0.96	0.88	0.78	0.93	0.94	0.84
Within R^2	0.08	0.08	0.11	0.07	0.09	0.06	0.06

Notes: All specifications include individual fixed effects, state-year fixed effects, and pre-treatment covariates interacted with year fixed effects.GDP estimates does not include include population weights, because GDP varies more smoothly than homicides. Traffic deaths are considered a proxy for economic activity and urbanization. *p<.1; **p<.05; ***p<.01. All errors are clustered at the municipality level. Western Amazon municipalities with less than 100,000 people. Excludes the following municipalities with high infanticide rates: Caracaraí (RR), Alto Alegre (RR), Santa Isabel do Rio Negro (AM), and Barcelos (AM).

D.5 Robustness

Table D.6: Spatial Correlation: Exposure to Cocaine Trafficking in River Routes and Force-Down/Shoot-Down Policy, from 1996 to 2020

	Homicide Rate				
	Baseline	DK		Conley	
Model:	(1)	(2)	(3)	(4)	(5)
Exposure $\times$ $I(Year \geq 2005)$	0.84**	0.84***	0.84**	0.84***	0.84*
	(0.39)	(0.21)	(0.39)	(0.32)	(0.48)
Standard-Errors	Munic FE	L=2	100km	200km	300km
Observations	6,597	6,597	6,597	6,597	6,597
R^2	0.53	0.53	0.53	0.53	0.53
Within R^2	0.07	0.07	0.07	0.07	0.07

Notes: All specifications include individual fixed effects, state-year fixed effects, pre-treatment covariates interacted with year fixed effects, and population weights. *p<.1; **p<.05; ***p<.01. All errors are clustered at the municipality level. Western Amazon municipalities with less than 100,000 people. Excludes the following municipalities with high infanticide rates: Caracaraí (RR), Alto Alegre (RR), Santa Isabel do Rio Negro (AM), and Barcelos (AM).