Making a *Narco*: Childhood Exposure to Illegal Labor Markets and Criminal Life Paths

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Abstract

This paper provides evidence that exposure to illegal labor markets during childhood leads to the formation of industry-specific human capital at an early age, putting children on a criminal life path. Using the timing of US anti-drug policies, I show that when the return to illegal activities increases in coca suitable areas in Peru, parents increase the use of child labor for coca farming, putting children on a criminal life path. Using administrative records, I show that affected children are about 30% more likely to be incarcerated for violent and drug-related crimes as adults. No effect in criminality is found for individuals that grow up working in places where the coca produced goes primarily to the legal sector, suggesting that it is the accumulation of human capital specific to the illegal industry that fosters criminal careers. However, the rollout of a conditional cash transfer program that encourages schooling mitigates the effects of exposure to illegal industries, providing further evidence on the mechanisms.

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The only way to survive, to buy food, was to grow poppy and marijuana, and from the age of 15 I began to grow, harvest, and sell.

- Joaquin "El Chapo" Guzman, when asked how he became the leader of the Sinaloa drug cartel

1 Introduction

Illegal markets and the associated crime are critical concerns in developing countries and in marginalized areas of rich countries, as exemplified by the impact of the drug trade from Peru and Colombia on the inner cities of the U.S.[1] While criminal leaders such as Al Capone, Pablo Escobar and El Chapo draw a lot of attention, illegal markets operate thorough a much larger set of individuals who support these organizations. Yet, we know far less about how these individuals enter crime. Are these decisions simply a spot benefit-cost calculus or are there specific and persistent factors that lead people to enter a life of crime from an early age?

This paper finds evidence that exposure to illegal labor markets during childhood leads to the formation of industry-specific human capital at an early age, putting individuals on a criminal life path in the cocaine industry. There are three main results. First, using exogenous shocks to illegal labor markets in Peru, I show that when the return to illegal activities increases in areas suitable for coca production, parents significantly increase the use of child labor for coca farming. Second, I find that this response in turn may increase children's criminal capital and the chances that they remain in the cocaine industry. As adults, affected children are more likely to be incarcerated for violent and drug-related crimes. Third, I show that policies that target the incentives surrounding these early investments can mitigate the effects of exposure to illegal labor markets. In particular, I show that conditional cash transfers that encourage schooling can reduce child labor in the illegal sector, and drug production in coca suitable areas. This policy addresses an underlying cause of future criminality by limiting the formation of criminal capital while simultaneously increasing formal human capital.

To establish these results, I take advantage of drug enforcement policies in Colombia that shifted coca leaf production to Peru, where 90% of coca production is used to produce cocaine. In particular, in 1999, Colombia, then the world's largest cocaine producer, implemented Plan Colombia, a U.S.-supported military-based interdiction intervention. One of the main components was the aerial spraying of coca crops in Colombia. This intervention resulted in higher prices and expanded coca production in Peru, where production doubled in districts with the optimal agro-ecological conditions.[2] By 2012, Peru had become the largest producer of cocaine in the

[1] There is a growing awareness that crime and illicit drugs are major impediments for development (UNODC 2012). Crime may affect development by driving away business, eroding human capital, and undermining democracy (UNODC 2007a). This has been pointed out by several international organizations, which have increased efforts to improve citizen security in developing countries. Recent surveys find that crime is the top concern for citizens in emerging and developing countries (PewResearchCenter 2014). About half of the world's 450,000 annual homicides take place in Latin America and sub-Saharan Africa (UNODC 2019).

[2] There are only three countries that have the optimal agro-ecological conditions to grow coca: Colombia, Peru and Bolivia.

world.[3]

This setting yields three useful sources of variation: i) geographic variation in coca-growing in Peru, ii) over-time variation in coca prices induced by Colombian shocks, and iii) variation in the age of exposure, exploiting the fact that in Peru children are more likely to dropout from school in the transition between primary and secondary education at the ages 11-14. I thus define age-specific shocks by interacting coca suitability measures and prices. Differential exposure by age arises since children within a district or village experience the changes in coca prices at different ages and due to variation in coca suitability across districts, villages, and schools.[4]

To observe these sources of variation, I build a location-year panel linking coca production to a variety of labor market, schooling, and crime outcomes.[5] Data sources include geocoded school locations and satellite images of coca fields that allow me to link each school to a particular coca geographic cell; household level data; administrative data on all inmates in Peruvian prisons in 2015 and 2016; and black market coca prices. These data allow me to track cohorts that were exposed to high coca prices during key ages across areas with different coca suitability.

I first show that investments in children's human capital are negatively affected by the cocaine industry during the period 1994-2013. For example, the increase in coca prices induced by Colombia's anti-drug policy over 1997 to 2003 leads to a 30% increase in child labor in areas highly suitable for coca production. Children between the ages of 11 and 14 are most affected relative to younger and older children. In addition, the relatively high earnings in the cocaine industry induce some 11-14 aged children to drop out of school. In particular, when coca prices increase, there is a 26% increase in the dropout rate for students beginning secondary school in coca suitable areas. This large effect corresponds exactly to the years when most children drop out of school in Peru (i.e., the transition between primary and secondary education). Furthermore, I find that these results are not driven by violence, conflict, income, quality of education or migration.[6]

I then ask how childhood exposure to illegal labor markets affects children's long-run criminality at the ages of 18 to 30. I find that individuals who grew up in coca producing areas and experienced high coca prices during childhood are about 30% more likely to be incarcerated than their counterparts, i.e., those who were born in the same district but in a different year, and those who were born in a different district but belong to the same cohort. The effects are concentrated

[3]During the period of analysis, coca production decreased by 60% in Colombia. See "National Drug Control Strategy," Office of National Drug Control Policy, U.S. Department of State, 2012.

[4]For example, for criminal outcomes, I compare the probability of becoming criminal for children who were born in high coca suitable areas and had high prices during susceptible ages versus individuals who were born in the same areas but were exposed to high coca prices at older ages (not susceptible ages), and individuals who were born in a different area but belong to the same cohort.

[5]I also complement these data with field work interviews. In particular, I visited the region composed of the Apurimac, Ene and Mantaro River Valleys (VRAEM), which according to the United Nations, is the place with the most coca crops and laboratories for the production of coca base and cocaine in the world.

[6]In particular, I empirically tested whether the price shock was associated with: i) changes in conflict, enforcement and crime; ii) changes in the probability of migration across families or individuals with different characteristics; iii) changes of the supply to education; and iv) changes in mortality, and cohort size. Moreover, these short-term effects are also robust to the inclusion of time trends that differ across coca suitable districts, time effects by baseline characteristics, the inclusion of household fixed effects that compare siblings of different ages within the same household, and to using a coca agro-ecological index.

among children who experienced high coca prices at the ages 11-14, when child labor increases the most. Furthermore, I find no effect for individuals that had high coca prices when they were younger than 11 and older than 14, consistent with the claim that children at these ages are less likely to drop out from school.

These results are robust to different sets of specifications. First, I use satellite images of coca-growing areas to classify whether incarcerated individuals were born in a village inside a coca geographic cell and find that results are robust to the inclusion of district-by-year of birth fixed effects. This controls for political decisions, such as the level of enforcement, that are made at the district level. Second, results are robust to the inclusion of year-of-arrest fixed effects. Third, the negative effects of childhood involvement in coca growing are found not only for those who remain in coca growing districts as adults, but also for those who potentially move to districts without coca production. This finding implies that the long-term effects are not caused by contemporaneous exposure to the cocaine industry during adulthood but rather to exposure during childhood. Moreover, these results provide further evidence that effects are not driven by an increase in enforcement in coca areas.

The second focus of this paper is to understand the mechanisms underlying the link between childhood participation in coca farming and future criminality. There are two potential main mechanisms: a decline in general human capital and an increase in industry-specific human capital. First, exposed children have lower formal education and this deficiency can lead to criminality (the general human capital mechanism).[7] Second, individuals may acquire skills specific to the illegal sector such as knowledge about transforming coca into cocaine and smuggling, as well as social capital specific to the illegal industry, such as connections to buyers (the industry-specific human capital mechanism).[8]

I report several pieces of evidence suggesting that the increase in adult criminality is mainly driven by the acquisition of human capital that is specific to the illegal industry (as opposed to lower formal human capital due to less schooling). First, children who end up growing coca as a result of the price shocks are more likely to be convicted of violent and drug-related crimes in the future, but *not* of other types of crime, such as property crime, sexual assault, or white collar crime. This result shows that individuals are more likely to be involved in the types of crime that are specific to the cocaine industry (such as drug-trafficking and murder) but less likely to be involved in crimes related to a decline in formal human capital (such as property crime). Second, I find that price shocks to legal commodities that also increase child labor at the key ages of 11 to 14, have no effect on the likelihood of future criminality. Moreover, individuals from districts where most coca is grown for traditional medical and religious purposes are not involved in crime later in

[7] Lochner and Moretti (2004) show that schooling reduces the probability of incarceration, Anderson (2014) shows that dropping out of school increase juvenile criminal behavior, and Deming (2011) finds that access to better schools reduces criminal behavior. In a similar way, Aizer et al. (2015) shows that juvenile incarceration increases future criminal behavior by interrupting social and human capital accumulation during a critical period.

[8] Working in the illegal industry may also lead to exposure to criminal groups and other negative peer effects. For evidence on crime and peer interactions, see Glaeser et al. (1996), Bayer et al. (2009), Deming (2011) and Damm and Dustmann (2014).

life, even though they worked during childhood. Third, the overwhelming majority of individuals who are estimated to be in prison due to the price shock report that they were involved in illegal activities before the age of 18 and reported farming as their last occupation, indicating that they likely started their criminal career growing coca, leading to an increase in their criminal capital.[9]

I also examine other potential mechanisms for which changes in coca prices may increase future criminality but do not find evidence to support them. In particular, I do not find evidence that crime, conflict and enforcement increased in the short-term in these areas, suggesting that individuals were not exposed to significant changes in violence. Moreover, if long-run effects were driven by exposure to violence, the increase in coca prices should also affect younger cohorts, but I find that the results are concentrated in exactly the specific cohorts (11-14 years old) when the dropout from school increases the most.[10] This finding is consistent with the qualitative evidence, which suggests that when coca expanded in Peru in the 2000s there were no preexisting armed groups fighting for the extra resources that resulted from cocaine production. In addition, the Peruvian government did not respond with an increase in law and enforcement in these locations. Finally, I also show that future criminality in the cocaine industry cannot be explained by selective migration of individuals or changes in governance in coca suitable districts.

Having shown that criminal careers can develop during childhood, I then analyze how policy can address the underlying mechanisms that lead to future criminality by changing parental incentives in the affected areas. I exploit the gradual rollout of a conditional cash transfer program (CCT) during the period of high coca prices. The program provided monetary transfers to parents with the condition that children attended school on a daily basis. The program targeted school-aged children and was not intended to reduce drug production.

Consistent with the hypothesis that parental responses during childhood matter, I show that coca areas that implemented the program experienced a significant reduction in both coca production and child labor. These results suggest that CCTs can be potentially targeted toward coca-suitable districts in order to mitigate the effects of high coca prices. Moreover, even if there is substitution into adult labor, adults working in coca farms are less likely to engage in other stages of production and to start a criminal career in the industry. Finally, these results help to rule out other potential mechanisms which could not be mitigated by a CCT such as exposure to violence, changes in governance and enforcement.

These results have several potential policy implications. First, the formation of criminal human capital early in life can explain adult occupational choices and the perpetuation of illegal industries. While research on the prevention of crime has focused on enforcement measures, little is known about the root causes that are within the reach of policy. By documenting one potential cause of future criminality, this paper helps to understand what policies can limit the formation

[9]Even though no test separately provides conclusive information about the presence or absence of the criminal capital mechanism, these results taken comprehensively provide suggestive evidence that is supportive of the criminal path mechanism and would be difficult to reconcile with the general human capital mechanism.

[10]Previous literature finds that most of the effects of exposure to violence and conflict are concentrated at early childhood (Couttenier et al. 2019) while I find no effects of coca prices at those ages.

of illegal markets and associated crime. Since effects are driven by exposure during childhood, policies that target incentives for child labor can reduce the development of criminal careers and can potentially offer a more cost effective way to reduce coca production than enforcement alone. In other words, if location-specific factors affect parental incentives to use child labor and thus "create" criminality, then location-specific policies may be needed to target these incentives.[11] In addition, the results suggest that taking into account the ages when children are most vulnerable to switch to working for the specific illegal industry can be important to better design future policies. For example, a future CCT program aimed at decreasing child participation in the coca industry would be more efficient if it were to focus on ages 11 to 14. This point complements the existing literature, which generally assumes that younger age groups are the most vulnerable ones. Second, this paper provides a potential explanation for the geographic concentration of crime. There has been a growing consensus that enforcement alone can explain little of the variation in crime.[12] Rather than concurrent factors, this paper suggests that the concentration of crime has to do with location-specific factors such as coca suitability that lead to the development of criminal human capital that persists over time.

This paper speaks to several literatures. First, my results are closely related to the literature on the determinants of child labor (e.g., Edmonds 2007; Doepke and Zilibotti 2005, 2009, 2010; Baland and Robinson 2000; Edmonds et al. 2010; Dammert 2008; Basu and Van 1998). Part of this literature emphasizes the supply side, and sees the role of income and substitution effects as the main determinants of households' schooling and work decisions. In the case of a coca price shock, these two effects go in opposite directions, and I find that the substitution effect dominates the income effects, such that a coca price increase leads to increases in child labor. On the other hand, another strand of the literature highlights the importance of technological shocks affecting the technology and the productivity of child labor (Doepke and Zilibotti 2005). I provide anecdotal evidence of a high demand for children, and a low substitution between child labor and unskilled adult labor, in the cocaine industry. Thus, since children may have a comparative advantage in the local cocaine market, and in the absence of skilled-biased technological changes in an industry whose production is intensive in unskilled labor, cocaine price shocks will raise the incentives to employ child labor.[13]

Relatedly, this paper complements the literature studying how human capital investment decisions are affected by changes in labor market opportunities (e.g., Shah and Steinberg 2017; Adukia et al. 2020; Frankenberg and Thomas 2017; Shah and Steinberg 2015; Edmonds et al. 2010; Dammert 2008). While most of this literature has examined how legal labor market opportunities affect schooling and child labor in the short-run, I provide evidence on how working during child-

[11] Moreover, while most previous literature and policy has focused on studying traditional deterrence methods in developed countries, these methods may not work in the context of developing countries. For example, increased policing and incarceration may be particularly problematic given issues related to corruption, the limited capacity of the judicial system, and overcrowding of prisons.

[12] (See e.g., O'Flaherty and Sethi 2014; Fisman and Miguel 2007; Levitt 2004).

[13] Children are better suited to collect coca leaves, and they cannot be legally prosecuted in further stages of the production chain.

hood in one industry can have persistent effects on adult occupational choice. Moreover, I focus on changes in returns to the illegal sector as well as long-run effects. I emphasize that the development of human capital in the illegal sector is especially important given the negative externalities related to crime, especially in the long-run. In particular, I find that neither dropping out of school nor working on a farm as a child increases the probability of being convicted of a crime later on in life, except when the industry in which the child works is the illegal coca industry. I provide several pieces of evidence in favor of this hypothesis, suggesting that the path to criminality is related to investment of industry-specific capital in an illegal activity. This connection between child labor and criminality is further explained by anecdotal evidence. While working in the coca fields, individuals obtain knowledge and connections, which leads them to climb the ladder in the cocaine industry later on.

Second, I provide evidence on how location matters for long- term outcomes (Chetty and Hendren 2018; Chetty et al. 2016). Recent evidence from the US shows that growing up in particular locations can cause lifelong disadvantage. However, there is less evidence on the mechanisms behind why location matters. In the context of developing countries, I contribute to this question by showing that location may matter through labor markets and industry-specific human capital accumulation. Relatedly, this paper also contributes to the literature showing that early childhood conditions affect later outcomes (e.g., Currie and Almond 2011; Heckman 2006; Brooks-Gunn and Duncan 1997; Adhvaryu et al. 2018). Much of this empirical literature has analyzed how negative shocks early in life affect adult outcomes through general human capital.[14] In this paper, I focus on the development of one type of industry-specific human capital, namely criminal skills specific to the drug industry. Moreover, while much of this literature has focused on early childhood—before the age of five—I provide evidence that long-term outcomes can also be affected during early adolescence.

Third, this paper contributes to the literature on crime and illegal markets (e.g., Dell et al. 2019; Castillo et al. 2018; Dell 2015; Dube et al. 2016; Rozo 2014; Mejía and Restrepo 2013; Angrist and Kugler 2008). Much of the previous literature has focused on drug enforcement measures which can often lead to increased violence or to crime being displaced to different areas.[15] However, there is no evidence about how individuals start participating in narcotraffic groups and the role of conditions during childhood. A related literature in developed countries examines whether criminality is affected by incarceration (Bhuller et al. 2020; Mueller-Smith 2016; Aizer et al. 2015; Di Tella and Schargrodsky 2013; Bayer et al. 2009), early childhood conditions such as lead exposure (Reyes 2007) and pre-school programs (Heckman et al. 2013), the number of criminals (Damm and Dustmann 2014), recessions (Bell et al. 2018) and education (Deming 2011; Machin et al. 2011; Lochner and Moretti 2004). The closest related paper is Carvalho and Soares (2016) that provides

[14] Currie and Almond (2011) provide a review of the effects of early childhood influences on later life outcomes.

[15] Dell (2015) shows how drug enforcement caused a large increase in homicide rates in Mexico. Also, Abadie et al. (2015) finds that aerial eradication exacerbated armed conflict and violence in Colombia, by reducing guerrillas' main source of income. Castillo et al. (2018) show how changes in drug enforcement in Colombia generated an increase in violence in Mexico (for a review on drug enforcement measures and violence see Werb et al. (2011) and Miron (1999), which document a positive relationship).

detailed descriptive evidence on how individuals start a criminal career in gangs in Brazil. I complement this literature by providing causal evidence on how criminal careers start in narcotraffic groups, whose activities are among the major contributors to the increase in violent crime in the last decade.

The remainder of the paper is organized as follows. In the next section, I present the setting and Section 3 describes the data. Section 4 presents the empirical strategy. Section 5 presents the results. Section 6 examines the effects of a specific policy targeting the underlying mechanisms. I return to the policy implications in the final section.

2 Institutional Context

In this section, I provide background information relevant to my analysis. First, I present an overview of the cocaine industry and describe the anti-drug policies in Colombia that I exploit for identification. This paper focuses on changes in coca prices induced by the US–led eradication efforts in Colombia. Second, I justify why coca price changes in the early teen ages 11-14 are likely to have particularly pronounced effects on education and future criminality. Further, I review qualitative evidence indicating that children are an attractive input in the production of cocaine. While young children (ages 6-10) are often used to pick coca leaves, older children (ages 11-14) are also used for other stages of the production process. Third, I summarize my conversations with coca farmers, school administrators, police officers, and government officials in Peru to understand better the potential long-term consequences of child labor in the cocaine industry.

2.1 Spillover Effects in the Drug Industry in South America

Most coca is grown in Bolivia, Colombia, and Peru and about 90% is used to make cocaine.[16] These are the only countries that have the optimal agro-ecological conditions to grow coca.[17] The high jungle areas on the eastern slope of the Andes Mountains are well suited for coca plants because coca grows best at altitudes over 2,000 meters with about 20 degrees of slope. Therefore, any changes in drug policy in one of these countries is likely to shift coca production within the Andean Region.

Figure 1 shows coca production in the Andean region. I argue that the shift in coca production between countries was exogenous. At the beginning of the 1990s, most coca was produced in Peru. However, the closing of the air bridge used to transport cocaine paste from Peru to Colombia shifted coca production to Colombia. This initiative was driven by a change in U.S. policy that shifted U.S. interdiction away from Caribbean transit zones toward Colombia to stop cocaine production.[18] As part of this U.S. effort, Colombia implemented a shoot-down policy for any plane

[16]In Peru, the remaining 10% is used for traditional purposes and is highly regulated. In particular, coca leaves are chewed directly or used for tea. Most of the legal production is concentrated in the region of La Convencion y Lares.

[17]Coca (*Erthroxylum spp.*), a plant native to South America, can be cultivated only under specific agro-ecological conditions. For instance, coca plants require specific ranges of altitude, slope, and soil conditions.

[18]For a more detailed description of this policy, see Angrist and Kugler (2008).

ferrying coca paste from Peru, generating the opposite effect of reducing coca production in Peru and increasing it in Colombia. Then, in the 2000s, U.S. backed eradication efforts in Colombia, again shifted production back to Peru. In particular, I take advantage of Plan Colombia, a coca spraying program implemented in Colombia in 1999 to reduce cocaine production. Colombian production declined sharply after 1999, followed by a steady increase in Peru.[19]

This paper exploits these changes in coca production in Peru induced by US-driven policies in Colombia, focusing on the period 1994 to 2013. I argue that these supply shocks are uncorrelated with time-varying factors in Peru. In addition, I exploit the fact that these changes in prices primarily affected those areas in Peru that were suitable for coca production, and within these areas, they particularly affected children at the ages 11-14.

Figure 2 shows the 1994 distribution of coca production in Peru. There is substantial variation across districts in coca production. There are 1,839 districts in Peru, and coca is grown in about 190 of these. While the Andes region in the south of Peru is highly productive, northern areas are less so. This is mainly because certain districts have better agro-ecological conditions than others. According to FAO-Eco crop, there are optimal ranges of soil, precipitation, slope, and altitude to grow coca. These conditions are highly correlated with the areas that were producing in 1994—about 80% of high producing districts have the optimal conditions. I describe these conditions in detail in the data section.

In districts suitable for coca production, the economy is not only dependent on the production and selling of primary goods but also on the processing of coca into coca paste and cocaine for illegal markets. For example, about 2,000 laboratories and maceration pits were found hidden in the jungle in 2007 (UNODC 2007b). In general, local family-run organizations control production and domestic transportation of cocaine, while Colombian and Mexican intermediaries handle international trafficking.

2.2 Child Labor and Coca Prices at Key Ages of Exposure

In this paper, rather than relying only on coca cross-sectional variation, the identification strategy for the long-run analysis also exploits differences in exposure to changes in coca prices at different ages across cohorts within the same district. In this section, I justify why changes in coca prices at the ages 11-14 are likely to have particularly pronounced effects on education and crime. This includes a theoretical justification that is consistent with qualitative and empirical evidence. I argue that the returns to entering the cocaine business will vary by year of entry, depending on the coca prices in that year. First, I argue that this heterogeneity in returns will disproportionately affect the decisions of the cohorts that are in the transitioning ages between primary and secondary

[19]The phenomenon in which reducing drug production in one region causes it to expand elsewhere is often called the "balloon effect." For example, Rozo (2014) suggests that since eradication efforts in Colombia did not move production to other areas within the country, it is very likely that coca production moved to other countries with similar conditions for growing coca. In a similar vein, Mejia and Restrepo (2016) develops a model of the war on drugs to understand the effects of Plan Colombia. This model predicts a reallocation of cocaine production to other countries due to eradication efforts in Colombia.

education, which are the ages when children are more likely to drop out and join the labor market. Second, using previous qualitative evidence and a short survey I conducted in the field, I describe how the cocaine industry's labor demand may also be greater at these ages.

Many models have shown how individuals face a trade-off between lower earnings in the present (the opportunity cost of schooling), versus more earnings in the future (e.g., Basu and Van 1998; Baland and Robinson 2000; Ferreira and Schady 2009; Santos 2018). This trade-off will depend on the labor market opportunities available when individuals (or parents) are facing such a decision. An increase in coca prices will, therefore, affect the schooling decision by increasing the opportunity cost of schooling. In this context, I argue that shocks to the opportunity cost of education can be more pronounced in the early teen years. Two potential reasons may be driving the aforementioned result.

First, from the supply side, these are the ages of transition between primary and secondary education, when children in rural areas are more likely to drop out. This increase in dropout rates is mainly due to the lower supply of secondary schools in rural areas (Lavado and Gallegos 2005; Alcázar 2009), forcing rural children to travel farther to continue their education beyond primary school. Thus, the density of children on the margin between continuing their schooling and dropping out is largest around these ages. Primary education in Peru ends with grade 6. Therefore, after finishing primary school, children tend to drop out. This occurs right after primary or at the beginning of secondary education. Figure A1a shows a histogram of education attainment using 2007 Demographic Census Data. We can see a jump in grade six, indicating that most of the individuals drop out after grade 6. This result is also confirmed with data from the ENAHO household surveys, showing that dropout peaks after individuals finished grade 6 (see Figure A1b). We thus observe a decline in enrollment in secondary schools. Figure A1c shows the age distribution in the transition between primary and secondary education. More than 90% of students in this transition are between 11 and 14 years old. Therefore, shocks to the opportunity cost of schooling at these ages will induce a particularly large number of children at these ages to leave school and participate fully in the labor market.[20] Section 5.1 confirms this conjecture by showing that child labor increases the most after shocks to the opportunity cost of schooling at these ages and that school dropout increases in the transition.

Second, from the demand side, the cocaine production process and labor demand at each stage also help to explain the ages of exposure. Cocaine production primarily involves three phases: the collection of coca leaves, the transformation of coca into cocaine paste, and transportation.[21] Children and adolescents are an important input in every stage. While young children may only pick the coca leaves, older children may also become involved with the transformation of coca into cocaine paste and transportation.

Children are ideally suited for picking coca leaves, a low-skill process. Most of the cited rea-

[20] Previous research has also shown that exposure to adverse events during the transition between primary and secondary school can have long-term effects on years of schooling (Shah and Steinberg 2017).

[21] Given that in coca producing areas there is also the processing of cocaine paste and cocaine, for the rest of the paper, I use the terms drug, coca, and cocaine interchangeably.

sons for the use of children in the cocaine industry has to do with the production function in the first stages and the sector's organization. Since harvesting coca requires relatively low-skilled workers and the plants grow close to the ground, young children are well suited for collecting coca leaves. Moreover, the farming of coca is very labor-intensive. Harvests of coca can occur up to 6 times a year and at different times of the year, which means that children can be working all year in the coca fields.[22] On some occasions, children work from 4 am to 4 pm, overlapping with school hours (usually 7 am to 1 pm). The harvest of an average size farm results in about 125 kg of coca leaves, but only 0.3 kg of processed cocaine. Given that Peru produces 300 to 400 tons of cocaine annually, coca farming in Peru demands a large amount of child labor. Consequently, working for the cocaine industry can have negative consequences on children's schooling. If children are in school in addition to picking coca, the long hours in the field likely affects their school performance.

Another reason for the use of children has to do with the organization of the business. Unlike big Colombian cartels, the drug trade in Peru mostly consists of family firms that control all production stages. Since a high level of trust is necessary, they rely on family and friends networks. Moreover, the higher-level individuals who control the organizations are often men who started when they were children as coca farmers and worked their way up the hierarchy. This organizational structure reduces the risks of being caught (Balbierz 2015; Beriain 2014; Pachico 2012; Van Dun 2012).

While young children often pick coca leaves, older children are also exposed to other stages of the production process. Once coca leaves are collected, the leaves are dried and manually crushed in maceration pits. The leaves are then processed into cocaine and transported. Older children often transport coca leaves to the maceration pits, exposing them to other stages of production. This exposure may be one reason why they start a criminal career in the drug trade. There is anecdotal evidence that as children grow older, they become involved in all of these stages of the production process.[23] For instance, during my fieldwork, one participant involved in the industry stated that: "A child that grows up in a coca valley [in rural Peru] will follow an employment

[22] Given that each plot can be harvested at different moments multiple times, even within a village we can find harvests almost all year. According to UNODC (2004), the number of harvests per year depends on the terrain's slope, the plants' age, and fertilizers. Thus, while in legal coca districts, the use of fertilizers is minimal and there are only 3 to 4 harvests per year, in illegal coca districts, the intensive use of fertilizers and the higher plant density ensure 4 to 6 harvests per year. Furthermore, the harvest periods are related to the climatic conditions of the district. In general, the first harvest occurs between February and March, the period of highest rainfall. The second harvest takes place 3 to 4 months later, i.e., between May and June. The third harvest takes place between August and September, and the fourth and additional harvests, between November and December. In addition, other sources highlight that given that the same plot can be harvested multiple times, there are no specific months for a harvest to occur. Indeed, data from 2010 shows that the harvest of coca can occur in any month (UNODC 2011). Moreover, each family owns several coca plots, which they also harvest at different moments during the year. This pattern of production suggests that even within a family, a child can be working all year in coca.

[23] Several local and international newspapers have documented that young children in these areas often work in coca fields, while teenagers are involved in production and narco-trafficking. See, for instance, "Children are the workforce in coca fields in Peru," El Comercio, February 5, 2007. Another article notes that "Peru now produces more cocaine than any other country. But there is no easy way to smuggle it out, so traffickers hire young men to carry it on foot [...] It's one of the most perilous jobs in the cocaine industry" (Pressly 2015).

cycle in the drug industry: first picking coca leaves, then transforming into cocaine, and then transporting drugs. It wouldn't be unusual that this early start in the business leads him to be a drug trafficker or sicario (hit-man)." Similarly, a 21-year-old man said, "I started working in coca farms when I was 8, and since I knew all of the people in the business, I was hired to work in the maceration pits."

Even though I do not have data on the type of activities per each age group in the cocaine industry, several pieces of qualitative evidence presented in Appendix F suggest this division of labor. Descriptive evidence from the field from ethnographers and media shows that younger children tend to work in coca collection and older ones in the other stages of production. Further, some sources indicate that there is a high demand for children because they cannot be legally prosecuted (Gastelumendi 2010; Mejía Fritsch 2003).[24]

Moreover, I went to the field in Peru in January 2020 to interview 109 participants in the coca industry. I asked at which grade individuals dropped out of school and what their main activity was at different ages of childhood. From all participants, 40% dropped out from school in the transition between primary and secondary education. If we only consider those participants that at some point were in the illegal parts of the business (transforming and transporting), this percentage goes up to 59%. In terms of the activities, 90% of participants started mainly collecting coca leaves and studying between the ages of 6 and 10. At the ages 11 to 14, 45% of participants reported doing other activities such as transforming coca into cocaine and transporting. Moreover, if I restrict the analysis to those that dropout from school in the transition between primary and secondary education, this percentage goes up to 90%. Although this is mainly qualitative, it helps to show the intensity of labor at different ages, given that the younger ones were combining school with only collecting coca leaves.

Appendix F also presents some quotes from the field that convey a sense of the employment cycle in the cocaine industry. A majority of primary school children interviewed during my field visits expressed that they spend a significant part of their time in coca fields . Also, teachers stated that older students were very attracted by potential high earnings in the cocaine industry. "When I started working as a teacher, the returns to coca were so high that many children between the ages of 13 and 14 stopped studying because they preferred to be fully involved in the cocaine economy."

In conclusion, 11 to 14 are "key exposure ages," since primary education ends while demand for labor in the cocaine industry increases at these ages. On the one hand, I expect changes in coca prices to affect young children in the intensive margin only by reducing their school performance, since they tend to be enrolled at schools and combine school with coca collection. On the other hand, I expect changes in coca prices to have a particularly pronounced effect on the future crimi-

[24]Children can be legally prosecuted when they are over 14 years old. Moreover, a testimony in the media of an ex-sicario [former hit-man] who worked in drug trafficking in Peru confirms this view: "In general, young people are chosen to be sicarios because they can go unnoticed and are easily manipulable to do the work. Moreover, even if they are caught, they can only send them to a juvenile detention center for only a 6-year period for being a murderer" (VICE 2015).

nality of cohorts aged 11-14 since these are the ages where children tend to drop out of school and thoroughly participate in the cocaine industry. Section 5.2 confirms this conjecture by analyzing how changes in coca prices affect future criminality at other ages of exposure.

3 Data

This paper makes use of four main datasets that provide variation across geographic regions and time at different levels of aggregation for a variety of labor market, schooling, and crime outcomes. The first two datasets–time-series and agriculture data– provide the tools to construct the main treatment variable. Time variation comes from changes in the black market price of coca induced by eradication policies in Colombia. I interact the time-series variation with measures of whether districts are suitable for growing coca. Alternatively, for precisely geocoded outcomes, I use data from satellite images that indicate whether a village/school is located near a coca farm and thus affected by the drug industry. The household and school-level data provide information on labor and schooling outcomes. Finally, the incarceration dataset allows me to explore whether young individuals exposed to high coca prices during childhood are more likely to be involved in criminal activities when they are adults.

3.1 Agriculture Data

The geographic variation in coca suitability that defines the treatment group is drawn from two sources: the Agriculture Census at the district level and geocoded satellite data on coca density. Having the treatment defined at different levels of aggregation is useful since the labor and school outcomes are also measured at varying levels of aggregation (district and school level). Furthermore, since the geographical measures of coca specialization are defined before the expansion of Peru's coca industry, they do not reflect potentially endogenous production efforts correlated with the main outcomes over the period of analysis.

I use the Agriculture Census of 1994 to define historical coca production by the number of planted hectares of coca per district. Since districts are the lowest level of disaggregation in the Agriculture Census of 1994, I also use coca density maps for the period 2002 to 2013 from the United Nations Office of Drugs and Crime (UNODC). Around 1999, the UNODC started the Illicit Crop Monitoring Programme, which uses annual satellite images to obtain the location of coca fields in Peru. The photos are verified by flying over randomly chosen areas each year. The UNODC gives the satellite images in categories that range from zero to five. The categories reflect coca intensity as follows: category zero indicates no coca, one indicates 0.1 to 1 ha of coca per km^2, two indicates 1.1 to 2 ha/km^2, three indicates 2.1 to 4 ha/km^2, four indicates 4.1 to 8 ha/km^2, and five indicates more than 8 ha/km^2. The UNODC data allows me to perform a more disaggregated analysis for geocoded schooling outcomes and for a subsample of incarcerated individuals for which I can obtain geocoded information on the location of birth. In addition, these data also allow me to confirm that districts that were already producing coca in 1994 are also where coca crops expanded during the 2000s.

Figure 2 shows the coca satellite images during the 2000s. Most coca production was located in districts that also produced coca in 1994. This suggests that 1994 coca production is a good proxy for the areas that saw expansion during the 2000s. Panel (c) presents coca crops' evolution in one of the main coca basins from 2002 to 2013, showing how crops expanded during the period when prices increased.

To rule out the possibility that results are driven by endogenous factors that may affect the outcomes of interest, I construct a coca agro-ecological index that shows which areas have ideal agro-ecological conditions to produce coca. I use information from the FAO Eco Crop and Henman (1978), which report ideal ranges for precipitation, temperature, slope, altitude, and soil conditions.[25] Appendix E shows the areas using this definition. Most of the areas that were producing coca in 1994 are suitable to produce coca according to this index.

In addition, to further compare my coca estimates with other commodities, I obtained data on mineral gold deposits per district in the 1970s from the United States Geological Survey's Mineral Resource Database and data on other crops (i.e., coffee, sugar, cacao, and cotton) suitability from the FAO's Global Agro-ecological Zones (GAEZ). These suitability indexes are constructed from models that combine climate data (e.g., rainfall and temperature) and soil characteristics (e.g., water supply) with crops characteristics to generate raster data of the suitability of 53 crops at a 5 arc-minutes resolution conditional on the input level for the 1961-1990 period.

3.2 Time Series Data

The other identifying source of variation comes from changes in the price of coca over time. The UNODC program has recorded information on coca prices in the black market since 1990. The data is collected once a month by project staff through semi-structured interviews with informants who are selected from coca farmers, grocers, and people involved in the production and distribution of coca derivatives. Figure 3 shows that during the expansion of the drugs industry in Peru in the 2000s, coca prices doubled.

The prices reported by UNODC represent the price of coca on the international market. After 1994, prices decline due to the effective U.S-supported air interdiction, in which the main air bridge used to send coca paste from Peru to Colombia was disrupted. In 1999, Plan Colombia decreased coca production and increased cocaine seizures in Colombia. I use data on the number of coca hectares in Colombia provided by the Colombia Ministry of Defense to instrument for coca prices.

[25] Most of the geographical data required to construct the coca suitability index is available at the 30 arc-second resolution (an area around $1km^2$) in the FAO Map Catalog. For the temperature information, I use historical data (1970-2000) available from `https://www.worldclim.org` at the same agreggation level, 30 arc-second resolution. I create $1km^2$ grids all around the Peruvian territory, and using both source of data I create indicator variables for each category that takes the value of one if the $1km^2$ grid agro-ecological condition is within the optimal interval. Then I define a suitability index that takes values between 1 and 6 depending on how many of the agro-ecological indicators are true in the corresponding grid.

Finally, I obtained data on the international prices for other commodities from the World Bank Global Economic Monitor Commodities Database. The volume of gold exports was obtained from United Nations Statistical Division (COMTRADE).

3.3 Household Data

I examine the effects on child labor using household data from the Peruvian National Household Survey (ENAHO) and the Peruvian Living Standards Measurement Survey (PLSMS) for the years 1994, 1997 and the period from 2001 to 2013. Both surveys are nationally representative.[26] My final sample consists of 416,163 individual observations distributed across district-years. Table A1 shows summary statistics. Child labor is defined using the main activity reported in the last week by children between 6 and 14 years of age. Nationally, about 30% of children are working.[27]

There are two main limitations with this data that are worth discussing. First, there could be reporting bias in the child labor measure. This could generate attenuation bias, and my estimates would be a lower bound if affected children are less likely to report their labor due to the changes in prices. Second, I am not able to know if the child is particularly working in coca. To deal with these concerns, I complement this data with school data, which is not reported by children or their families but by teachers and school principals. Moreover, since the school data are geocoded at a high resolution, I can link each school to a coca field and have a very fine measure to analyze how coca production affected children. In addition, I compare the findings with shocks to other commodities that may also increase child labor and explore heterogeneity by age bins based on the discussion presented in Section 2.2.

3.4 School Data

The school data I use are geocoded and cover the universe of schools in Peru from 1998 to 2013. The geographic coordinates allow me to combine these data with satellite image data on coca production location, allowing for an analysis at the most disaggregated level. Using a similar identification strategy as for labor market outcomes, I can examine the effect of coca production on school outcomes. However, unlike labor market outcomes, the disaggregated data allows me to explore the impact within each district-year.

The schooling datasets I use are the School Censuses (Censo Escolar, CE) and Census Evaluation of Students (Evaluacion Censal de Estudiantes, ECE). The school data contain not only information on dropout rates, but also measures of school achievement such as age for grade, and grade repetition. About 25% of schools do not report dropout rates, while about 5% do not report grade repetition measures. I complement these data with the Census Evaluation, a national standardized test administered every year since 2007 to all students in second grade in all primary schools. Figure 5 shows the distribution of schools across Peru. Of the approximately 50,000

[26] I use household data since it is the most precise source of information on child and adult labor outcomes in Peru.

[27] I also use data from the National Institute of Statistics (INEI) for baseline characteristics at the district level, such as malnutrition rates, and the fraction of households exposed to violence during the civil conflict in the 1980s.

primary and secondary schools in Peru, about 8,000 are located in coca-growing districts.

3.5 Incarceration Data

In order to examine whether children exposed to illegal labor markets are more likely to engage in crime as adults, I use confidential data on the universe of individuals in prison in 2015 from the *Instituto Nacional Penitenciario* in Peru. These data allow me to track cohorts that were exposed to high coca prices during key ages across different areas with different coca suitability. I exploit variation in place of birth and date of birth to explore how childhood exposure to the drug industry affects criminal behavior in later life. I complement these data with a census of the incarcerated population from the first quarter of 2016, which contains additional information about prisoners' social and family environment. I use this information to characterize the individuals that were affected by the shock.

This dataset contains 77,244 individuals incarcerated in Peru between the ages of 18 and 60 in 2015 (Figure A2 presents the age of arrest distribution). It contains information about their exact district and date of birth, their education, type of crime, year of arrest, and main occupation. About 60% of offenders did not complete secondary education. The percentage increases to 66% for offenders born in coca areas. The most common stated previous occupation of offenders is manual workers. However, about 35% of offenders born in coca areas were previously agricultural workers.[28]

From this sample, I keep the individuals who were born in Peru and for whom I can construct a complete history of coca prices during childhood (individuals aged 18-30). The final sample contains 29,151 individuals. I collapse these to the cohort and place of birth level. There are 4.8 offenders per cohort-district-of-birth-cell on average. As a robustness check, I also construct a sample at the cohort-village-of-birth level.

From the incarceration data, I construct the number of crimes by type, cohort, and district of birth. Cohorts in districts that do not appear in the incarceration data take a value of zero, which means that there is no one in prison from that cohort in that specific district. I construct incarceration rates by dividing the number of offenders by the number of people born per district and cohort. On average, there are 3.4 offenders per 1,000 people (see Table A1); in coca areas, it is almost twice as high.

4 Empirical Strategy

4.1 Econometric Specification for the Short-Term Analysis

In this section, I present the identification strategy to estimate the causal effect of coca production on short-run labor market and education outcomes. It exploits plausibly exogenous variation in prices and geographic coca suitability.

[28] About 5,500 individuals do not report information on place of birth and age.

In order to estimate the causal effect of cocaine production on education and child labor, I would ideally use data on who is producing cocaine. Unfortunately, these data are unavailable since cocaine production is an illegal industry. Moreover, I do not have information on coca production by year.[29] As an indirect way to measure the effects of cocaine production, I combine a difference-in-difference strategy with an instrumental variables approach. First, I exploit geographic variation in coca suitability, defined by whether a district historically produced coca or whether a school is located in an area that has coca farms, as identified from satellite images. Second, I exploit exogenous time variation in coca prices induced by anti-drug policies in Colombia.

To estimate the effects of the drugs industry's expansion on child labor, I use a linear probability model in which the outcome is an indicator of whether the individual was working the week before the survey. The treatment variable is the price of coca on the black market interacted with a coca suitability measure indicating the number of hectares of coca in the district in 1994. I further interact the main treatment shock by age categories to analyze if the ages 11-14 are affected the most following the qualitative evidence presented in Section 2.2. Finally, since Peru is a major coca producer and local dynamics may affect the prevailing price, I instrument the coca price in Peru with the number of hectares dedicated to coca in Colombia.

Equation 1 presents the baseline specification:

$$Y_{i,d,t} = \beta_0 \underbrace{(\mathit{PriceCoca}_t \times \mathit{Coca}_d)}_{PriceShock_{d,t}} + \sum_k \beta_k Age_k \times \underbrace{(\mathit{PriceCoca}_t \times \mathit{Coca}_d)}_{PriceShock_{d,t}} + \alpha_d + \phi_t + \sigma_r t + X_{i,d,t} + \epsilon_{i,d,t} \tag{1}$$

where $Y_{i,d,t}$ is a dummy indicating whether the child in household i in district d in year t reported working as the main activity last week. Coca_d is a measure of coca suitability for district d, which is defined by the number of coca hectares in thousands in district d in 1994 before the Colombian shock. $\mathit{PriceCoca}_t$ is the instrumented log price of coca in Peru in year t during the period 1994-2013. It is instrumented by the log of the number of coca hectares in Colombia (per 100,000) in that year. Age_k are dummy variables per each age bin k (6-10, 11-14, and 15-18). These age categories correspond to the ages children can attend primary schooling (6-10), the transition ages when children tend to drop out of school (11-14), and the ages in the last years of secondary schooling (15-18). The omitted age category is 19-21. The coefficient of interest is β_{11-14} which is the marginal effect of experiencing a boom in coca prices at the ages of transition between primary and secondary education and when the demand for child labor in the illegal part of business is the highest. The α_d are district fixed effect, and ϕ_t year fixed effects. By including these fixed effects, I control for invariant differences between coca and non-coca producing districts, and for changes in aggregate time trends across years. The regressors $\mathit{PriceCoca}_t$ and Coca_d are collinear to the year and district fixed effects. $X_{i,d,t}$ controls for poverty and age.

This strategy is similar to the standard difference-in-difference model, where the estimates

[29] This data is only available from the UNODC for the years 2010-2014.

compare low and high suitability areas, in years following high coca prices relative to years with low coca prices. The main difference is that the treatment is a continuous variable since both the cross-sectional variation and time variations are continuous.[30]

To test how the drug industry affects schooling outcomes, taking advantage of the fact that schools are geocoded, I interact $PriceCoca_t$ with a more disaggregated measure of treatment. In particular, I redefine the main treatment at the school level by linking each geocoded school to the geocoded data on coca geographic cells from satellite images in 2002. Thus, I am able to classify each school based on the coca intensity in the surrounding area. This is more precise than estimation at the district level. Specifically, I replace $Coca_d$ with $DenCoca_s$, the measure from UNODC which ranges from zero to five (with five indicating the highest coca intensity) and estimate the following specification:

$$Y_{s,t} = \beta_k \underbrace{(PriceCoca_t \times DenCoca_s)}_{PriceShocks_{s,t}} + \alpha_s + \phi_t + \sigma_r t + \epsilon_{s,t} \tag{2}$$

where $Y_{s,t}$ is the outcome of interest at the school and year level (e.g., the dropout rate). All specifications include school fixed effects α_s and year fixed effects ϕ_t. $\sigma_r t$ are department-by-year fixed effects to control for omitted variables that change over time within a department.[31] In particular, it controls for the fact that low-education departments may be catching up with high-education ones. Given that this data is not at the individual level but at the school level, I cannot interact the main treatment with age categories. Therefore, rather than providing interactions of different ages with the treatment variable, I estimate Equation 2 separately for grades corresponding to each relevant age bin k (6-10,11-14, and 15-18).

4.2 Econometric Specification for the Long-Term Analysis

In order to examine the long-term effects of the drug industry on criminality in a given district, I estimate the impact of high prices during childhood at relevant schooling ages on adult incarceration. Identification comes from coca price variation at different ages and coca suitability across districts of birth. I construct the full history of coca prices at different ages for each adult individual in the incarceration data. I exploit the fact that incarcerated individuals experienced different price trajectories, which allows me to exploit variation in prices across cohorts combined with variation in coca suitability at their district of birth. Figure A3 in the appendix shows how each cohort in the incarceration data experienced different trajectories of coca prices during childhood.[32] In this way, I assess whether changes in prices at ages 11 to 14 have a long-term impact

[30]This strategy is commonly used to estimate the effect of commodity shocks (e.g. Dube and Vargas 2013).

[31]Peru is divided into 25 departments. The inclusion of department-by-year fixed effects is relevant given that departments are in charge of the largest public investments, such as education, water, and electricity provision and infrastructure. As robustness, I also include department-specific time trends for the schooling and child labor outcomes to control for regional-specific time trends that departments have control over.

[32]For example, some cohorts experienced high coca prices at younger ages but then low prices at older ages while other cohorts experienced the opposite.

on adults who were born in districts with high coca suitability.

Equation 3 presents the baseline specification:

$$Y_{d,c} = \beta PriceShockAge11to14_{d,c} + \sum_k \beta_k \times PriceShockAge(k)_{d,c} + \alpha_d + \delta_c + \sigma_d c + \epsilon_{c,d} \quad (3)$$

where d indexes the district of birth and c the birth year. As explained in Section 2.2, the main explanatory variable is *PriceShockAge11to14*$_{d,c}$, which is the interaction between *Coca*$_d$ and the log average price of coca at ages 11-14. The set of control variables $PriceShockAge(k)_{d,c}$ are the interaction between *Coca*$_d$ and *PriceAge(k)*$_c$ the log price of coca at other childhood ages where k=0-5, 6-10, and 15-17.[33] The outcome of interest $Y_{d,c}$ is the crime propensity of individuals born in district d in year c conditional on the number of individuals born in that district-year. The term δ_c indicates year of birth fixed effects and controls for specific cohort effects. The term α_d indicates district of birth fixed effects and controls for time-invariant characteristics of the districts that may be correlated with both childhood exposure and future incarceration, including baseline *Coca*$_d$. Control variables at the district of birth level are not available for all years of birth. Therefore, to control for potential changes across districts of birth, I include district-specific cohort trends, $\sigma_d c$. District specific cohort trends account for the differential enforcement measures of each district through time. This is particularly important since districts can decide on security patrolling at the village level. Furthermore, this isolates the deviation in the outcome from the long-run trend in a given district of birth.

Given that part of the inference relays on spatial variations, I adjust standard errors for both spatial and serial correlation following Conley (1999) and Hsiang et al. (2011). In the spatial dimension, I use a radius of 100 kilometers (the median distance in the sample of districts) and in the temporal dimension, I assume an infinite location-specific serial correlation (i.e., 100,000 years).[34]

The parameter of interest is β, the effect of experiencing the boom in coca prices at ages 11 to 14, which is identified from variation in prices across districts and birth cohorts. Therefore, the control group is composed of those who were born in the same district but in a different year, and those who were born in a different district but belong to the same cohort.[35]

[33] In particular, given that the youngest individuals in the prison data are 18, I control for prices of coca up to age 17. Nevertheless as a robustness check, I also include as control variables, price shocks from early childhood to adulthood (ages 0 to 30). In this specification given that I do not observe future prices for individuals that are in prison, I impute zero for those cases. For example, if an individual aged 20 is in jail in 2015, prices shocks at the age of 21 onward are zero.

[34] In particular, I use the commands *acreg* (Colella et al. 2019) and *reg2hdfespatial* (Fetzer 2015) in Stata.

[35] For example, changes in $PriceShockAge11$ compares individuals born in high coca suitable areas that experience high coca prices at the age 11 against two groups: i) individuals of the same age that experience high coca prices at age 11 but were born in a low coca suitable area, and ii) individuals of different ages that were born in the same coca suitable area but experience low coca prices.

5 Results

5.1 The Short-Term Effects of Cocaine Production on Child Labor and Schooling

I present two sets of findings related to short-run outcomes. First, the increase in coca prices in Peru significantly increased child labor in coca suitable districts. As a consequence, test scores declined, and the probability of failing a grade for primary school children increased in these districts. Second, the relatively high earnings in the cocaine industry induced some secondary-school-age children to drop out (11-14 years old). Students finishing primary school and starting secondary school were particularly affected. All of these results are robust to the inclusion of baseline covariates interacted with year, department-by-year fixed effects, district-by-year fixed effects, coca district-specific time trends, household fixed effects, migration patterns, and using the agro-ecological coca suitability index. In addition, I provide evidence that child labor and schooling effects are mostly not driven by changes in violence, income effects, or the supply of education in affected areas.

5.1.1 Child labor

Effect of Childhood Exposure to Illegal Activities on Child labor— Figure 4 shows the fraction of children working in coca and non-coca districts across time using the raw data.[36] Two observations are relevant. First, in periods during which the cocaine industry expands in Peru (shown by the decline in Colombia), child labor increases, specially in areas suitable for coca production. This is the case at the beginning of the 1990s and during the 2000s. Second, while in 1997 child labor is at similar levels in coca and non-coca districts, after the 2000s, coca areas consistently have more children working.

Next, I turn to estimate the causal effect of coca prices on child labor following Equation 1. Table 1 presents the results. Higher coca prices increase labor participation among all age groups, but consistent with the qualitative evidence presented in Section 2.2, I find that results are significantly larger for those children who are 11 to 14 years old at the time of the shock, while this added effect dissipates after age 14.[37] To gauge the magnitude of the estimated coefficients, consider the rise in child labor associated with the increase in coca prices between the low point in 1997 and the peak in 2002. During this period, coca prices doubled. The estimates suggest that this increase in coca prices led to an 12 percentage point increase in child labor in coca suitable districts (i.e., with a suitability of 0.3) for those aged 11 to 14, compared to a roughly 7 percentage point increase in the other groups. This translates to an approximately 30% increase relative to the mean (= 12/37).

Exploiting the fact that results on child labor are concentrated in the ages 11-14, in Column (2) of Table 1, I compare siblings of different ages within households. Column (2) includes household

[36] Notice that for child labor, I only have data for 1994, 1997, and 2001 onwards. Thus, I cannot identify the effects between 1997 and 2001 year by year.

[37] Moreover, I can reject the null hypothesis that the estimate associated with 11-14 ages is equal to the other age bins.

fixed effects and still finds an increase in child labor for siblings who were 11 to 14 years of age compared to other ages.[38] This result provides evidence that results are not driven by differential time trends in coca districts. Any potential confounder needs to mimic the variation in coca prices and differentially affect children between 11 and 14 in high suitable coca districts. Moreover, the fact that the effects are robust to the inclusion of household fixed effects rules out any general impact due to changes in income at the household level not specific to the 11-14 age group.

Appendix B further addresses some potential concerns regarding differential changes across households and geographic areas such as shocks to other commodities, as well as the instrument's validity.

Other commodity shocks— Given that the period of analysis is characterized by a steep increase in commodity prices, in the Appendix in Table A2, I repeat the same analysis but controlling for changes in prices in other commodities such as cacao, coffee, sugar, cotton and gold.[39] To do so, for coffee, sugar, cotton and cacao, I interact each crop's international price with their suitability measures obtained from FAO as well as with age category variables. In the case of gold, I define the shock as the interaction of mineral gold deposits per district in the 1970s with international gold prices instrumented by gold exports of top producing countries. Conditional on changes in prices in coffee, cacao, sugar, cotton, and gold, I find that the magnitude and significance of an increase in coca prices on child labor do not change.[40]

Robustness Checks— Table A3 presents a series of robustness checks. First, Column (1) presents the results from a regression that includes all observations from the post period (2001-2013). Second, to control for changes in income at the household level, Column (2) controls for poverty. Third, to control for changes at the department level, Columns (3) and (4) include department-by-year fixed effects and department specific trends; results do not change.[41] Fourth, Column (5) controls for potential biases coming from differential trends in districts that have had more violence in the past due to the civil conflict, and that have worse child health outcomes. It includes interactions of year with time-invariant variables at the district level that are in general used to assign social programs such as the proportion of households exposed to violence during the civil conflict in the 1980s and childhood malnutrition. When I include all these covariates, the coefficient is similar to the baseline estimate and significant. Finally, results are also robust to the inclusion of time trends that differ across coca suitable districts in Column (6).

Instrument validity— Given that I use the number of coca hectares in Colombia as an instru-

[38]This specification includes only the households that have more than one child.

[39]Gold is an important commodity in Peru and children often work in gold production. Santos (2018) finds that the boom in international gold prices increased child labor in Colombia. For comparison, I also choose coffee, cacao, sugar and cotton since there is substantial variation across districts in their production, and there is exogenous variation across time in prices during the period of analysis.

[40]In the particular case of gold and coffee, I also find that when prices double child labor at ages 11 to 14 increased.

[41]Ideally, as robustness, I would like to include district-by-year fixed effects as I do with the schooling and incarceration data. However, one limitation with the child labor data is that I can only link individuals to their district of residence and not to lower levels of geography , as would be required in order to be able to include these type of fixed effects. Nevertheless, by including department-by-year fixed effects, I can control for most of public investments as in Peru, departments are in charge of the largest public investments, such as education, water, and electricity provision and infrastructure.

ment for prices, I also provide a formal test for the *relevance assumption* (Imbens and Angrist 1994) in Table A4. The Kleibergen and Paap F statistic is large, indicating that the weak instrument problem is not a concern. A second important assumption that must be satisfied for the validity of my identification strategy is the *exclusion restriction*. This could be violated if the local government in Peru increased the enforcement or resources in coca areas when Colombia increased its drug enforcement policies. To address this concern, Table A5 presents evidence that rules out a violation of the exclusion restriction for covariates such as a district's public income, taxes, and total transfers from the central to the district governments. The information on municipal income is available since 2001 and contains revenue information disaggregated by source of funding.[42] The table shows the estimates of a regression of the instrument on these variables and none of these variables are significantly affected due to the shock.

I also check whether eradication efforts in Peru are correlated with the eradication efforts in Colombia that form the basis of my identification strategy. I find a non-significant relationship over the analysis period, providing additional evidence that the exclusion restriction is valid (see Figure A4).[43] Table A6 in the Appendix also presents the reduced form results estimating the effect of an increase in Colombian coca hectares on child labor, and results are of a similar magnitude and significance. Another potential concern is whether the instrument has any effect on child labor before 2005, given that from Figure 4, it seems that there are no differences in child labor between coca and non-coca areas before 2005. Thus, I also analyze whether production in Colombia affects child labor in the first eight years of the price boom in Column (5), and I still find significant and larger effects on child labor for those years.[44]

Spillovers in control districts— In the main specification, I assume that only districts that produced coca in 1994 were suitable for coca in later years and responded to the changes in coca prices. One concern is that non-producing districts could have started producing coca after 1994 in response to booming prices during the 2000s. However, I observe that most of the satellite images showing coca crops are located in the districts that historically produced coca in 1994. More formally, I estimate the increase in hectares allotted to coca production from 2002 to 2012 based on an indicator for growing status in 1994. Results show a strong correlation between coca intensity in the 2000s and 1994 growing status. Cultivation grew by about 300 more hectares in the growing districts than elsewhere (see Table A7). None of the intercepts are significant (suggesting no significant growth in the districts with no initial coca). The results are in line with the intuition that areas with higher production in 1994 are suitable for coca and respond more to changes in coca

[42]The municipal income variables are obtained from the Integrated System of Financial Administration (SIAF) of the Ministry of Economy and Finance. The SIAF is a financial management application that municipalities use on a daily basis to program the use of their revenues and record their expenditures.

[43]Peru does not conduct aerial spraying eradication, only small-scale manual eradication. Moreover, most of the alternative development programs in Peru that sought to substitute coffee and cacao production for coca production were implemented at the very end of the period of analysis. I provide more qualitative evidence of this in the Appendix (Section C.1).

[44]In addition, to understand if the link between production in Colombia and Peru is weaker after 2005, I have checked separately for weak instrument indications in the period before 2005, and I do not find evidence of this. The F-statistics are very similar.

prices induced by Colombian shocks.[45]

Coca agro-ecological index– To address the potential endogeneity of coca production in 1994, Table A27 in Appendix E presents results in which the coca agro-ecological index is interacted with log coca prices instead. Column (1) presents the total effect at ages 11 to 14 controlling for price shocks at the other ages. Results are similar to using 1994 coca production.

In sum, the child labor patterns are consistent with qualitative evidence presented in Section 2.2. I observe large effects, especially for children between 11 and 14 years old when coca prices increase. One limitation is that I cannot observe whether children that increased their labor participation belong to families growing coca. The next section attempts to address this concern by using geocoded school data that allows me to link a particular school to a coca field. Another limitation is that I cannot observe whether individuals switch between sectors. However, I do not find evidence of a decline in the production of other cash commodities, such as coffee and cacao during the period of analysis.[46] This is likely because when the returns to the illegal industry increase, farmers who have historically produced coca or have relatives in the business are most affected. Therefore, most of the changes are at the intensive margin; when prices increase, districts that historically produced coca are the ones that expand production, and within these districts existing coca farmers increase production.

5.1.2 Schooling

Effect of Childhood Exposure to Illegal Activities on Human Capital— In line with the evidence presented in Section 2.2 and in the previous section that shows differential effects on child labor by age, I start by analyzing the effect on dropout rates and school achievement for different levels of education: primary school (ages 6-10), the transition between primary and secondary education (ages 11-14), and last years of secondary education (ages 15-18).

Table 2 presents the results. Panel (A) presents the effects on the dropout rate and shows that the probability of dropping out of school increases for those students aged 11-14 and decreases once students move to higher grades. For schools located in areas that have between 2 to 4 ha of coca per km^2, the increase in coca prices during the period of analysis led to a 26% increase in dropout rates (=0.021/0.08). These results are consistent with census data presented in Section 2.2, showing that most dropouts occur when children enter secondary education as well as with the results on child labor, showing that child labor increases the most at the ages 11-14. Therefore, this result suggests that individuals in the transition between primary and secondary education are dropping out to work full time in the illegal section, and potentially in other stages of production as well, namely transforming coca into cocaine and drug trafficking.

[45] I also check whether the districts that first responded to the increase in prices are those closer to the Colombian frontier and find that it is not the case. This may be due to the lack of soil suitability in Peruvian districts close to Colombia. However, these areas started producing in recent years due to better technology developed by Colombian producers that allowed them to produce coca at lower altitudes.

[46] These results are available upon request. In particular, I estimate whether coca and coffee production increased from 1994 to 2012 in coca suitable districts.

Next, I analyze whether school achievement measures are affected by the increase in coca prices. Panels (B) and (C) in Table 2 present the results. For primary school students, the increase in coca prices during the period of analysis led to a 34% increase in the proportion of students with higher age for the grade, and a 24% increase in the probability of failing compared to the baseline levels. I find no effects for older students that are in the transition between primary and secondary school, nor for students in the last years of secondary education. In the Appendix, I also study whether students are affected in the national exam and I find that children in the second grade seem to exhibit lower scores in math (Table A8). These results suggest that younger children working in coca fields are technically enrolled, but they are spending less time studying.[47]

Robustness Checks— Section B.5 in the Appendix presents several robustness checks. To control for changes in expenditures in education that are decided at the department level, Table A9 adds department time trends (Columns (1)-(3)) and further includes department-by-year fixed effects as well as school covariates (Columns (4)-(6)). In particular, I control for the number of classrooms at the school, the distance of the school to the capital and whether the school has access to basic services. The estimates are robust to all these specifications. Moreover, the magnitude of the effects does not change.

Table A10 add time trends specific to coca-suitable areas, and year effects interacted with baseline characteristics such as malnutrition and proportion of villages affected by violence in the 1980s to the model. Columns (1)-(3) show that results do not change. Columns (4)-(6) in Table A10 implement a more demanding comparison by controlling for district-by-year fixed effects. Since the school data are geocoded, I am able to conduct analysis at a much finer level than district by linking schools to the coca satellite images (which are also at a finer level than district) and compare schools within the same district. The identification assumption in the baseline model is that schools in high-density coca areas would otherwise have changed similarly, on average, to those control schools in low or no-coca geographic cells (identified by satellite images). By controlling for district-by-year fixed effects, the identification assumption is that affected schools would otherwise have changed similarly, on average, to control schools within their same district. This specification controls for any characteristic that may vary at the district and year level. I find that results are qualitatively similar with the exception of the probability of failing the grade. For dropout rate, I find that results are similar in significance and larger in magnitude.[48] These results

[47]Notice that this exam is only taken by students in the second grade. Thus, I also analyzed whether children in the second grade (7-9 years old) increase their labor supply. I find an increase of 20% on child labor for children at these ages (coefficients not reported here), which is similar to the increase in child labor for the 6-10 years old. Table 1 shows that when prices double, child labor at the ages 6 to 10 increases by 8 percentage points in coca suitable districts, which is equivalent to a 22% increase relative to the mean of 0.37. This provides further evidence that children at these ages are also combining work and studying, affecting their school performance. Further, the fact that there is no effect on their dropout rate suggests that the results on school achievement are not biased by the selection of particular students taking the exams.

[48]The smaller effects on achievement can be explained by the fact that for coca collection, farmers may also hire children from nearby villages. Thus, children in the control group that are in the same district but in a village with no- or low-coca suitability can be working in coca farms, implying that when we compare schooling outcomes of children that are in coca villages versus children that are in nearby villages, the effects are smaller than when comparing across districts. However, this may not happen for older children working at higher stages of the production chain since

rule out the possibility that schooling effects are driven by any changes over time at the district level, such as an increase in corruption or violence. Finally, given that coca production can be endogenous, in Appendix E I check the robustness of the results by replacing the main treatment variable by the coca agro-ecological index. It shows that results are qualitatively similar.

Taken together, these results show that the expansion of the drug industry in Peru had a large negative impact on children's schooling in coca districts relative to districts with little or no coca. I argue that one of the main mechanisms driving the schooling results is through participation in the drug industry. The dropout results are concentrated among those aged 11 to 14, which are the ages when child labor increases the most. I find no effects for children younger than 10 and older than 15. Moreover, even within districts, effects are larger for schools located in high-intensity coca cells, providing additional evidence for the child labor channel. Regression results are consistent with the qualitative evidence: younger children (6-10) are harvesting coca leaves and attending school less often, or reducing their school effort. Older children (11-14) are likely to be involved in other parts of the cocaine industry, including production and transportation. The results suggest that these are the students who drop out of school entirely to be part of the illegal stages of the business.

5.1.3 Other Potential Mechanisms behind Child Labor and Schooling Results

In this section, I analyze whether child labor and schooling results can be explained by other mechanisms such as an increase in violence, migration, cocaine consumption, or changes in the supply of education. I find no evidence that these mechanisms play a significant role, which further suggests that the opportunity cost channel is the one driving the results.

Changes in violence— Another possible pathway through which the expansion of the cocaine industry could impact schooling is by increasing violence, affecting the returns to education.[49] To understand this mechanism, in Section C.1 in the Appendix, I present the following analysis. First, I study the effects of the high coca prices on short-run violence using different datasets and measures of crime, violence, number of criminal actors/cartels, police enforcement, and conflict. I find that violence and enforcement did not increase when coca prices increased. This result is consistent with previous theoretical and empirical literature (e.g., Kalyvas 2006; Snyder and Duran-Martinez 2009; Castillo and Kronick 2020; Mesquita 2020), which suggests that commodity booms in the illegal sector can have ambiguous effects on violence and conflict, depending on idiosyncratic characteristics of the country. I find that Peru resembles a case in which the literature suggests no increases in violence should be expected after the price shock due to the weak level of law enforcement and the lack of competition among armed groups by the time cocaine expanded in the 2000s. Second, as a robustness check and to guard against an increase in violence not captured by the data, I use the common finding in the literature that the long-term effects of violence

individuals tend to hire local children from the same village to work in the illegal part of the business.

[49] There is substantial evidence that exposure to violence may reduce human capital investment (e.g., Shaw and Gross 2008; Akresh and de Walque 2008; Akresh et al. 2017; Leon 2012; Duque 2019)

are concentrated in early childhood, whereas I find effects on 11 to 14 year-olds.

Changes in the supply of education— Changes in educational resources may be driving schooling results in the affected areas. For instance, it could be the case that teachers' attendance decreases or turnover rates increase, affecting student outcomes. While I do not have access to data on teacher attendance, the fact that I find differential effects by grade suggests that results are driven by changes in the behavior of specific cohorts and not to changes that would affect the entire school. To understand the possibility that teachers are directly affected by coca production, I also analyze whether there is a decrease in the number of teachers per school in Section C.2 in the Appendix. Table A16 presents the results and shows no effect. I draw similar conclusions in Column (2), where I look at the teachers' quality as measured by the number of teachers with a post-secondary degree.

Migration— Migration could bias my results if high coca prices alter the composition of out-migrants in high coca suitable areas for example, if higher coca prices in coca-suitable areas discourage criminals or individuals with low levels of education from migrating out. These migrating decisions would then change the pool via selection, leaving coca suitable areas with less educated individuals, even though the relevant cause was a migratory one and not a schooling/working decision. I address this concern in Section C.3 in the Appendix and find that contemporaneous coca prices did not affect migration patterns in coca-suitable districts. In addition, I find no evidence that negatively selected migrant families are explaining all the effects on child labor.

Other programs— Another potential concern is whether the Peruvian government increased the number of projects aimed at providing farmers alternative high-value crops to generate incentives to return to legal farming. If these programs were a response to the peaks in coca production, this could be an important factor driving the results. However, most of the alternative development programs were at a very small scale targeting a few farmers. In particular, there was only manual eradication affecting a few places, and most of these programs expanded after my period of analysis. Furthermore, these programs or any other government program aiming at mitigating the effect of price shocks would go against my results, thus implying that that my estimates are a lower bound.

5.2 The Long-Term Consequences of Early Participation in the Illegal Industry on Crime

Thus far, the analysis has focused on how the expansion of the cocaine industry affected children's short-run outcomes, but it may also affect long-run adult outcomes. Relative to those working in the legal sector, children who harvest coca leaves and participate in other illegal stages may be more likely to follow a criminal path later in life. In this section, I study the long-run effects of the drug industry on crime by examining the cohorts most affected by the increase in coca prices. I find that adult criminal behavior is significantly affected by exposure to the drug industry during childhood. Cohorts born in coca districts exposed to high prices between ages 11 and 14 are more likely to be incarcerated as adults. Comparing the effects with other commodities and exploiting variation in districts where coca production is legal, the results suggest the development of industry-specific human capital, namely criminal capital in the drug trade. I also discuss other relevant mechanisms, such as exposure to violence, differential enforcement, and selective migration.

5.2.1 Criminal Paths

Effect of Childhood Exposure to Illegal Activities on Criminal Behavior—I start by estimating the incarceration effects of being exposed to high coca prices at different ages of childhood. The dependent variable is the number of individuals in prison per cohort-district of birth divided by the population born in that cohort-district per 1000 individuals. Figure 6 shows that effects start increasing when children are exposed at age 11 and dissipate if exposed after age 14. These results are consistent with the previous child labor estimates showing that large and significant effects are concentrated between these ages. Also, it is at these ages when children drop out of school in Peru since they are in the transition between primary and secondary education.

Table 3 presents the results from estimating Equation 3. Column (1) shows that higher prices during the relevant ages lead to a statistically significant increase in the subsequent propensity for crime. A doubling of coca prices induces a 24% increase in the probability of incarceration for an individual who grew up in a coca district and experienced high coca prices at ages 11 to 14.[50] As price shocks are likely to be serially correlated, Column (2) includes other age bins in the same regression. Consistent with Figure 6, a rise in coca prices at the key ages of exposure (11-14) leads to the largest increase in future criminality. For example, higher coca prices at ages 6 to 10 increase future criminality by less than 10% for individuals born in a coca suitable district while price increases at ages 11 to 14 increase future criminality by more than 30%. Moreover, higher prices at other ages do not affect the probability of being incarcerated. The more pronounced effects at the ages of 11-14 are consistent with the maintained assumption that those ages are the critical ages of exposure for future criminality. In Column (3), I further control for price shocks at non-childhood ages, the same pattern is observed. While point estimates and standard errors increase since price shocks are serially correlated, I still find that higher coca prices at ages 11-14 increase future criminality.

One limitation of the incarceration data is that I cannot observe individuals who entered prison and were released before the beginning of my sample. This could bias my results if these individuals are not evenly distributed across treatment and control groups. To address this concern, however, Column (4) in Table 3 uses the length of the sentence as the dependent variable. The estimates are non-significant, suggesting that measuring the sample conditional on being in prison is a good proxy for the total number of convicted individuals in a given year.

Robustness Checks— Section B in the Appendix presents a series of additional analysis and ro-

[50] All magnitudes are calculated as the effects on incarceration of a doubling of the coca price for an average district with 0.3 coca hectares, relative to the average criminality (= 3.6*0.3/4.5).

bustness checks. In Table A11, I show the results for different samples.[51] Results are similar to previous results. In particular, there are larger effects for those who experienced high prices at the key ages of exposure 11-14. Moreover, higher prices at older ages do not affect the probability of being incarcerated, providing further evidence that results are driven by exposure prior to adolescence. In Table A11, I also study whether the effects of being exposed at the ages 11-14 dissipate by age at incarceration. I interact the main explanatory variable with (mutually exclusive) decade dummies indicating the current age of the cohorts. The interaction terms show that childhood exposure to the boom in coca prices not only increases an individual's chance of committing a crime as a young adult (in their early 20s) but also later in life (around 20-30s). However, I find no effects for those in their 30-40s.[52]

Table A12 presents a series of robustness checks. To control for the fact that incarceration may trend upward at different rates across Peru, Column (1) adds department-time fixed effects. It also controls for trends that may arise because younger cohorts have had less time to be arrested, and the degree of measurement error for younger cohorts may vary by department. In addition, since convictions of affected cohorts may be correlated with overall changes in policing in Peru, in Column (2), I control for year-of-arrest fixed effects.[53] Results are robust to these different specifications.[54]

Another related concern is that increased enforcement may be correlated with exposure to the variation in coca prices. I address this issue by comparing outcomes for individuals in different cohorts and different villages within coca districts. For the sub-sample of individuals with the village of birth information, I classify the treatment status of the village of birth using the geographic cells from the coca satellite images.[55] This more granular classification allows for the inclusion of district-by-year fixed effects in Column (3). I compare individuals who were born in the same district and year across villages with different coca density. This specification controls for any district-by-year-specific shocks to incarceration rates across districts, such as those resulting from changing enforcement at the district level. Individuals from a village located inside a coca geographic cell (identified by satellite images) who experienced high prices at key ages are 39% more likely to be incarcerated (=0.007/0.018).[56] Any potential confounder needs to mimic the evolution

[51] I separate the sample so that I have the same number of cohorts between young and old offenders and so that each sample has enough variation in prices. On the one hand, I have old offenders who were children in 1982 to 1999 and thus were affected by the first period of expansion of the drugs industry in Peru and also by the fall in prices from the shut down of the main air bridge. On the other hand, I have young offenders who were children from 1993 to 2009 and thus were affected by the fall in prices and the expansion induced by Colombian policies.

[52] These results are consistent with the evidence on age-crime curves in the criminology literature (Freeman 1999).

[53] Using the incarceration data, I construct a panel of arrests by year. I measure the probability of being incarcerated in a particular year, given that the individual was born in a coca district and experienced high coca prices at a particular age. For this specification, the data is aggregated so that there is one observation for each combination of the year, district of birth, and year of the arrest.

[54] While the estimates are smaller when including year of arrest fixed effects, the magnitude of the effects do not change when comparing relative to the average criminality in the offenders' district of birth in a given year. When coca prices double at key ages, individuals born in coca districts experience an increase in future criminality of about 24% (=0.3*0.129/0.159).

[55] The incarceration data from 2016 includes the village of birth information, but the 2015 data does not.

[56] Consistent with the dropout analysis, the estimates are larger when I compare individuals across villages rather

of coca prices and differentially affect villages within a district that have higher coca suitability. This result suggests that differences across districts over time that are not accounted for in the main specification are not important for explaining variation in incarceration rates.

Another potential concern is that individuals affected by the changes in coca prices could also be affected by civil conflict during childhood. Although the period of civil war in Peru is before my main period of analysis, it is possible that the oldest cohorts in the sample were affected during childhood. To account for this possibility, in Column (4), I control for the number of victims due to civil conflict per district per year of birth. The results are very similar. Finally, Column (5) controls for the average sentence length of the cohort; results do not change.

To account for potential endogeneity of coca producing areas, Appendix E presents the results using the coca agro-ecological index. This specification produces similar estimates: the increase in coca prices after eradication efforts in Colombia induces a 20% increase in future criminality for an individual who grew up in a district with an average agro-ecological suitability of 1.6.

5.2.2 Mechanisms behind the Criminal Paths

Next, I examine potential mechanisms driving these results by reviewing other outcomes as well as heterogeneous effects. While I cannot disentangle the exact mechanism, several pieces of evidence suggest that an increase in criminal capital related to working in the drug industry as a child could potentially explain the increase in future criminality.

Criminal capital— There are two main mechanisms that could be driving the effects on adult criminal activity: an increase in criminal capital, or a decrease in formal human capital. On the one hand, it could be the case that illegal labor market opportunities increase criminal exposure during childhood, and that these investments in industry-specific criminal capital increase the benefit of future involvement in the industry. This criminal capital may include violent skills as well as knowledge of how the industry works, obtained from interactions with individuals at various stages of cocaine production, or social capital, such as contacts with buyers. On the other hand, the results could also be explained by a reduction in schooling during childhood. As children drop out of school, they may have fewer opportunities and lower wages in the formal sector, increasing future involvement in crime.

To shed light on these mechanisms, Table 4 presents the results by type of crime. I find a positive significant effects on drug trafficking and violent crimes and no effects on other crimes. These results are consistent with the criminal capital channel. Children who start working in this industry at an early age are more likely to be involved in the drug trade later on, leading to incarceration for industry-specific crimes such as drug trafficking and murder. Moreover, in Table A19 in the Appendix, I further separate the results into homicides, white collar crimes and property crimes. I find no effects for the types of crime that are in general associated with a decline in formal human capital such as property crime. I do, however, find positive and significant effects

than districts since families hire very local people to work in the illegal part of the business.

for homicides.[57] When prices double, individuals born in a coca suitable district experience about a 30% increase in the probability of being involved in a homicide between the ages of 18 and 30. These results suggest that the effects of coca prices on future criminality are not driven by a general decline in formal human capital.[58]

Panel (B) in Table 4 presents the results for women. I find that affected women are more likely to be incarcerated for drug trafficking, but not other offenses. This is consistent with the qualitative evidence that women are primarily involved in the non-violent parts of the drug trade.[59] Moreover, I interpret the absence of an effect for other crimes as an indication that the correlation between childhood exposure and drug trafficking crimes is unlikely to be spuriously driven by omitted factors (unless such factors affect differentially more drug trafficking crimes than other crimes).[60]

Next, to further understand whether the effects are driven by an increase in criminal capital or just by a reduction in formal human capital, I exploit price shocks to other commodities that also increase child labor in similar magnitudes at the relevant ages 11-14, but are in the legal sector. First, I examine the differential effect for districts where most coca production goes to the legal industry.[61] In these districts, coca leaves are legally sold for medicinal and religious purposes.[62] Therefore, workers have no contact with the cocaine industry. However, the use of child labor in coca legal production is still very common. Moreover, price changes in coca in the legal sector follow similar trends as price changes in the illegal sector (see Figure A7 and Section C.4 in the Appendix, where I provide more details). Therefore, as child labor is also common in areas that produce coca for the legal sector, changes in coca prices may also increase child labor and dropout rates in these districts but may not affect future criminality as there is no illegal drug industry. I test this by interacting the shock with a dummy indicating whether the individual is from an area where coca is produced legally. In Panel (C) in Table 4, I find that individuals from these districts are less likely to be involved in drug-related crimes during adulthood. The entire effect on drug-related crimes is due to areas with illegal coca, not areas with legally grown coca. This provides further evidence that exposure to the cocaine industry, rather than coca production alone, leads

[57] Since it is an illegal activity, violence is still selectively used as a mean for enforcing contracts and for protection during large-scale cocaine transport operations.

[58] There is a consensus in the literature on crime and education regarding the sensitivity of property crime to education policies that encourage school completion. Further, an increase in educational attainment can also reduce violent crime, but this effect is not as robust as the reduction in property crime (Lochner and Moretti 2004; Machin et al. 2011; Hjalmarsson et al. 2015; Buonanno and Leonida 2009; Cano-Urbina and Lochner 2019; Anderson 2014; Jacob and Lefgren 2003; Luallen 2006). For an extensive review, see Lochner (2020).

[59] According to Van Dun (2012), while men are employed in large-scale operations as *traqueteros* (large-scale smugglers) and *sicarios* (bodyguards or hitmen), women work mainly in small-scale transport of cocaine as *mochileros* (small-scale smugglers). These *mochileros* receive a fixed payment for delivering small quantities of cocaine to a particular location within Peru or across an international border.

[60] For example, the existing literature studying the effects of exposure to violence and conflict during childhood on future criminality finds no effects for women (Couttenier et al. 2019; Sara 2020).

[61] These districts are located in the region of La Convencion and Lares, which has historically produced coca for traditional use. To sell to the legal sector, farmers have to be registered with government agencies. In general, prices for legal coca are much lower than prices paid by the illegal industry.

[62] Coca leaves are often consumed in teas or chewed directly.

to future criminality. Moreover, in Tables A20 and A21 I show that the increase in coca prices indeed increases child labor and dropout rates in districts that produced for the legal sector, but does not increase incarceration in adulthood, suggesting that the decline in formal human capital alone cannot explain future criminality.

Second, as further robustness, in Table 5, I control for price shocks to legal commodities such as coffee, cacao, sugar, cotton and gold. In particular, as shown in Section 5.1 child labor is sensitive to price changes in some of these commodities (see Table A2).[63] However, I find no evidence that early life participation in these sectors affects subsequent incarceration rates. This result provides further evidence that it is child labor in illegal activities that drives the crime results, rather than child labor alone. This suggests that children acquire industry-specific criminal capital when working in the illegal sector, but not in the legal sector.

One limitation of my analysis is that, so far, I cannot directly link incarcerated individuals to their child labor status, only indirectly through an aggregate analysis. Thus, to gain insight into whether individuals who are more likely to be incarcerated due to high coca prices during childhood (i.e., compliers) were the ones who were affected by child labor and schooling, I investigate the labor, schooling, and family characteristics of offenders. I can compute the proportion of compliers who have particular characteristics using two-stage least squares (in Section C.4 in the Appendix I provide the details for this estimation). The results for the characteristics of compliers can be found in Column (1) in Table A23. About 80% of those who were affected by the shock had less than a high school degree. I also repeat the analysis using an indicator for whether each offender's occupation was farming and find that about 60% of affected individuals declared farming as their main previous occupation. Finally, I analyze the compliers' family characteristics and childhood conditions. When comparing these proportions to the proportions in the actual population in Column (2), about 80% of compliers had participated in illicit activities before the age of 18, and 43% had at least one of their family or friends in prison. In the general population, those percentages are 50% and 31%, respectively. These results are in line with the previous short-term results showing that the most affected individuals were those whose schooling was also affected and had a farming background. Moreover, the fact that an overwhelming proportion of affected cohorts also participated in criminal activities before the age of 18 suggests that coca shocks put children on a criminal path and that adult criminality is likely related to criminal capital acquired during childhood.

Exposure to violence during childhood—Another potential mechanism could be the exposure to violence during childhood. It could be that children who grew up in a coca suitable district may also be more exposed to violence when coca prices increase, leading to future incarceration. Three pieces of evidence suggest that exposure to violence is not the main mechanism driving the results. First, as shown in Appendix C.1 I do not find evidence that violence or civil conflict increased in the short-term in these areas, suggesting that individuals were not exposed to significant changes in violence. Second, previous literature on exposure to violence shows that effects are concentrated

[63]Table A22 in Appendix C.4 also shows that the dropout rate is sensitive to price changes in gold.

in early childhood, whereas I find the effects predominantly on 11-14 years old children. Indeed, I explore whether there are effects in early childhood in Figure A6, and I find no effects. Third, based on the prior literature estimates of exposure to violence in Peru (Sara 2020), I would expect an increase in future criminality for children in primary schooling ages, and I found no effect at those ages.

Adult criminal exposure and enforcement— An alternative hypothesis is that adult outcomes are driven by adult exposure to illegal industries rather than exposure to them during childhood. However, in the previous section, I found that coca price changes at older ages (older than 15) do not predict future incarceration. Nevertheless, to explore this channel in detail, I examine individuals exposed to the illegal industry as children but who were incarcerated in non-coca districts as adults. In particular, I divide the sample between individuals who are in prisons in coca areas and individuals who are in prisons outside of these areas, as a proxy for where they lived as adults.[64] Table A24 shows that there are significant effects for individuals incarcerated outside of coca areas, implying that exposure during childhood affects adult criminality even if individuals are not exposed to the illegal sector as adults. This finding suggests that individuals bring their criminal capital with them when they migrate to areas that do not produce coca. Moreover, these results provide further evidence that the main effects are not driven by differential enforcement in coca areas.

Family selection process— These results could also be driven by unobserved characteristics of the families and children. For example, if a child is violent at school, the parents may decide to send him or her to work in the coca industry. Similarly, violent-type families may self-select to work in an illegal industry. It may therefore not always be the case that exposure to the cocaine industry was what made a child more criminal; rather, it could be the result of a process of self-selection. While I cannot fully rule out this potential mechanism, several pieces of evidence suggest that self-selection is not be the primary mechanism.

First, in the previous section, by comparing siblings, I showed that the effects on child labor are robust to the inclusion of household fixed effects, suggesting that family characteristics could not explain all the results. Second, in Section 2 of Appendix C.3, I find no evidence that poorly educated parents are driving the effects on child labor. Third, descriptive evidence suggests that a process of self-selection in families should not be a concern in the Peruvian context. In particular, parents in Peru do not associate child labor in the coca industry with exposure to violence. This is mainly conditioned by two factors. On one hand, coca production is still seen as part of indigenous tradition, even when families sell to the illegal drug trade. The fact that coca was originally cultivated solely for such traditional purposes as chewing, alternative medicine, and ritual ceremonies mitigates the negative connotation of coca's connection with drug trafficking. Moreover, the 1988 United Nations Convention against Illicit Traffic in Narcotics categorized all

[64]Unfortunately, there is no data available on the location where individuals were living when they were arrested. Thus, as a second-best method, I use the location of prisons as a proxy of where they lived when they were arrested. According to my conversations with officers from *Instituto Penitenciario* in Peru, when possible the location of imprisonment is usually close to where individuals were living before their arrest.

of these Peruvian activities as "traditional licit uses" (UNODC 1988). On the other hand, child labor in general in Peru is very common. According to the Peruvian Child Labor Survey (ETI), among households that reported having at least one child working, parents or guardians have a tolerant perception of child labor. About 45.5% of parents or guardians in rural areas believe that the ideal situation for children is that they combine work with school attendance (this can go up to 60% in coca-growing areas). Moreover, for 58% of parents or guardians, the main reason for children to work is to gain skills, make good use of time, and learn the family business (INEI 2015). Fourth, in the long-run analysis, since I am estimating the intention to treat based on year and district of birth exposure, family selection biases are less likely to play a role.

Other channels: general exposure, social preferences, and personality development—I have argued that criminal capital develops during childhood through direct participation in the drug industry and through interactions with other participants. However, it could also be the case that children acquire criminal capital even if they do not work in the drug industry (e.g., through peer effects or district exposure). Furthermore, it could also be that 11-to-14-year-old children who are affected by the coca shock are also affected by changes in their personality development at these ages affecting their probabilities of becoming a criminal, independently of working in coca.

While I cannot completely rule these mechanisms out, three pieces of evidence suggest that results are not merely driven by general exposure or changes in personality. First, since I find evidence of a long-term impact on crime for the ages 11 to 14, which are not the main ages when their preferences and attitudes are more susceptible to shocks, personality development is less likely to play a role in explaining the long-term effects on criminality.[65] Moreover, if changes in social preferences were driving the effects, we would also observe significant effects on other crimes. Second, the vast majority of affected individuals (i.e., compliers) state that they were involved in illegal activities before the age of 18 and report farming as their most recent occupation, suggesting that child labor could be an important mechanism. Third, even within a district-year, the effects are larger for individuals born in a high coca density cell than individuals born in low coca density cells in the same district. If it was only general exposure, it is more likely that all children in coca districts could be affected.

Differential mortality— Finally, to verify that results are not driven by differential mortality across cohorts and across regions with different degrees of coca suitability, I use homicide data from the police for the years 2011 and 2013.[66] These data contain information about the district of birth and age of the victim. I repeat the analysis in Equation 3 but replace the dependent variable with homicide victims per capita. Figure A8 presents the results. There is no differential effect by age and district of birth. I also analyze whether the size of the cohort changes, and I find no effect.

[65] Most of the literature in behavioral economics indicates the formation of pro-social preferences earlier on, before the age of 12, especially between 6 and 12 years (Alms et al. 2010; Bauer et al. 2014, 2018; Fehr et al. 2008, 2013; Harbaugh and Krause 2000). For instance, Bauer et al. (2014) examine the formation of other-related preferences among 4-to-12-year-olds. They find that children become significantly less selfish, less weakly spiteful, and more altruistic, in primary school ages (7-to-12-year-olds).

[66] These are the years in which there are available data.

6 Can Parental Incentives Mitigate the Effects on Child Labor, Drug Production and Crime?

So far, I have examined how the expansion of the drug industry in Peru affected children, leading to long-term consequences for adult criminality. In this section, I study how policy can address the underlying mechanisms that lead to future criminality by changing parental incentives. I exploit the differential rollout of a conditional cash transfer (CCT) program during the period of high coca prices. This second analysis helps further disentangle the mechanisms of the previous results (whether they are driven by human capital investments during childhood) and sheds light on the role of policy to mitigate the effects of illegal markets. These results have several potential implications. First, by increasing the opportunity cost of child labor, CCTs could increase the cost of production and thus decrease drug production. Second, even if there is substitution into adult labor, adults working in coca farms are less likely to engage in other stages of production and to start a criminal career in this industry.

6.1 Conditional Cash Transfers

In this section, I show that providing incentives for parents to send their children to school mitigates the effect of exposure to the illegal drug industry. In particular, the CCT program reduces child labor. I also provide suggestive evidence that the CCT reduces coca production and adult incarceration rates among children from coca areas who experienced high coca prices in childhood.

The CCT program consists of a monthly lump-sum payment of about 30 dollars and represents a 20% increase of the family income on average. This amount does not depend on the number of children in the household. The transfer is given to mothers conditional on their children having 85% school attendance, complete vaccinations, and pre- and post-natal care.

Figure 7 in panel (A) presents a map showing the rollout of the CCT program. There is substantial variation across districts and across years. By 2014, about 1,400 districts—covering 80% of the coca-growing districts—had CCTs. There were two large expansions in 2007 and then in 2012. The selection of districts was based on an index that includes poverty and the percentage of villages in the district affected by violence during civil conflict.

I start by estimating a version of Equation 1 including interactions with $CCT_{d,t}$, a dummy indicating whether the district d had a CCT in year t. Table 6 presents the results. I find that CCTs mitigate the effect of the price shock on child labor. Moreover, results are robust to controlling for trends in the selection index. This is consistent with previous analysis showing that results did not change when controlling for the variables included in this index, suggesting that the pre-trends assumption is satisfied. Nevertheless, using an event study analysis, I examine whether there are any pre-trends in Figure 7. The results support the validity of the identification strategy, showing an absence of a strong pre-trend and evidence of a trend break after the introduction of CCTs, decreasing child labor. This evidence suggests that potential confounders would have to mimic the timing of the CCTs' expansion extremely closely.[67] Next, I analyze whether this reduction in child labor led to a reduction in coca production. I use data on coca production from 2010 to 2014, the years for which data are available. Panel (C) in Figure 7 presents the event study estimates and shows that coca production decreases after the introduction of CCTs. I find that CCTs decreased coca production by 34%.[68]

In the Appendix, Table A25 presents the effect of CCTs on schooling outcomes. I find that the CCTs also mitigate the negative effects on schooling. Finally, I turn to incarceration outcomes. Only 3% of the incarceration sample was affected by both the coca shock and the CCTs during the relevant ages. Nevertheless, Table A26 suggests that incarceration effects are also mitigated when individuals have the CCTs during childhood.

These findings have several implications. On the one hand, they help to disentangle the mechanisms driving the previous estimates. If long-term effects were driven by other factors apart from child labor in the criminal sector, increasing the returns to schooling would not mitigate the effects. One the other hand, these results shed light on the role of policy. Policy makers can potentially solve some of the problems related to criminal involvement by incentivizing the development of formal human capital. Not only does this have implications for reducing coca production in the short run, but these policies could also reduce future criminality by putting individuals on a non-criminal path. Moreover, if we are willing to extrapolate what we have learned from the shock to coca prices, we have a few lessons for designing future policies such as CCT.[69] First, if CCTs work through the same incentives as price shocks, its effects are mainly due to changing relative incentives in the household, as opposed to changing income. That is, they work because they increase the opportunity cost of having children working in the field (i.e. increasing the present monetary value of education). Second, future policies that aim to decrease child labor or drug-related criminality should study which section of the population would be the most impacted by them. For example, in the Peruvian case under study, the best policy design might include not only direct incentives for education, as previously noted, but also target children ages 11-14 specifically in order to maximize impact-per-dollar.[70]

[67] In particular, I estimate:

$$Y_{i,d,t} = \alpha + \sum_{i=-4}^{5} \beta_i(\tau_{d,t} = i) + \alpha_d + \phi_t + \sigma_r t + \epsilon_{i,d,t} \tag{4}$$

where τ_{dt} denotes the event year, defined so that $\tau = 0$ for the year the CCT program started in that district, $\tau = 1$ for one year after the CCT started, and so on. For $\tau \leq -1$, households were untreated by the CCT. The coefficients are measured relative to the omitted coefficient ($\tau = -1$).

[68] On average, the CCT reduces the area in which coca is grown by 200 hectares. On average, districts were producing 600 hectares during this period. Given that I only have data on coca per year and district for the years with high coca prices, I cannot analyze whether effects are mitigated as with the other outcomes.

[69] Although I cannot disentangle the exact mechanism for which a CCT affects households' decisions, a CCT may act in a similar way as an increase in the price of coca at least from the point of view of economic incentives.

[70] Note that the analyzed policy did not have these objectives in mind when it was designed and implemented.

7 Conclusion

This paper provides evidence that childhood exposure to illegal markets leads to a substitution from formal human capital to criminal capital, putting children on a criminal life path. I contribute to the literature by showing that geographic conditions and returns in the illegal market can generate future criminality and perpetuate illegal industries, providing an explanation for the persistence of crime and violence in specific locations. I then provide evidence that these effects can be mitigated by changing parental incentives through conditional cash transfers that incentivize schooling.

I emphasize that there are large externalities associated with growing up in an area that specializes in illicit activities. The results suggest that in the long-term, exposure could lead to the formation of criminal groups. Though the situation in Peru is unique in some ways, there are many other examples of illegal labor markets which might have similar unintended consequences for children. For example, children are heavily involved in opium poppy cultivation in Afghanistan, and often recruited by armed groups funded by the heroin trade.[71] Similarly, in rural Mexico, there are reports that many children work in opium poppy fields rather than go to school. Although child labor is rare in developed countries, children may still be exposed to illegal industries, increasing their criminal capital and future propensity to commit crime. In the U.S., drug-related crime is geographically concentrated (e.g. urban Chicago is a hot-spot for heroin trafficking). It is possible that criminal capital plays an important role in this context as well.

In the last part of this paper, I focus on whether policy can mitigate the effects of exposure to illegal industries. If location-specific factors affect parental incentives to use child labor in the illegal market and thus create criminality, location-specific policies may be needed to target these incentives. I argue that policies like CCTs can decrease criminal capital and therefore future criminality, while only increasing enforcement against drug production directly may simply lead to production and criminality moving elsewhere, as happened when enforcement in Colombia increased production in Peru in this period.

Overall, this paper provides a first step at understanding how illegal labor markets function and criminality develops, motivating the use of policies that address the root causes of crime and illegal industries.

[71] See "The Opium Economy in Afghanistan," United Nations Office on Drugs and Crime, 2003.

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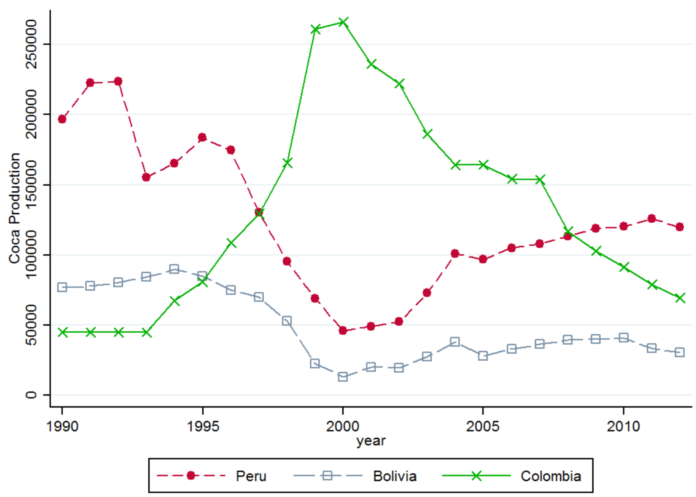
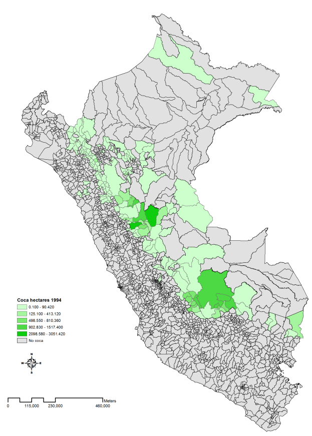
Figures and Tables

Figure 1: Coca production in the Andean region

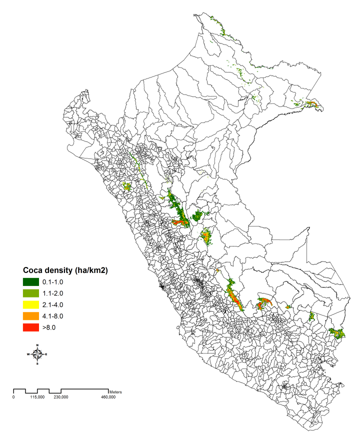


Notes: This graph shows coca production in tons per year in the Andean region using UNODC data.

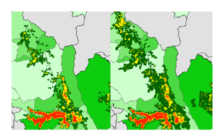
Figure 2: Geographical variation in coca production



(a) Coca production in 1994 across districts



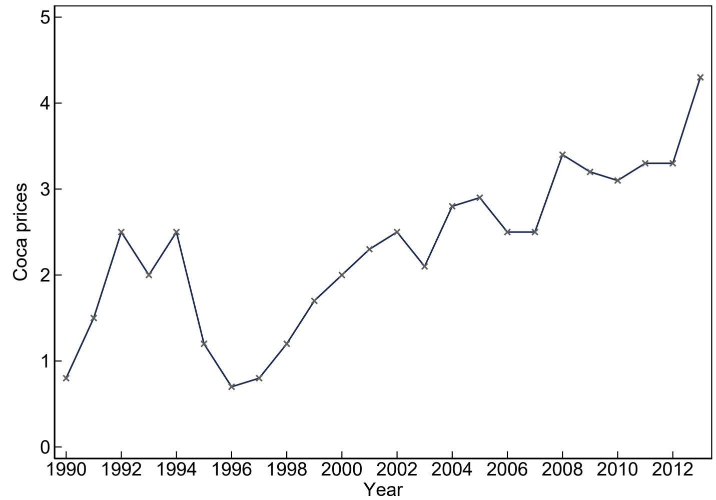
(b) Coca satellite images during the 2000s



(c) Alto Huallaga region in Peru in 2002 and 2013

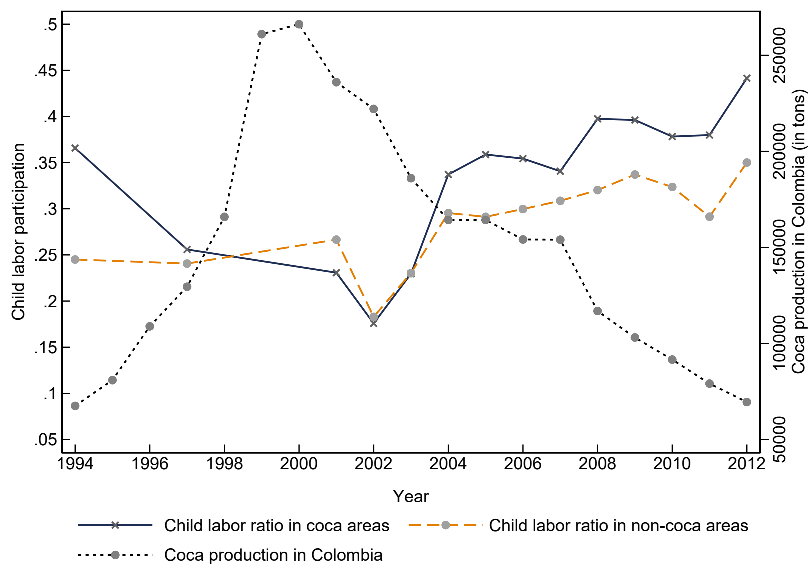
Notes: Figure 2 Panel (a) shows the number of hectares dedicated to coca in 1994 per district in Peru from the Agriculture Census. Panel (b) shows coca density from UNODC satellite images. Panel (c) provides an example of how coca expanded between 2002 and 2013 in the Alto Huallaga region using UNODC satellite images. It can be seen that the more intensively cultivated areas in 1994, represented by the deep green shades in the center and lower-center in Panel (a), are also the areas marked with higher coca density in the 2000s, as marked by the orange and red areas in Panel (b).

Figure 3: Coca prices in USD/kg between 1990-2013



Notes: Figure 3 shows black market coca prices in Peru from UNODC data during the period 1990-2013.

Figure 4: Child labor in coca and non-coca districts in Peru vs coca production in Colombia



Notes: Figure 4 shows the fraction of children working in coca and non-coca districts across time from the Peruvian National Household Survey (ENAHO) and the Peruvian Living Standards Measurement Survey (PLSMS). Two observations are relevant. We can see that in periods during which the cocaine industry expands, child labor increases in areas suitable for coca production. This is the case in the beginning of the 1990s and during the 2000s. Second, while in 1997 child labor is at similar levels in coca and non-coca districts, after the 2000s, coca areas consistently have a higher proportion of children working.

Figure 5: Primary and secondary schools distribution

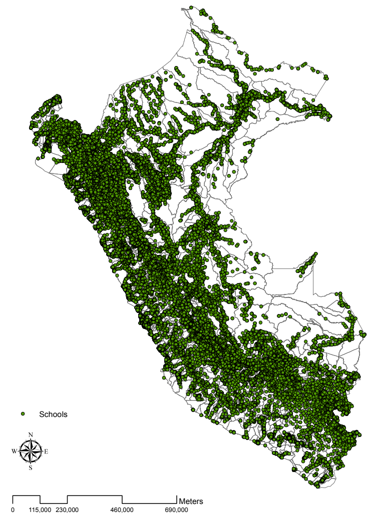
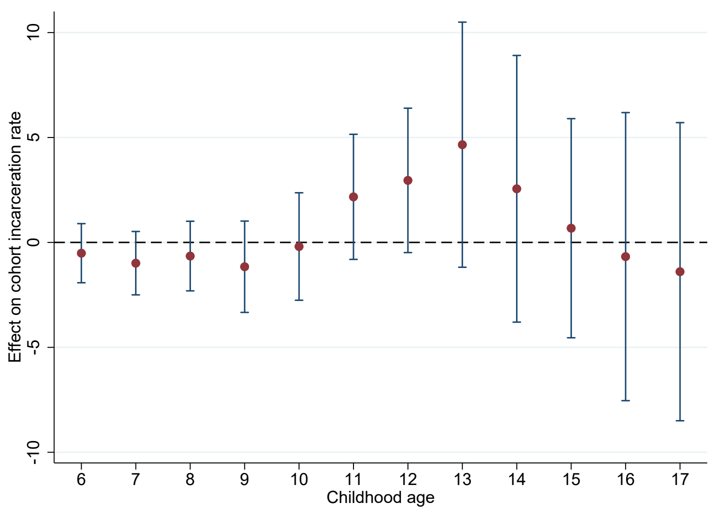
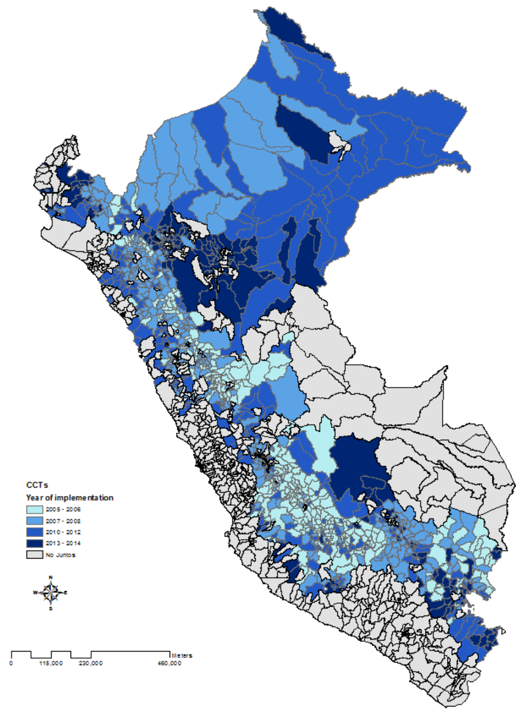


Figure 6: Incarceration rate effects by age

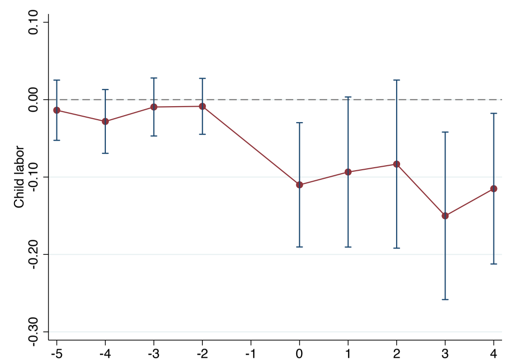


Notes: This graph plots the coefficients obtained from a regression of the incarceration rate on the interaction between the coca suitability in the district of birth and price at different childhood ages. The regressions control for district of birth, district time trends, and cohort fixed effects. The Y-axis shows the estimated coefficients on the interaction term and the X-axis shows the ages. Incarceration data comes from administrative records in the *Instituto Nacional Penitenciario* in Peru for the year 2015. The confidence intervals are at 95%. Standard errors are adjusted for spatial and time correlation using Conley standard errors.

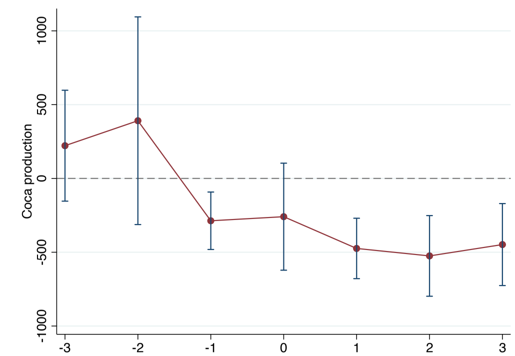
Figure 7: The effects of CCTs when coca prices are high



(a) Rollout of CCTs



(b) Child labor relative to years with CCT



(c) Coca production relative to years with CCT

Notes: Figure 6 panel (a) presents the staggered rollout of CCTs during the period 2004-2015 across districts in Peru. Panel (b) and (c) plot the event and year coefficients from estimating Equation 6 using child labor and coca production as the dependent variable, respectively. The confidence intervals are at 95%. Coca production comes from UNODC data for the period 2011-2014 (only years available at the district level).

Table 1: Effect of coca prices on labor participation by ages

	(1) Labor participation	(2) Labor participation
$PriceShock_{d,t}$	0.244***	
	(0.086)	
$PriceShock_{d,t} \times 6x10$	0.043	
	(0.029)	
$PriceShock_{d,t} \times 11x14$	0.144***	0.209***
	(0.028)	(0.030)
$PriceShock_{d,t} \times 15x18$	0.070*	
	(0.036)	
Total effect at age 11-14	0.388***	
	(0.094)	
Observations	412,026	167,901
Number of districts	1,469	1,467
Dep. var. mean	0.369	0.299
District FE	✓	✓
Year FE	✓	✓
Household FE		✓

Notes: This table presents the estimates from Equation 1, where the dependent variable is dummy variable indicating if the individual worked last week. $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in the district in 1994. $6x10$, $11x14$ and $15x18$ are dummy variables corresponding to each age bin. The omitted category is the age 19 to 21. Column (1) includes district and year fixed effects. Column (2) further controls for household fixed effects, exploiting the heterogeneity across ages.The sample is defined at the individual-household-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Table 2: The effect of coca prices on schooling

	Panel A: Dropout rate		
	(1) 6-10	(2) 11-14	(3) 15-18
$PriceShock_{s,t}$	-0.000	0.007**	-0.006
	(0.003)	(0.003)	(0.006)
Observations	287,629	362,130	100,039
Number of schools	33,849	42,933	11,385
Dep. var. mean	0.060	0.080	0.080
	Panel B: Failed the grade		
$PriceShock_{s,t}$	0.681***	0.213	-0.480
	(0.185)	(0.260)	(0.401)
Observations	425,606	513,334	125,006
Number of schools	36,825	47,651	12,476
Dep. var. mean	8.480	6.871	5.126
	Panel C: High age for grade		
$PriceShock_{s,t}$	0.021***	0.005	-0.014
	(0.004)	(0.007)	(0.010)
Observations	433,408	514,551	129,340
Number of schools	36,840	47,145	12,487
Dep. var. mean	0.187	0.273	0.230
School FE	✓	✓	✓
Year FE	✓	✓	✓

Notes: This table presents the estimates from Equation 2, where $PriceShock_{s,t}$ is the interaction of coca prices and the coca density associated with the school. In Panel (A), the dependent variable is the proportion of students that drop out from school in a given level of education; in Panel (B) the dependent variable is the share of students that failed the grade and in Panel (C) it is the share of students that have a high age for grade. In line with the evidence presented in Section 2.2, Columns (1)-(3) present the analysis for different levels of education: primary school (ages 6-10), the transition between primary and secondary education (ages 11-14), and last years of secondary education (ages 15-18). The sample is at the school-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table 3: Coca prices during childhood and subsequent criminal behavior

	(1) Crime	(2) Crime	(3) Crime	(4) Sentence
$PriceShockAge11to14_{d,c}$	3.607***	5.676**	5.462*	20.271
	(0.917)	(2.765)	(2.858)	(17.085)
$PriceShockAge0to5_{d,c}$		-0.693	-0.895	
		(1.274)	(1.580)	
$PriceShockAge6to10_{d,c}$		1.363	1.287	
		(1.480)	(1.501)	
$PriceShockAge15to17_{d,c}$		-0.602	-0.739	
		(2.352)	(2.368)	
$PriceShockAge18to30_{d,c}$			0.138	
			(0.341)	
Observations	23,853	23,853	23,853	23,853
Dep. var. mean	4.565	4.565	4.565	98.244
District of birth FE	✓	✓	✓	✓
Year of birth FE	✓	✓	✓	✓

Notes: This table presents the estimates from Equation 3 where $PriceShockAge11to14$ is the interaction between the coca suitability in the district of birth and the log average price between the ages 11 and 14. In Columns (1) to (3), the dependent variable is the propensity to crime of a given district-cohort and in Column (4) it is the average sentence length of incarcerated individuals from the given district-cohort. The sample is at the district and year of birth level. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Table 4: Coca prices during childhood and subsequent criminal behavior

	Panel A: All prisons					
	(1) All	(2) Drugs	(3) Violent	(4) Sexual	(5) Family	(6) Other
$PriceShockAge11to14_{d,c}$	3.607***	2.127***	1.304***	-0.107	0.046	0.237
	(0.917)	(0.732)	(0.384)	(0.212)	(0.088)	(0.356)
Observations	23,853	23,853	23,853	23,853	23,853	23,853
Dep. var. mean	4.565	0.616	2.269	0.401	0.089	1.190
	Panel B: Women					
$PriceShockAge11to14_{d,c}$	0.436***	0.355**	0.057	0.001	-0.000	0.024
	(0.135)	(0.150)	(0.037)	(0.001)	(0.000)	(0.063)
Observations	23,853	23,853	23,853	23,853	23,853	23,853
Dep. var. mean	1.528	0.623	0.324	0.009	0.001	0.571
	Panel C: Legal Coca					
$PriceShockAge11to14_{d,c}$	4.091***	2.542***	1.379***	-0.305	0.030	0.445
	(1.046)	(0.862)	(0.405)	(0.189)	(0.105)	(0.342)
$PriceShockAge11to14_{d,c} \times Legal$	-3.749**	-2.654***	-0.965	0.994	0.049	-1.173
	(1.675)	(1.014)	(1.485)	(0.683)	(0.149)	(1.346)
Observations	23,853	23,853	23,853	23,853	23,853	23,853
Dep. var. mean	4.565	0.616	2.269	0.401	0.089	1.190
District of birth FE	✓	✓	✓	✓	✓	✓
Year of birth FE	✓	✓	✓	✓	✓	✓

Notes: This table presents the estimates from Equation 3 where $PriceShockAge11to14$ is the interaction between the coca suitability in the district of birth and the log average price between the ages 11 and 14. The dependent variable is the propensity to crime of a given district-cohort by type of crime in each column. Panel (A) includes the whole sample. Panel (B) only includes the sample of women. Panel (C) includes an interaction of the main treatment variable with a dummy variable indicating if the district produces coca for the legal sector, using the whole sample of individuals incarcerated. The sample is at the district and year of birth level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$

Table 5: The effects of price shocks to other commodities on future criminality

	(1) All crimes
$PriceShockAge11to14_{d,c}$	3.523***
	(0.901)
$PriceGoldAge11to14_{d,c}$	0.025
	(0.124)
$PriceCoffeeAge11to14_{d,c}$	0.001
	(0.011)
$PriceCottonAge11to14_{d,c}$	-0.042
	(0.032)
$PriceSugarAge11to14_{d,c}$	-0.019
	(0.025)
$PriceCacaoAge11to14_{d,c}$	0.016
	(0.015)
Observations	23,853
Dep. var. mean	4.565
District of birth	✓
Year of birth	✓

Notes: Building upon the specification presented in Equation 3, this table also includes price shocks to other commodities such as gold, coffee, cacao, cotton and sugar. The dependent variable is the crime propensity of a cohort born in district d in year c. The sample is defined at the district and year of birth level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table 6: Conditional cash transfer and coca price shocks on child labor

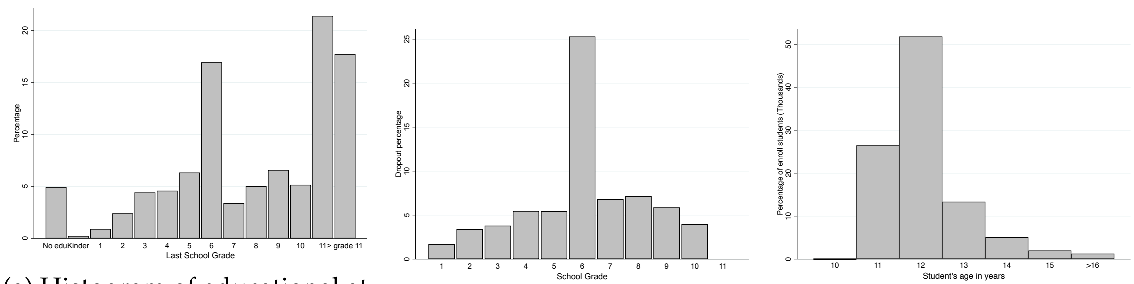
	(1) Labor	(2) Labor	(3) Labor
$PriceShock_{d,t}$	0.262**	0.213*	
	(0.104)	(0.112)	
$PriceShock_{d,t} \times CCT_{d,t}$	0.010	0.024	
	(0.071)	(0.072)	
$PriceShock_{d,t} \times 6x10$	0.050	0.048	
	(0.043)	(0.043)	
$PriceShock_{d,t} \times 11x14$	0.163***	0.161***	0.215***
	(0.043)	(0.043)	(0.035)
$PriceShock_{d,t} \times 15x18$	0.099**	0.098**	
	(0.042)	(0.042)	
$PriceShock_{d,t} \times CCT_{d,t} \times 6x10$	-0.108*	-0.107*	
	(0.064)	(0.064)	
$PriceShock_{d,t} \times CCT_{d,t} \times 11x14$	-0.122**	-0.121**	-0.163**
	(0.048)	(0.048)	(0.065)
$PriceShock_{d,t} \times CCT_{d,t} \times 15x18$	-0.120**	-0.119**	
	(0.053)	(0.053)	
Total effect at age 11-14	0.425***	0.374***	
	(0.104)	(0.115)	
Total effect at age 11-14 including CCT	0.313***	0.277***	
	(0.090)	(0.099)	
Observations	412,026	401,941	167,901
Number of districts	1,469	1,469	1,467
Dep. var. mean	0.369	0.369	0.299
District FE	✓	✓	✓
Year FE	✓	✓	✓
Department Trend		✓	
Baseline Trend		✓	
Household FE			✓

Notes: This table presents the estimates of Equation 1 with interactions with $CCT_{d,t}$, a dummy equal to 1 if the district d had the CCT program in year t and zero otherwise. $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in the district in 1994. $6x10$, $11x14$ and $15x18$ are dummy variables corresponding to each age bin. The omitted category is ages 19 to 21. Column (1) includes district and year fixed effects. Column (2) further controls for baseline characteristics interacted with year and department time trends. Column (3) includes household fixed effects, exploiting the heterogeneity across ages. The dependent variable is a dummy variable indicating if the individual worked last week. The sample is at the individual-household-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Online Appendix

A Additional Descriptive Figures and Tables

Figure A1: Ages of exposure



(a) Histogram of educational attainment from 2007 Census

(b) Dropout rates 2013

(c) Ages at transition grades 6-7

Figure A2: Age distribution of incarcerated individuals in 2015

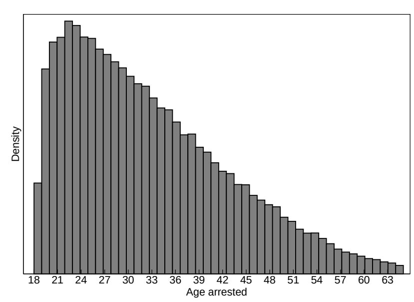
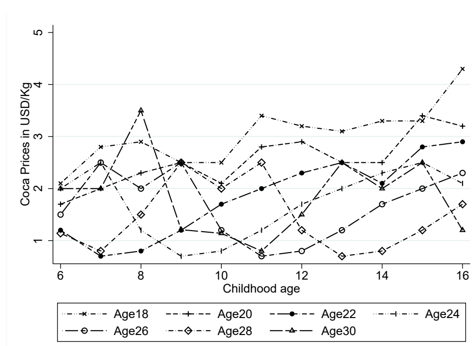


Figure A3: Variation in coca prices during childhood across cohorts



Notes: This figure shows the different coca prices experienced at all ages in childhood for a sub-sample of cohorts.

Table A1: Summary statistics of main variables

	Unit	Obs	Mean	Std. Dev.
Panel level variables				
Child labor (6-21)	Individual	413174	0.369	0.483
Child labor (6-14)	Individual	242593	0.298	0.458
Child labor (6-10)	Individual	131689	0.232	0.422
Child labor (11-14)	Individual	110904	0.377	0.485
Adult labor (15-18)	Individual	106287	0.422	0.494
Adult labor (19-21)	Individual	64294	0.548	0.498
Incarceration rate	District-Cohort	23853	3.365	23.501
District level variables				
Dropout rate (6-10)	School	289499	0.060	0.103
Dropout rate (11-14)	School	365115	0.080	0.142
Dropout rate (15-18)	School	100944	0.080	0.092
Fail rate (6-10)	School	427928	8.465	9.185
Fail rate (11-14)	School	514878	6.863	12.067
Fail rate (15-18)	School	125505	5.117	7.442
High age for grade (6-10)	School	434160	0.187	0.171
High age for grade (11-14)	School	516107	0.273	0.274
High age for grade (15-18)	School	129851	0.230	0.215
Coca intensity, thousands of hectares, 1994	District	1825	0.013	0.122
Gold deposits, 1970	District	1825	0.092	0.678
Coffee intensity, thousands of hectares, 1994	District	1825	3.070	9.996
Cotton intensity, thousands of hectares, 1994	District	1825	1.414	4.709
Sugar intensity, thousands of hectares, 1994	District	1825	2.495	8.848
Cacao intensity, thousands of hectares, 1994	District	1825	2.640	9.373
Time level variables				
Log internal coca price	Year	34	0.739	0.461
Log coca hectares in Colombia, hundred thousands of hectares	Year	26	-0.392	0.459
Log international coffee price	Year	34	1.175	0.375
Log international gold price	Year	34	1.756	0.423
Log international cacao price	Year	34	0.750	0.349
Log international sugar price	Year	34	0.311	0.153
Log international cotton price	Year	34	1.971	0.537

B Additional Analysis and Robustness checks

B.1 Additional analysis: the effects of shocks to other commodities on child labor

Table A2: Controlling for price shocks to other commodities

	Labor
$PriceShock_{d,t}$	0.201**
	(0.092)
$PriceShock_{d,t} \times 6x10$	0.056**
	(0.027)
$PriceShock_{d,t} \times 11x14$	0.144***
	(0.026)
$PriceShock_{d,t} \times 15x18$	0.074**
	(0.036)
$PriceShockGold_{d,t}$	0.035
	(0.025)
$PriceShockGold_{d,t} \times 6x10$	0.012*
	(0.006)
$PriceShockGold_{d,t} \times 11x14$	0.015**
	(0.006)
$PriceShockGold_{d,t} \times 15x18$	-0.007*
	(0.004)
$PriceShockCoffee_{d,t}$	0.003***
	(0.001)
$PriceShockCoffee_{d,t} \times 6x10$	-0.001
	(0.001)
$PriceShockCoffee_{d,t} \times 11x14$	0.003
	(0.002)
$PriceShockCoffee_{d,t} \times 15x18$	0.000
	(0.001)
$PriceShockCotton_{d,t}$	0.009***
	(0.003)
$PriceShockCotton_{d,t} \times 6x10$	-0.006**
	(0.003)
$PriceShockCotton_{d,t} \times 11x14$	-0.003
	(0.003)
$PriceShockCotton_{d,t} \times 15x18$	-0.001
	(0.002)
$PriceShockCacao_{d,t}$	-0.004***
	(0.001)
$PriceShockCacao_{d,t} \times 6x10$	0.001
	(0.002)
$PriceShockCacao_{d,t} \times 11x14$	-0.004
	(0.003)
$PriceShockCacao_{d,t} \times 15x18$	0.002**
	(0.001)
$PriceShockSugar_{d,t}$	-0.002*
	(0.001)
$PriceShockSugar_{d,t} \times 6x10$	0.001
	(0.001)
$PriceShockSugar_{d,t} \times 11x14$	0.001*
	(0.001)
$PriceShockSugar_{d,t} \times 15x18$	0.002***
	(0.000)
Observations	412,026
Number of districts	1,469
Dep. var. mean	0.369
District FE	✓
Year FE	✓

Notes: Building upon the specification presented in Equation 1, this table also includes price shocks to gold, coffee, cacao, cotton and sugar. $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in the district in 1994. $6x10$, $11x14$ and $15x18$ are dummy variables corresponding to each age bin. The omitted category is ages 19 to 21. $PriceShockGold_{d,t}$ is the interaction between log gold prices and mineral gold deposits in the district in 1970. $PriceShockCoffee_{d,t}$ is the interaction between log coffee prices and the average coffee suitability in the district for the period 1960-1990. $PriceShockCotton_{d,t}$ is the interaction between log cotton prices and the average cotton suitability in the district for the period 1960-1990. $PriceShockCacao_{d,t}$ is the interaction between log cacao prices and the average cacao suitability in the district for the period 1960-1990. $PriceShockSugar_{d,t}$ is the interaction between log sugar prices and the average sugar suitability in the district for the period 1960-1990. It includes district and year fixed effects. The dependent variable is labor participation (whether an individual in a given district-year had worked in the previous week). The sample is defined at the individual-household-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

B.2 Robustness checks: child labor

Table A3: Robustness checks, labor participation by ages

	(1) Labor	(2) Labor	(3) Labor	(4) Labor	(5) Labor	(6) Labor
$PriceShock_{d,t}$	0.191**	0.186**	0.163*	0.168	0.241***	0.264***
	(0.091)	(0.091)	(0.091)	(0.156)	(0.091)	(0.088)
$PriceShock_{d,t} \times 6x10$	0.002	0.001	0.041	0.037	0.042	0.043
	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)	(0.030)
$PriceShock_{d,t} \times 11x14$	0.079***	0.076***	0.139***	0.135***	0.144***	0.143***
	(0.026)	(0.026)	(0.028)	(0.027)	(0.028)	(0.028)
$PriceShock_{d,t} \times 15x18$	0.003	0.002	0.067*	0.065*	0.070*	0.069*
	(0.028)	(0.028)	(0.036)	(0.035)	(0.036)	(0.036)
Observations	399,246	398,935	412,026	412,026	401,941	412,026
Number of districts	1,442	1,442	1,469	1,469	1,469	1,469
Dep. var. mean	0.370	0.370	0.369	0.369	0.369	0.369
District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Post 2001	✓	✓				
Covariates		✓				
Departament trends			✓			
DepYear FE				✓		
Baseline characteristics					✓	
Coca time trends						✓

Notes: Column (1) presents the results from Equation 1 using only the observations from the post period (2001-2013). Column (2) includes controls for poverty at the household level. Column (3) includes department time trends as a regressor. Column (4) includes department-by-year fixed effects. Column (5) further controls for baseline characteristics interacted with year such as the proportion of villages affected by conflict in the 1980s and malnutrition rates, variables that are in general used to assign social programs. Column (6) also includes linear trends specific to coca-suitable areas as regressors. The dependent variable is labor participation (whether an individual in a given district-year had worked in the previous week). The sample is defined at the individual-household-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

B.3 Validity of the instrument

Table A4: First stage

	(1) $PriceShock_{d,t}$	(2) $PriceShock_{d,t}$
$Coca_d \times CocaColombia_t$	-0.418***	-0.412***
	(0.123)	(0.121)
Observations	412,026	401,941
Kleiberg-Paap F-stat	1409.095	1466.590
District FE	✓	✓
Year FE	✓	✓
Baseline trends		✓

Notes: This table presents the first stage associated with Equation 1. $Coca_d \times CocaColombia_t$ is the interaction between the number of hectares dedicated to coca in Peru in 1994 (the coca suitability measure) and the log number of hectares in Colombia. The dependent variable is $PriceShock_{d,t}$ which is the interaction between log coca prices and the coca suitability measure. Column (1) includes district and year fixed effects. Column (2) further controls for baseline characteristics interacted with year. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Figure A4: Coca eradication in Peru and Colombia

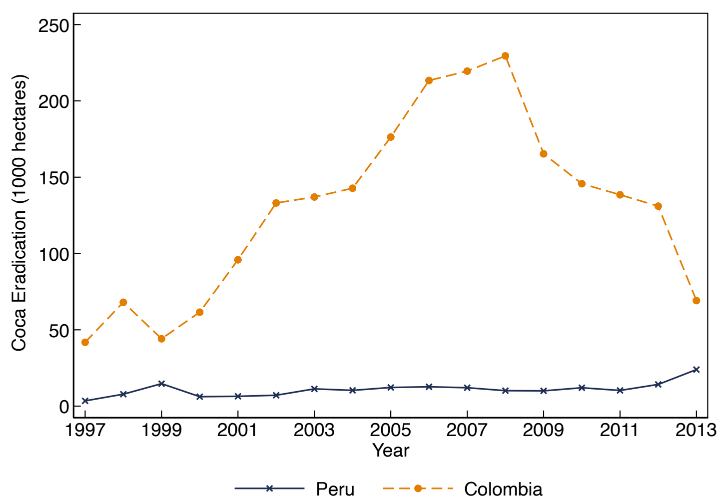


Table A5: Validity of the exclusion restriction

	(1) Taxes	(2) Property taxes	(3) Contributions	(4) Other non-tax revenues	(5) Customs	(6) Other transfers
$Coca_d \times CocaColombia_t$	0.038	0.004	0.001	-0.214	0.022	-0.467
	(0.128)	(0.121)	(0.003)	(0.376)	(0.016)	(0.434)
Observations	23,702	23,702	23,702	23,702	18,286	18,286
Number of districts	1,831	1,831	1,831	1,831	1,831	1,831
Dep. var. mean	0.674	0.575	0.005	0.971	0.072	0.586
Magnitude of the effect	0.51%	0.06%	2.30%	-1.99%	2.73%	-7.18%
District FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: This table presents the estimates from the reduced form specification of Equation 1 where $Coca_d \times CocaColombia_t$ is the interaction between the coca suitability measure and the log number of hectares dedicated to coca in Colombia. All dependent variables are expressed in real values per million. All specifications control for district and year fixed effects, as well as department time trends. Column (1) presents as dependent variable the total municipal revenues, which are composed of tax revenues (taxes and contributions), non-tax revenues (sale of goods, provision of services, fees, among others), transfers and capital revenues; Column (2), the total property taxes collected by the municipality, which include building and vehicular taxes; Column (3), the income received by the municipalities for the execution of government activities; Column (4), the total non-tax revenue of the municipality that includes income from fees, sale of goods, provision of services, property rentals, penalties, among others; Column (5), the transfer received by municipalities for income collected by maritime, air, river, lake and terrestrial ports located in their jurisdiction (this variable is only available for the period 2001-2011); and Column (6), special transfers received by the municipality for the Municipal Compensation Fund. and other transfers received by municipalities in addition to transfers for royalties, and fees (this variable is only available for the period 2001-2011). The magnitudes of the effects are calculated for a district with 0.3 hectares of coca and for an average increase of 30% in the number of hectares in Colombia during the period of analysis. The sample is at the district-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A6: OLS and reduced form estimates

	(1) Labor	(2) Labor	(3) Labor	(4) Labor	(5) Labor
$PriceShock_{d,t}$	0.009	0.004			
	(0.043)	(0.043)			
$PriceShock_{d,t} \times 6x10$	0.032	0.032			
	(0.034)	(0.034)			
$PriceShock_{d,t} \times 11x14$	0.098**	0.098**			
	(0.042)	(0.042)			
$PriceShock_{d,t} \times 15x18$	0.021	0.021			
	(0.022)	(0.022)			
$Coca_d \times CocaColombia_t$			-0.009	-0.006	0.007
			(0.049)	(0.049)	(0.063)
$Coca_d \times CocaColombia_t \times 6x10$			-0.063	-0.063	-0.122
			(0.052)	(0.052)	(0.081)
$Coca_d \times CocaColombia_t \times 11x14$			-0.242***	-0.242***	-0.380***
			(0.048)	(0.048)	(0.065)
$Coca_d \times CocaColombia_t \times 15x18$			-0.121*	-0.121*	-0.298***
			(0.063)	(0.063)	(0.041)
Observations	412,026	401,941	412,026	401,941	153,017
Number of districts	1,469	1,469	1,469	1,469	1,077
Dep. var. mean	0.369	0.369	0.369	0.369	0.322
District FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Baseline trends		✓		✓	
Period	94-13	94-13	94-13	94-13	94-05

Notes: This table presents the OLS and reduced form estimates associated with Equation 1. The dependent variable is labor participation (whether an individual in a given district-year had worked in the previous week). $PriceShock_{d,t}$ is the interaction between log coca prices and the number of hectares dedicated to coca in the district in 1994. $6x10$, $11x14$ and $15x18$ are dummy variables corresponding to each age bin. The omitted category is the age 19 to 21. $Coca_d \times CocaColombia_t$ is the interaction between the coca suitability measure and the log number of hectares in Colombia. Columns (1) and (3) include district and year fixed effects. Columns (2) and (4) further include baseline characteristics such as poverty and violence interacted with year. Column (5) restricts the analysis to pre-2005. The sample is at the individual-household-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Table A7: Growing status in 1994 and coca production growth in 2002-2013

	(1) Coca growth	(2) Coca growth	(3) Coca growth
Growing status in 1994 (=1)	331.043***	509.135***	197.879***
	(24.032)	(29.265)	(18.803)
Constant	4.258	4.258	4.258
	(8.026)	(7.397)	(4.713)
Observations	1,847	1,753	1,751

Notes: This table analyzes whether production in 1994 predicts coca growth during the period of analysis. Growing status in 1994 takes the value of 1 if the district has coca production in 1994 and 0 otherwise. Columns (2) and (3) divide the sample between high and low coca suitable districts in 1994. The sample is at the district level. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

B.4 Additional analysis: the effects of coca price shocks on test scores

Table A8: The effect of coca prices on test scores for second grade students (aprox. ages 7-9)

	(1) Math	(2) Level 1 Math	(3) Reading	(4) Level 1 Reading
$PriceShock_{d,t}$	-12.389*	4.502	-7.919	-3.006
	(6.847)	(3.696)	(5.935)	(3.393)
Observations	95,039	70,847	95,034	70,759
Dep. var. mean	514.847	49.934	518.897	21.739
School FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: This table presents the estimates from Equation 2, where $PriceShock_{s,t}$ is the interaction of log coca prices and the coca density associated with the school. The dependent variables in Column (1) and (3) are the average scores in math and reading at the national exam. The dependent variables in Column (2) and (4) are the proportion of students that got the lowest score in math and reading. The sample is at the school-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

B.5 Robustness checks: schooling outcomes

Table A9: Robustness checks, schooling outcomes: including department time trends; and department-by-year fixed effects and school level covariates

	Panel A: Dropout rate					
	Dep. time trends			Dep-by-year FE and school cov.		
	(1)	(2)	(3)	(4)	(5)	(6)
	6-10	11-14	15-18	6-10	11-14	15-18
$PriceShock_{s,t}$	0.001	0.007**	-0.007	-0.000	0.007**	-0.008
	(0.003)	(0.004)	(0.006)	(0.003)	(0.003)	(0.006)
Observations	287,629	362,130	100,039	263,325	324,624	85,223
Number of schools	33,849	42,933	11,385	30,759	38,295	9,622
Dep. var. mean	0.060	0.080	0.080	0.063	0.083	0.084
	Panel B: Failed grade					
	Dep. time trends			Dep-by-year FE and school cov.		
$PriceShock_{s,t}$	0.711***	0.256	-0.448	0.595***	0.041	-0.496
	(0.218)	(0.281)	(0.416)	(0.186)	(0.266)	(0.405)
Observations	425,606	513,334	125,006	383,337	452,880	103,636
Number of schools	36,825	47,651	12,476	33,244	42,232	10,484
Dep. var. mean	8.480	6.871	5.126	8.925	7.140	5.294
	Panel C: High age for grade					
	Dep. time trends			Dep-by-year FE and school cov.		
$PriceShock_{s,t}$	0.021***	0.005	-0.012	0.021***	0.007	-0.004
	(0.004)	(0.007)	(0.010)	(0.004)	(0.007)	(0.009)
Observations	433,408	514,551	129,340	389,956	453,846	107,322
Number of schools	36,840	47,145	12,487	33,267	41,790	10,497
Dep. var. mean	0.187	0.273	0.230	0.198	0.291	0.254
School FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Department Trend	✓	✓	✓			
DepYear FE				✓	✓	✓
School cov.				✓	✓	✓

Notes: Building upon the specification presented in Equation 2, this table also includes department specific time trends, department-by-year fixed effects, and school covariates as regressors. The sample is at the school-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table A10: Robustness checks, schooling outcomes: including coca specific time trends; and district-by-year fixed effects.

	Panel A: Dropout rate					
	Coca trends			District-by-Year FE		
	(1)	(2)	(3)	(4)	(5)	(6)
	6-10	11-14	15-18	6-10	11-14	15-18
$PriceShock_{s,t}$	-0.001	0.007**	-0.008	0.000	0.012**	0.008
	(0.003)	(0.003)	(0.006)	(0.004)	(0.006)	(0.012)
Observations	283,103	356,492	98,539	285,400	360,908	92,718
Number of schools	33,328	42,268	11,234	33,737	42,867	10,889
Dep. var. mean	0.060	0.079	0.080	0.060	0.080	0.079
	Panel B: Failed grade					
	Coca trends			District-by-Year FE		
$PriceShock_{s,t}$	0.621***	0.109	-0.499	-0.135	-0.580	-0.747
	(0.186)	(0.264)	(0.394)	(0.280)	(0.395)	(1.011)
Observations	417,862	504,177	123,108	424,383	512,766	117,780
Number of schools	36,242	46,899	12,315	36,754	47,628	12,015
Dep. var. mean	8.397	6.785	5.081	8.483	6.872	5.084
	Panel C: High age for grade					
	Coca trends			District-by-Year FE		
$PriceShock_{s,t}$	0.019***	0.005	-0.007	0.011*	0.012	-0.003
	(0.004)	(0.006)	(0.009)	(0.006)	(0.009)	(0.016)
Observations	425,185	505,176	127,366	432,195	513,962	122,284
Number of schools	36,261	46,402	12,328	36,769	47,119	12,026
Dep. var. mean	0.185	0.270	0.228	0.187	0.273	0.225
School FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
DepYear	✓	✓	✓			
Coca Trends	✓	✓	✓			
Baseline Trends	✓	✓	✓			
DistYear FE				✓	✓	✓

Notes: Building upon the specification presented in Equation 2, this table also includes coca specific time trends and baseline time trends; and district-by-year as regressors. The sample is at the school-year level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

B.6 Additional analysis: heterogeneity by ages at incarceration

Table A11: Coca prices during childhood and subsequent criminal behavior

	(1) All crimes	(2) All crimes	(3) By age at incarceration
$PriceShockAge6to7_{d,c}$	1.029	-0.308	
	(0.716)	(0.847)	
$PriceShockAge8to9_{d,c}$	1.564*	1.661**	
	(0.848)	(0.840)	
$PriceShockAge10to11_{d,c}$	2.455**	1.614	
	(1.003)	(1.037)	
$PriceShockAge12to13_{d,c}$	4.559**	1.972***	
	(1.981)	(0.686)	
$PriceShockAge14to15_{d,c}$	7.309**	1.346**	
	(3.177)	(0.650)	
$PriceShockAge16to17_{d,c}$	2.812	0.293	
	(2.391)	(0.324)	
$PriceShockAge18to19_{d,c}$		0.497	
		(0.796)	
$PriceShockAge11to14_{d,c} \times 18x19$			4.607**
			(1.816)
$PriceShockAge11to14_{d,c} \times 20x29$			5.401***
			(1.853)
$PriceShockAge11to14_{d,c} \times 30x39$			0.274
			(1.428)
Observations	23,853	22,028	38,541
Dep. var. mean	4.565	4.256	4.360
Age sample	18-30	28-39	18-39
District of birth FE	✓	✓	✓
Year of birth FE	✓	✓	✓

Notes: This table presents the estimates from Equation 3 where *PriceShock Age* $x_{d,c}$ is the interaction between the coca suitability in the district of birth and log average coca prices at different ages. Column (1) restricts the sample to those aged 18-30 in the incarceration data. Column (2) restricts the sample to those aged 28-39. Column (3) includes interaction of the main explanatory variable with (mutually exclusive) dummies indicating the current age category of the cohorts. The sample is defined at the district and year of birth level. All specifications control for district and year of birth fixed effects, as well as district specific time trends. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

B.7 Robustness checks: crime

Table A12: Robustness checks, coca prices during childhood and subsequent criminal behavior

	(1)	(2)	(3)	(4)	(5)
$PriceShockAge11to14_{d,c}$	3.405***	0.129***	0.007**	2.878***	3.859***
	(0.907)	(0.033)	(0.003)	(1.105)	(1.021)
Observations	23,853	667,884	1,295,788	23,853	23,853
Dep. var. mean	4.565	0.159	0.018	4.565	4.565
Department by yob FE	✓				
Year of Arrest FE		✓			
District by yob FE			✓		
Control for victims in civil conflict				✓	
Control for sentence length					✓

Notes: This table presents the estimates from Equation 3 where *PriceShock Age11to14*$_{d,c}$ is the interaction of log average price of coca between 11 to 14 years old and coca suitability measure of the district or village of birth. Column (1) further controls for department-by-year fixed effects. The sample is at the district and year of birth level. Column (2) includes year of arrest fixed effects as a regressor. The sample is at the year of birth, year of arrest and district of birth level. Column (3) uses 2016 census to obtain information on the village of birth and classifies the treatment status of the village of birth using the coca density maps. In particular, it replaces the coca suitability measure at the district level with a dummy indicating if the village is located in a coca geographic cell (identified by satellite images). The sample is at the village and year of birth level and allows to include district-by-year fixed effects. Column (4) controls for the number of victims during the civil conflict in each district of birth. Column (5) controls for the average sentence length. The sample in Columns (4) and (5) is at the district and year of birth level. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

C Mechanisms

C.1 Violence, Enforcement and Governance

In this section, I explore the effect of changes in coca prices on violence and enforcement in order to understand whether exposure to violence during childhood may explain the results on future criminality. First, I briefly review the theoretical and empirical literature. Second, I provide a description of the Peruvian context, which is relevant for understanding whether violence may be driving the main results. Third, I analyze the effects of the high coca prices on short-run violence using different datasets and measures of crime, violence, and conflict. I show that violence did not increase when coca prices increased. Finally, to further understand whether the long-term effects are driven by violence (for example, violence that I am not able to observe with my data), I discuss previous literature on the long-term effects of violence as well as several pieces of evidence from my analysis that suggest that the results could not be mainly driven by violence.

Literature and background: from a theoretical point, previous literature has suggested that there could be ambiguous effects on the role of illegal commodity booms on violence (Kalyvas 2006; Snyder and Duran-Martinez 2009; Castillo and Kronick 2020; Mesquita 2020). The sign of the effects mainly depends on the opportunity cost of committing violence, the number of groups competing for the control of the extra resources, and the law enforcement against illegal activity. Hence, the literature distinguishes between four different scenarios. Depending on the scenario, opportunity cost effects are more or less likely to dominate contestation effects, driving a net positive or negative effect on violence (Snyder and Duran-Martinez 2009; Gehring et al. 2020): A. High enforcement and multiple groups competing, B. High enforcement and no competition, C. Low enforcement and multiple groups competing , D. Low enforcement and no competition.

In scenario A, since the contestation effects dominate the opportunity cost of committing violence, we expect shocks to illegal commodities to raise violence. This resource-conflict curse is common in the empirical literature, especially in countries like Colombia (Angrist and Kugler 2008; Mejía et al. 2017; Ibanez and Carlsson 2010; Ibanez and Martinsson 2013; Wright 2016), Mexico and El Salvador (Dell 2015; Sobrino 2019; Sviatschi 2019).[72] Moreover, in the case of Mexico, Dell (2015) shows that while there is an increase in violence from government suppression since 2007, the paper also documents a non-violent equilibrium with extensive drug trafficking before the 2007 election (when there was no government suppression).

On the one hand, scenario B describes dominance and enforcement from the incumbent government. Hence, we expect weak opportunity cost, but also low contestation effects. This case resembles the evidence for Afghan Districts under the rule of the Afghan government (Gehring et al. 2020). On the other hand, in scenario C, we expect not only a strong contestation, but also strong opportunity costs, since more farmers benefit from higher prices. Thus, opportunity costs offset contestation effects. Finally, scenario D describes a context with low enforcement and lack of contestation. In this case, booms to illegal commodities may reduce the violence, since the opportunity cost effects related to higher prices outperform the weak contestation effects. This case resembles the evidence for Afghan Districts under the rule of the Taliban (Gehring et al. 2020), and according to my interviews and other anecdotal evidence, it describes the Peruvian context.[73]

The case of Peru during my period of analysis is closer to this last case because of the weak level of law enforcement prevailing then and the lack of competition among armed groups by the time cocaine expanded in the 2000s. This is mainly because the two armed groups (the main one, the Shining Path, which was controlling cocaine production and instigating violent confrontations with state officials, and the Tupac Amaru Revolutionary Movement) had already been defeated by state officials when coca prices increased during my period of analysis (Palmer 1994; Brienen and

[72] When cocaine expanded in Colombia in the 1990s, armed groups were already involved in the ongoing civil conflict: a left-wing guerrilla known as FARC (the Spanish acronym for Revolutionary Armed Forces of Colombia) and right-wing paramilitary groups known as AUC (the Spanish acronym for United Self-Defense Forces of Colombia). These groups took advantage of the boom and engaged in the coca sector to fund their criminal operations. Following the increase in the cocaine supply, in 1999, the Colombian and the US governments announced a top-down joint strategy to crack down on illegal markets and strengthen the security conditions in the coca-growing regions, known as Plan Colombia. This strategy consisted of such coercive actions as an increased military presence and the aerial spraying of coca crops with glyphosate (see Mejía (2015), for a thorough description of Plan Colombia).

[73] In these insurgent-controlled districts, the Taliban behaves like a stationary bandit (Sánchez de la Sierra 2020). They are the only insurgent group controlling the drug trade by providing security to the opium farmers and traffickers in exchange for rents or "taxation."

Rosen 2015). This was part of the presidents' policy of reducing conflict and armed groups in rural areas.[74] Thus, from mid 1990s to today there have not been large violent confrontations. Furthermore, anecdotal evidence from my field interviews as well as from Peruvian anthropologists and sociologists suggests that drug trafficking today is managed by a few Peruvian family clans (called *firmas*), which are not contesting territory as in the case of Colombian or Mexican cartels. Instead, the *firmas* rely on local networks of long-lasting relationships and operate with the support of the inhabitants and, in most of the cases, the local authorities. Hence, as opposed to the Colombian or Mexican context, the cocaine industry, in either Huallaga Valley or the Peruvian Amazonian Borderlands, has infiltrated all aspects of everyday social relations in the coca-growing communities (Van Dun 2012, 2014, 2016; Vizcarra 2018, 2019).[75] A quote from a coca farmer in Huallaga: "We live peacefully here as long as nobody gets involved with other peoples' businesses. It is not like in the TV shows and movies where you see different cartels fighting and many people being killed. We manage to keep violence low since fighting will only call the attention of authorities and damage the business." In fact, while Colombia had a homicide rate of over 38 per 100,000 inhabitants in 2007 and over 80 at the peak of cocaine production (Policia Nacional de Colombia), Peru has only 3 homicides per 100,000 inhabitants. In Peru, violence has been mainly used, if at all, to enforce contracts.[76] Violent episodes associated with the contestation of territories are scarce due to the relevance of the social bonds between *firmas* and the communities (Van Dun 2012, 2014, 2016).

Further, Peru, unlike Colombia, did not have a strong eradication or enforcement policy during the period being studied, which in general tends to increase violence (as seen with the evidence in Mexico and Colombia). In the case of Peru, eradication efforts were only manual and very small in scale. Figure A4 presents the number of eradicated coca hectares in Peru and Colombia. It shows that eradication did not increase during the period of analysis, and that it was very small in scale compared to Colombia. The minor eradication efforts in Peru were mainly due to the social mobilization and the bargaining power of *cocalero* peasant movements. Before the 2000s, the central government feared that crackdowns on the coca farms would increase the collaboration between *cocaleros* and Shining Path. Hence, eradication campaigns ceased, and the central government presented itself as an ally of the farmers instead of an enemy, to gain their hearts and minds.

[74] Under the Fujimori administration, the struggle against the left-wing insurgent movements through militarization was the primary concern. The capture of Abimael Guzman, head of the Shining Path, resulted in a significant reduction in insurgent activities and the subsequent disintegration of the group due to organizational matters and disagreements among the remaining insurgents (Waynee 2008).

[75] In addition, coca production is not associated with violence in general, given the Peruvian history of the crop, which again is very different from its history in Colombia. In Colombia, the first coca leaf crops were found on the farms and properties of the "emeralds," organizations in charge of controlling the smuggling of emeralds, which already had private security forces. These organizations became the first drug traffickers, forcing Colombian peasants to grow the leaf, replacing their previous crops (Escobedo 2011). In contrast, the production of coca leaf in Peru is legal if it is grown for medicinal purposes or for chewing the leaves, a traditional practice among indigenous communities. For this reason, coca leaf cultivation dates back to well before the nineteenth century. It was not illegal, but instead represented the cultivation of a plant with high personal and medicinal value for the general population. It was therefore easy for cartels to convince farmers to produce coca without exerting violence or linking it to an illegal activity.

[76] Disputes and contestation among local firmas are scarce. According to (Van Dun 2016), drug barons usually agree on *pactos de caballeros* (gentlemens agreements) that define property rights on the territories.

Anecdotal evidence suggests, moreover, that the family clans that control the business have preferred not to confront the police and instead pay bribes. As one of my interviewers mentioned: "Peru has long eluded the levels of bloodshed that have fueled displacement and indiscriminate violence in Colombia and Mexico. Peruvian drug traffickers prefer bribes to bullets." Nevertheless, since it is an illegal industry, violence could still occur, for example, as a means of enforcing contracts. Thus, in the following analysis, I estimate the contemporaneous effects of coca prices on violence using different datasets.

Empirical analysis: to analyze the effects on enforcement and violence, I use data on 1) the number of officers, 2) the perception of violence, 3) victimization, 4) major criminal records from different sources, and 5) conflict, criminal organizations and terrorist events. I analyze the contemporaneous effects of the coca price shock on these measures.[77] First, I use data from the *Ministerio del Interior* in Peru on the number of patrolling rural officers per district per year for the period 2004-2014. Second, I use data from the National Registry of Municipalities (RENAMU), which is an administrative registry completed by all the districts of the country on an annual basis since 2001. It contains general information on municipalities, as well as information on human resources, competencies and functions, public infrastructure, and local public services, including citizen security. Among the questions on citizen security, I used the dichotomous question on problems that affect the safety of the district during the year, such as robbery, prostitution, drug trafficking, and terrorism. Third, I use data from the module of victimization and security from the Peruvian National Household Survey (ENAHO), where individuals are asked whether they were victims of any violent crime and whether insecurity or corruption is a main problem in their neighborhood (2002-2017). Fourth, I use confidential data from Affidavit and Veritas which have information on the criminal records of all mayors and candidates in each district in Peru during the period of analysis.

Tables A13 to A14 present the results. Column (1) and (2) in Table A13 show that an increase in coca prices in coca districts did not affect the probability of having police patrols in the district nor did it increase the number of officers. Moreover, I find no evidence that individuals living in coca areas are more likely to perceive drug trafficking, terrorism, and crime as a threat to their own safety as coca prices increase. Table A14 also shows that higher coca prices do not increase the likelihood of being a victim of violence in coca districts. Further, results from the survey in Column (2) show that the probability of considering crime the main problem decreases as coca prices increase in coca-suitable districts. This decline could be explained by the opportunity cost channel (when there is a boom in the cocaine sector, there are fewer incentives to be involved in robberies) as well as the fact that the drug business provides some social order and reduces other types of crimes (Van Dun 2014; Vizcarra 2019).[78] While violent crime may not have increased,

[77]In particular I estimate the following equation:

$$Y_{d,t} = \beta \underbrace{(PriceCoca_t \times Coca_d)}_{PriceShock_{d,t}} + \alpha_d + \phi_t + \epsilon_{i,d,t} \tag{5}$$

[78]Indiscriminate violence and other types of crime (robbery, kidnapping, extortion, rape, etc.) are harmful to the

it is still possible that because of the coca boom, changes in governance may occur at the local level. However, Columns (3)-(6) in Table A14 show that the number of individuals reporting corruption at the district level as a leading problem did not increase due to the increase in coca prices. Moreover, Columns (7) and (8) show the effects on the probability that a municipality has a mayor with a criminal record and of the number of candidates with criminal records. I find no evidence that the rise in coca prices increases the criminality of the mayor and candidates. These results are consistent with the lack of contestation and the degree of alignment between the local governments and the coca sector in the coca-growing communities.[79]

Finally, while the incidence of armed conflict plummeted in 1990, there were still remnants of armed groups in rural areas in Peru, who may have exerted violence due to the boom in coca prices. Thus, to analyze the effects on armed conflict, I used information on the number of terrorist events by department. I used terrorist events because terrorist groups were the ones managing the drug trafficking in the 1980s, and were the ones that historically generated violence and conflict in Peru (Palmer 1994; Brienen and Rosen 2015). Moreover, the measure of terrorist events is the number of armed conflict events.[80] Thus, I used the variable terrorist events as a proxy of violence to show that it did not increase during the period of the paper (see Figure A5). Nevertheless, to analyze whether new criminal groups arose and contested the area, following Sobrino (2019)'s methodology, I scraped all news that mentioned the presence of a cartel and homicide per district per year since 2002 (when newspapers began to have online editions). Using this proxy, Columns (1)-(3) in Table A15 show no change in the number of cartels per district per year when coca prices increased. In addition, I use UCPD-GED data for Peru that has the number of deaths related to conflicts geocoded for the years 1987 to 2017 and I find no increase in the number of deaths due to conflict, ruling out that an increase in the return of coca increased conflict in coca suitable districts (see Columns (4)-(8) in Table A15).

Childhood exposure to violence and future criminality: There could still be a concern that children growing up could be exposed to a type of violence I cannot measure in the datasets presented above. However, existing literature has suggested that the long-term effects of exposure to violence/conflict on human capital and future criminality are concentrated on individuals who were exposed in early childhood (before age 5) whereas I find the effects concentrated in 11-14 years old.[81] Moreover, Figure A6 shows that prices before the age of five do not affect future

functioning of the *firmas*, because they quickly attract the attention of the national authorities and the media. Hence, leaders of *firmas* (also known as *patrones*) use selective violence to maintain tranquility in their communities.

[79]Unlike the central government, the independent local parties actively advocated the right to cultivate coca. Beyond that, the mayors and candidates often rely on local *patrones* to fund their political campaigns (see Van Dun (2014), for a thorough description of the bonds and relations of *firmas* with mayors and local politicians). The entrenchment of the cocaine industry in the communities and the lack of violence around it therefore makes the entry of violent candidates unlikely.

[80]In Peru, the conflict was among the government and the leftist insurgent groups (the Shining Path and the Tupac Amaru Revolutionary Movement). According to the Truth and Reconciliation Commission, the Shining Path has been responsible for most of the casualties during the conflict.

[81]See for example Shaw and Gross (2008); Akresh and de Walque (2008); Akresh et al. (2017); Leon (2012); Duque (2019); Couttenier et al. (2019). Moreover, a recent paper on the Peruvian civil war in the 1980s shows that exposure to civil war in Peru has no effects on future criminality for those who were older than 11 (Sara 2020).

criminality.

Table A13: The effect of coca prices on enforcement and perceived safety

	Police enforcement		Perceived Safety				
	(1) Patrolling (=1)	(2) Patrolling officers pc.	(3) Robb.	(4) Gang	(5) Narco	(6) Terror.	(7) Prost.
$PriceShock_{d,t}$	0.400	-0.219	0.010	0.333	0.196	-0.082	0.348***
	(0.362)	(0.201)	(0.381)	(0.318)	(0.240)	(0.291)	(0.133)
Observations	19,814	19,814	20,002	20,002	20,002	20,002	20,002
Dep. var. mean	0.245	0.340	0.682	0.166	0.047	0.019	0.119

Notes: This table presents the estimates from Equation 5 on several outcomes. The dependent variable in Column (1) is a dummy variable indicating whether the district has police patrolling in a given year, and in Column (2) is the number of police officers per district and year. In Columns (3)-(7), the dependent variable is a dummy indicating whether the individual considers that in a given year robbery, gang, drug trafficking, terrorism or prostitution as a threat for the local community in the district. $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in the district in 1994. The sample is at the district-year level, and all specifications include district and year fixed effects. Conley standard errors presented in parentheses. Significant at $^{***}p < 0.01, ^{**} p < 0.05, ^{*} p < 0.1$

Table A14: Perceived problems; and mayor and candidates criminal records

	Perceived problems						Mayor and cand.	
	(1) Victim	(2) Crime Prob.	(3) Corrup Prob.	(4) Bribe.	(5) +Corrup	(6) -Corrup	(7) Mayor offender	(8) Cand. offender
$PriceShock_{d,t}$	0.026	-0.256***	-0.040	0.013	-0.311*	0.040	-0.019	0.065
	(0.026)	(0.062)	(0.070)	(0.014)	(0.171)	(0.088)	(0.173)	(0.315)
Observations	13,287	11,269	12,130	10,657	8,815	8,815	6,446	6,446
Dep. var. mean	0.039	0.118	0.167	0.024	0.416	0.102	0.233	0.444

Notes: This table presents the estimates from Equation 5. In Column (1), the dependent variable is a dummy variable indicating if the respondent was a victim of crime in the district. In Columns (2) and (3), the dependent variable is a dummy variable indicating if the respondent considers crime and corruption as a main problem in the district. In Column (4), the dependent variable indicates whether the respondent has paid a bribe. In Columns (5) and (6), the dependent variable is a dummy variable indicating if the individual considers that corruption has increased or declined in the last year. In Column (7), the dependent variable is a dummy variable indicating if the mayor elected had a criminal record and in Column (2) the dependent variable is the share of election candidates with criminal records. $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in the district in 1994. The sample is at the individual-district-year level, and all specifications include district and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**} p < 0.05, ^{*} p < 0.1$

Figure A5: Number of terrorist events

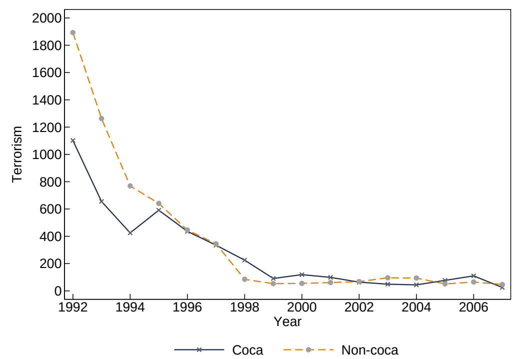
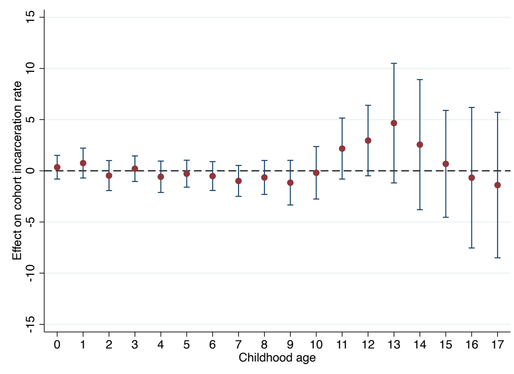


Table A15: Presence of cartels and homicides; and conflicts and deaths

	Cartel violence			Deaths and conflicts				
	(1) Cartel and Hom.	(2) Cartel	(3) Hom.	(4) Num. conflicts	(5) Total deaths	(6) Guerilla deaths	(7) Gov. deaths	(8) Civil. deaths
$PriceShock_{d,t}$	-0.032	-0.029	-0.003*	-4.312	-42.675	-42.808	-36.629	-5.990
	(0.026)	(0.025)	(0.001)	(4.880)	(46.142)	(46.153)	(39.224)	(6.967)
Observations	18,720	18,720	18,720	46,775	46,775	46,775	46,775	46,775
Dep. var. mean	0.002	0.002	0.000	0.015	0.118	0.115	0.105	0.014

Notes: The first part of this table presents the estimates from Equation 5. The dependent variable for each of these columns uses the number of news related to cartels and homicides per district and year using newspaper data. In particular, Column (1) indicates if there was any news related to homicides and cartel in that year for a particular district; and Columns (2) and (3) indicate the presence of homicide or cartel respectively. The second part presents the estimates from Equation 5. The dependent variables in each column are: the number of conflicts (Column 4), total deaths (Column 5), guerrilla deaths (Column 6), government officials deaths (Column 7) and civilian deaths (Column 8). $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in the district in 1994. All specifications include district and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Figure A6: Incarceration rate effects by age



C.2 Supply of Education

Table A16: The effect of coca prices on the supply of education

	(1) Log teachers	(2) Log teachers with post secundary education
$PriceShock_{d,t}$	-0.009	0.006
	(0.030)	(0.031)
Observations	749,621	700,122
Dep. var. mean (levels)	6.660	6.134

Notes: This table presents the estimates from Equation 2 on the log number of teacher in Column (1) and on the log number of teachers with post secondary education in Column (2). The sample is at the school-year level. All specifications include school and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

C.3 Migration

As discussed in Section 5.1.3, migration could bias my results if high coca prices alter the composition of out-migrants in highly coca-suitable areas. For example, higher coca prices may deter poorly educated and criminal-type families from migrating, but have no impact on the migration decisions of highly educated families. Thus, the average criminality of non-migrants would then increase due to the reduced out-migration of criminal or poorly educated families.

To analyze the extent to which migration may be affecting the results, I conducted the following analysis. First, I test whether higher coca prices between the ages 11 to 14 increase the size of the sample cohort. I estimate the same model as in the long-term analysis in specification 3. There is no evidence that cohort size responds positively to changes to coca prices at the key ages of exposure. In fact, the specification finds a small non-significant decline in cohort size (Column 1 in Table A17). Second, to test out-migration, I directly estimate how contemporaneous coca prices may have affected the proportion of migrants (people who left per district by year) in coca-suitable districts using the ENCO survey. This survey asks about the number of people in the family who left per year of migration. I can also, using ENCO, get an estimate of the number of people who left by year of birth by district and analyze the effect of coca prices at key ages of exposure on the probability of migrating out of the district by cohort. To test this hypothesis, I replace cohort incarceration with cohort out-migration in specification 3. Columns (2) and (3) in Table A17 present the results and show no effects on out-migration.

In addition, I also test how in-migration may generate heterogeneity in the impact of high coca prices in highly coca-suitable areas. At the extreme, if the cocaine sector only employs migrants, then higher coca prices should have no impact on the local children (children born in the affected district). Column (1) in Table A18 tests this hypothesis using the household surveys, for which I have information on the migrant status of individuals. In particular, I am able to determine whether the individual was born in the district of the interview or came from another district. Thus, I restrict the analysis to non-migrants, and I still find effects on child labor, suggesting that the results are not entirely driven by migrant families.

Next, I also test whether negatively selected families that may have decided to stay due to the increase in coca prices explain all of the effects on child labor. I test this by analyzing the effects on children of non-migrant parents who have low levels of education attainment. Column (2) shows that, among non-migrants, there are no differential effects on child labor for children whose parents are poorly educated. Further, to provide evidence that non-migrants are not a selected sample affected by coca prices, I also test directly how coca prices in coca suitable districts may affect the proportion of non-migrant families and I find no significant effects in Column (3). Moreover, I do not find differential effects on migration based on the parent's education. These results are in line with the results from the household fixed effects specification, which also deals with the negative selection of families.[82]

C.4 General human capital channel

As discussed in Section 5.2.2, it could be the case that criminality effects are merely driven by a reduction in human capital independently of children working on illegal activities and gaining criminal capital. In this section, I address this mechanism in the following way. First, I further estimate the effects on crimes where a decline in general human capital is more likely to have an effect. Second, I estimate the effects on child labor and criminality for other relevant commodities in Peru. Third, I study the characteristics of compliers to shed light on whether those affected by the shock have characteristics that are related to working in the cocaine industry as children.

[82]In addition, using incarceration data I also examine whether incarcerated individuals who were exposed to price changes in their early teens were more or less likely to migrate (using as proxy the location of jails) and whether this probability differed by individuals' observable characteristics such as education and occupation. In particular, I estimate the effects of high coca prices on migration as well as interactions between coca prices and the individual's education and occupation. Overall, I find no evidence that the probability of migrating is associated with changes in coca prices during childhood (for brevity these estimates are not shown). Moreover, I do not find differential responses across individuals, for instance, those in jail who have less than primary education or were unemployed are not less likely to migrate in response to changes in coca prices in their childhood.

Table A17: Coca price shocks and migration

	(1) Log Cohort size	(2) Cohort out-migration	(3) Contemporaneous out-migration
$PriceShockAge11to14_{d,c}$	-0.051	0.169	
	(0.064)	(0.159)	
$PriceShock_{d,t}$			0.106
			(0.146)
Observations	23,853	23,777	21,952

Notes: Columns (1) and Columns (2) present the estimates from Equation 3 on the log of the cohort size and the number of people who left by year of birth in each district. Column (3) presents the estimates from Equation 5 on the number of people in the family that left per year of migration and district. All specifications include district and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Table A18: Coca price shocks and migration

	(1) Labor	(2) Labor	(3) Non-migrant	(4) Non-migrant
$PriceShock_{d,t}$	0.198	0.186	-0.107	-0.124
	(0.167)	(0.168)	(0.106)	(0.112)
$PriceShock_{d,t} \times 11x14$	0.148***	0.132***	0.008	0.006
	(0.042)	(0.045)	(0.022)	(0.030)
$PriceShock_{d,t} \times HighEduParent$		0.037		0.039
		(0.038)		(0.036)
$PriceShock_{d,t} \times HighEduParent \times 11x14$		0.036		0.002
		(0.052)		(0.033)
Observations	185,517	185,517	401,107	401,107
Dep. var. mean	0.449	0.449	0.663	0.663
Sample	Non-migr.	Non-migr.	All sample	All sample

Notes: This table presents the estimates of Equation 1 in Columns (1) and (2) keeping only non-migrant families. For these specifications, the dependent variable is labor participation (whether an individual in a given district-year had worked in the previous week). In Columns (3) and (4), the dependent variable is a dummy variable indicating whether an individual was born in the district of the interview. $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in the district in 1994. $11x14$ is a dummy variable corresponding to the ages 11 to 14. $HighEduParent$ is a dummy variable indicating whether the head of the household has more than a high school education. The sample is at the individual-household-year level. All specifications include district and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

General human capital specific crimes: Table A19 presents the results for the type of crimes that are more likely to be affected by the general human capital mechanism and for homicides where this mechanism is less likely to play a role. I find that the price shock has no effect for property and white collar crimes. Moreover, the effects are positive and significant for homicides, which are crimes specific to the cocaine industry.

Table A19: Other crimes

	(1) Property Crimes	(2) White Collar Crimes	(3) Homicides
$PriceShockAge11to14_{d,c}$	0.068	-0.025	0.252***
	(0.113)	(0.097)	(0.076)
Observations	23,853	23,853	23,853
Dep. var. mean	0.231	0.142	0.289

Notes: This table presents the estimates from Equation 3 where *PriceShock Age11to14*$_{d,c}$ is the interaction of log average price of coca between 11 to 14 years old and the coca suitability measure of the district or village of birth. The dependent variable is the propensity to crime of a cohort in a given district by different types of crime. The sample is defined at the district of birth and year of birth level. All specifications include district of birth and year of birth fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Shocks to coca in the legal sector: I exploit shocks to coca in the legal sector for two main reasons. First, the first stages of production are exactly the same as in coca for the illegal sector. However, in these areas, there is no processing of coca into cocaine paste and thus, less likely that children will be in involved in the illegal chain of production and gain relevant criminal capital. Second, prices in the legal sector follow trends similar to those followed by the coca price in the illegal sector (but at different levels). By looking at the data on coca prices in the legal sector since 1998, we can see that the trends are very similar (see Figure A7 below), allowing me to exploit shocks to the illegal sector. Tables A20 and A21 show a significant increase in child labor and dropout rates at the key ages of exposure 11-14. For an average coca district when prices double, child labor increases by about 30% in the legal sector. However, as shown in the main paper, there is no increase in future criminality for individuals born in districts where coca production is legal.

Figure A7: Coca prices in the legal sector

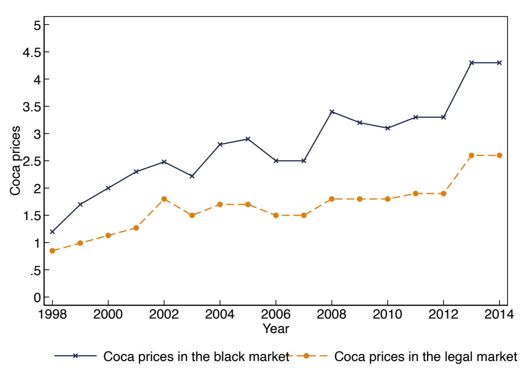


Table A20: Child labor and price shock in coca legal districts

	(1) Labor
$PriceShock_{d,t}$	0.178**
	(0.076)
$LegalCoca \times 6x10$	0.110***
	(0.043)
$LegalCoca \times 11x14$	0.232***
	(0.049)
$LegalCoca \times 15x18$	0.132*
	(0.072)
Observations	412,026
Number of districts	1,469
Dep. var. mean	0.369

Notes: This table presents the estimates from Equation 1. $PriceShock_{d,t}$ is the interaction between log coca prices and the number of coca hectares in districts that produce coca for the legal sector. $6x10$, $11x14$ and $15x18$ are dummy variables corresponding to each age bin. The omitted category is the age 19 to 21. It includes district and year fixed effects. The dependent variable is labor participation (whether an individual in a given district-year had worked in the previous week). This specification includes district and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$

Table A21: Dropout and price shock in coca legal districts

	Dropout rate		
	(1) 6-10	(2) 11-14	(3) 15-18
$PriceShock_{s,t}$	0.011***	0.010***	-0.000
	(0.004)	(0.004)	(0.005)
Observations	287,629	362,130	100,039
Number of schools	33,849	42,933	11,385
Dep. var. mean	0.060	0.080	0.080

Notes: This table presents the estimates from Equation 2, where $PriceShock_{s,t}$ is the interaction of coca prices and the coca density associated with the school in legal coca districts. The dependent variable is the proportion of students that drop out from school in a given level of education. In line with the evidence presented in Section 2.2, Columns (1)-(3) present the analysis for different levels of education: primary school (ages 6-10), the transition between primary and secondary education (ages 11-14), and last years of secondary education (ages 15-18). All specifications include school and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$

Shocks to other commodities: Table A22 presents the impacts on dropout rates of price changes in sugar, cotton, cacao, coffee and gold. In particular, shocks to gold increase the dropout rate from school at the key ages of exposure 11-14, consistent with previous results in Table A2 showing an increase in child labor in gold districts. However, when looking at incarceration rates, I find that none of the shocks increase future criminality (Table 5). These results suggest that future criminality may not be fully explained by just a reduction in human capital.

Table A22: The effects of price shocks to other commodities on dropout rates

	Dropout rate		
	(1)	(2)	(3)
	6-10	11-14	15-18
$PriceShock_{s,t}$	-0.000	0.007**	-0.006
	(0.003)	(0.003)	(0.006)
$GoldPriceShock_{s,t}$	0.000	0.002*	0.000
	(0.001)	(0.001)	(0.002)
$CoffeePriceShock_{s,t}$	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
$CacaoPriceShock_{s,t}$	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
$CottonPriceShock_{s,t}$	-0.000	-0.001*	0.000
	(0.000)	(0.000)	(0.000)
$SugarPriceShock_{s,t}$	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Observations	287,629	362,130	100,039
Number of schools	33,849	42,933	11,385
Dep. var. mean	0.060	0.080	0.080

Notes: Building upon the specification presented in Equation 2, this table also includes price shocks to other commodities such as gold, coffee, cacao, cotton and sugar. The dependent variable is the proportion of students that drop out from school in a given level of education. In line with the evidence presented in Section 2.2, Columns (1)-(3) present the analysis for different levels of education: primary school (ages 6-10), the transition between primary and secondary education (ages 11-14), and last years of secondary education (ages 15-18). The sample is at the school-year level. All specifications include school and year fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Compliers characteristics: to gain insight into whether individuals who are more likely to be incarcerated due to high coca prices during childhood (i.e. compliers) were the ones who were affected by child labor in coca farms, I investigate the labor, schooling, and family characteristics of offenders. I can compute the proportion of compliers who have characteristic X using two-stage least squares:

$$D_{c,d} = \phi Treated_{c,d} + \kappa_d + \nu_c + \pi_d c + \chi_t + \mu_{c,d} \tag{6}$$

$$X_{c,d} \times D_{c,d} = \beta D_{c,d} + \alpha_d + \delta_c + \sigma_d c + \gamma_t + \epsilon_{c,d} \tag{7}$$

where $D_{c,d}$ is the number of individuals who are in prison per cohort and district of birth. For ease of interpretation, I redefine the treatment as a discrete variable. I define $Treated_{c,d}$ for those whose average prices in the key ages were above the median and who were born in a district with coca. I also check the robustness of the results using the continuous treatment variable (the interaction of coca prices at specific ages and coca suitability). Note that $X_{c,d} \times D_{c,d}$ is the number of individuals per cohort who are in prison and have characteristic X (e.g., less than a high school degree). The coefficient β gives the proportion of compliers with characteristic X. Results for the characteristics of compliers can be found in Column 1 in Table A23. About 80% of those who were affected by the shock had less than a high school degree. I also repeat the analysis using an indicator for whether each offender's occupation was farming and find that about 60% of affected individuals declared farming as their main previous occupation.[83] When comparing these proportions to the proportions in the actual population in column (2), about 80% of compliers had participated in illicit activities before the age of 18 and 43% had at least one of their family or friends in prison. In the general population, those percentages are 50% and 31%, respectively.

Table A23: Complier characteristics

	(1) Compliers	(2) Population
Has less than high school education	0.819***	0.585
	(0.219)	[0.493]
Had farming as last occupation	0.598**	0.333
	(0.264)	[0.471]
Participated in illicit activities before age 18	0.776**	0.500
	(0.381)	[0.500]
Had friends in illicit activities before age 18	0.425	0.372
	(0.340)	[0.484]
Had a family member in jail	0.425	0.314
	(0.263)	[0.464]
Experienced gangs in neighborhood during childhood	0.466	0.505
	(0.337)	[0.5]

Notes: Column (1) presents the β estimates from Equation 7, which represents the proportion of individuals in prison due to the shock that have a particular characteristic. All specifications control for district and year of birth, as well as district specific time trends. Standard errors clustered at the district of birth level are in parentheses. Standard deviations are presented in brackets. Significant at *** p<0.01, ** p<0.05, * p<0.1.

[83] Notice that in coca-growing areas, there is also coffee and cacao production as well as services, trade, manufacturing and construction. For example, the agriculture sector employs 69% of the labor force. The remaining 31% of the labor force is employed in other sectors such as services (15%), trade (9%), manufacturing (3%), construction (3%), and others (1%). In the general population of the incarceration sample about 33% reported farming which contrast with the 60% of affected individuals.

C.5 Adult exposure

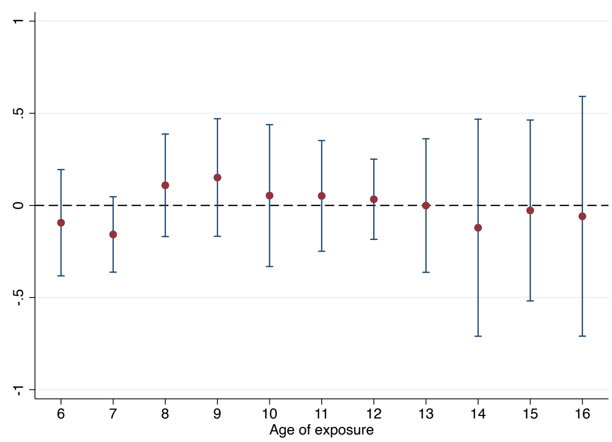
Table A24: Prisons in non-coca districts

	(1) All	(2) Drugs	(3) Violent	(4) Sexual	(5) Family	(6) Other
$PriceShockAge11to14_{d,c}$	2.253***	1.275*	0.881***	-0.136	0.062	0.172
	(0.809)	(0.701)	(0.319)	(0.201)	(0.079)	(0.263)
Observations	23,853	23,853	23,853	23,853	23,853	23,853
Dep. var. mean	4.516	0.607	2.255	0.395	0.088	1.170

Notes: This table presents the estimates from Equation 3 where $PriceShock\ Age11to14_{d,c}$ is the interaction of log average price of coca between 11 to 14 years old and the coca suitability measure of the district or village of birth. The dependent variable is the propensity to crime of a cohort in a given district by different types of crime. The sample is defined at the district of birth and year of birth level and includes the total of individuals in prisons located in non-coca districts. All specifications include district of birth and year of birth fixed effects. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$

C.6 Differential mortality

Figure A8: Effects on victims of homicides by age using police data



Notes: This graph plots the coefficients obtained from a regression of the victimization rate on the interaction between the coca suitability in the district of birth and price at different childhood ages. The regressions control for district of birth, district time trends, and cohort fixed effects. The Y-axis shows the estimated coefficients and the X-axis shows the ages. The confidence intervals are at 95%. Standard errors are adjusted for spatial and time correlation using Conley standard errors.

D Additional Results, CCTs

Table A25: CCTs and coca price shocks on schooling

	(1) Dropout rate: 11-14	(2) Failed the grade: 6-10	(3) High age for grade: 6-10
$PriceShock_{d,t}$	0.013***	1.069***	0.033***
	(0.004)	(0.300)	(0.006)
$PriceShock_{d,t} \times CCT$	-0.003*	-0.194**	-0.006***
	(0.002)	(0.097)	(0.002)
Observations	362,130	425,606	433,408
Number of schools	42,933	36,825	36,840
Dep. var. mean	0.080	8.480	0.187

Notes: This table presents the estimates of Equation 2, including interactions with $CCT_{d,t}$, a dummy that equals 1 if the district d had a CCT in year t and 0 otherwise. All specifications include school and year fixed effects as well as department time trends. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Table A26: CCTs and coca price shocks on crime

	(1)
$PriceShockAge6to10_{d,c}$	1.781
	(1.672)
$PriceShockAge11to14_{d,c}$	5.555**
	(2.611)
$PriceShockAge15to17_{d,c}$	-0.345
	(2.171)
$PriceShockAge6to10_{d,c} \times CCTsAge6to10$	-1.669
	(1.302)
$PriceShockAge11to14_{d,c} \times CCTsAge11to14$	-1.176
	(0.891)
$PriceShockAge15to17_{d,c} \times CCTsAge15to17$	-0.348
	(0.251)
Observations	23,853
Dep. var. mean	4.565

Notes: This table presents the estimates of Equation 3 with interactions with *CCTs*, a dummy indicating whether cohort c was exposed to CCTs at different ages and 0 otherwise. This specification includes district of birth, year of birth fixed effects and department time trends. Conley standard errors are presented in parentheses. Significant at $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

E Coca Agro-Ecological Index

Figure A9: Coca agro-ecological index across Peru

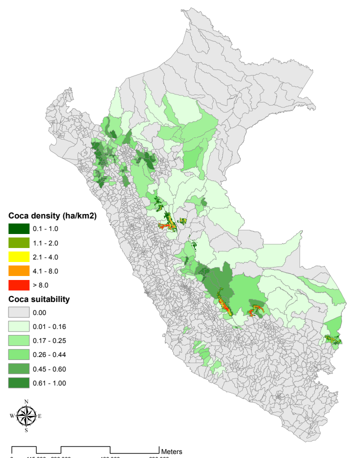


Table A27: Main regressions using coca agro-ecological index

	(1) Child Labor	(2) Dropout rate: 11-14	(3) Failed the grade: 6-10	(4) High age for grade: 6-10	(5) Crime
$PriceShock_{d,t} \times 11to14$	0.128**				
	(0.059)				
$PriceShock_{s,t}$		0.011	1.517***	0.027***	
		(0.007)	(0.306)	(0.006)	
$PriceShockAge11to14_{d,c}$					0.633***
					(0.217)
Observations	410,896	362,130	425,606	433,408	23,671
Dep. var. mean	0.369	0.080	8.480	0.187	4.581

Notes: Column (1) presents the estimates associated to the total effect at ages 11-14 from Equation 1 including price interactions with other age bins, where the dependent variable is a dummy indicating if the individual worked in a given district last week. $PriceShock_{d,t}$ is the interaction of coca prices and the coca agro-ecological index associated with the district. This specification includes district and year fixed effects. Columns (2)-(4) present the estimates from Equation 2, where the dependent variable for each column is the proportion of students that drop out from school in the transition, the share of students that failed the grade and the share of students that have high age for grade, respectively. $PriceShock_{s,t}$ is the interaction of coca prices and the coca agro-ecological index associated with each school. All theses specifications include school and year fixed effects. Column (5) presents the estimates from Equation 3, where the dependent variable is adult criminality. $PriceShockAge11to14_{d,c}$ in the interaction of the average coca prices at ages 11-14 and the coca agro-ecological index associated to the district. This specification includes district of birth and year of birth fixed effects. Conley standard errors are presented in parenthesis. Significant at $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$

F Qualitative Data Appendix

Since this paper studies an illegal industry, it is difficult to obtain data on the type of activities per each age group in the cocaine industry. Thus, during April and July 2015, I conducted interviews to understand what factors influence child labor decisions in Peru's coca areas. In addition in January 2020, I went back to some of the coca villages to better understand the production process and how child labor demand works at different ages. I conducted interviews in 6 districts: Monzon, Rupa-Rupa, Daniel Alomia Robles, Mariano Damaso Beraun, and Jose Crespo y Castillo. Since the interviews' objective was to understand how individuals started in the business, the sample mainly included individuals who are still participants or were part of the business at some point. These interviews were between 20 to 30 minutes each, and to get access to participants, I hired a local consultant who grew up in the area and was also a coca farmer in the past. For this sample, we used a snowball sampling procedure. We started with 30 individuals that the local guide knew well and then asked them to nominate other participants who met the eligibility criteria and potentially would contribute to the project. For all the interviews, we took care to preserve the participants' anonymity and freedom to consent. Indeed, the strategy for maintaining trust and safety was to be extremely clear to all participants that the purpose of the survey was only academic. As recording the conversations might have discouraged participants from speaking freely, an assistant typically took detailed notes. Whenever possible, we verified our observations from the interviews with multiple sources such as other relatives in the household or friends in the village that the local guide knew.

The survey mainly consisted of talking about their childhood experience and thus did not involve or increase participants' risk. In particular, I asked how they started being involved in the business, the grade and age at which individuals dropped out of school, and their main activity at different ages of childhood. Tables A28 and A29 present the results. Most of participants dropped out of school during the transition from primary to secondary school (Column 1 in Table A28). If I restrict the sample to individuals that today were involved in the illegal stages of production (Column 2), the share of individuals that dropped out in that transition is even larger. In terms of the main activities per age range, Table A29 shows that most of the participants started mainly collecting coca leaves while also attending school between the ages of 6 and 10. After dropping out of school (ages 11 to 14), they also started doing other activities such as processing coca into cocaine and transporting it. Moreover, if I restrict the sample further to those that drop out from school in the transition between primary and secondary education, 90% of them were involved in other stages of production such as processing coca into cocaine and transporting it. Although this is mainly qualitative, it shows the intensity of labor at different ages, given that the vast majority of participants were combining school with harvesting coca leaves. Below, I highlight some quotes from the field that convey a sense of the employment cycle in the cocaine industry:

> "I left school because my high school was too far. That's when I decided to obtain easy money by dedicating myself full time to the coca business."
>
> "Since I was 8 years old, when I was in primary school, I used to work in coca helping my father, and since very little, I had in my mind that once I grew up, I could generate money with drugs. Thus, when I dropped out of school, since I did not have anybody to guide me, I thought why should I not follow that path in the business? I have had this idea in my mind since very little as I started seeing people making lots of money with drugs. So once I was out of school, I decided to be fully in the business turning coca into cocaine."
>
> "Since I was 6, I helped in the farm growing subsistence crops, and then when I was 11, I started helping my uncle, who had coca farms. I had a clear contract where they paid me by arroba of coca, and then he taught me how to harvest. As I was carrying the leaves to maceration pits, I met several chemists [people

who process the leaves], and by just seeing what they were doing, I started very early quemiqueando (using chemicals to transform coca into cocaine paste). I learned just by being there. As a chemist, they paid me a lot per kilogram."

"I was starting high school, and at that point, I couldn't continue since it was far and I also needed to work. During my primary school, I worked helping my father harvesting coca and subsistence crops, and then at 11, when my father passed away, I dropped out and started processing coca into cocaine."

"When I was 5 years old, I helped my grandparents with coca production, and they gave me a tip by harvesting. When I was older, between 12 and 13, I went to live with my father, and he helped to dry the coca and put it in bags and many other things. For example, I got the chance to do the processing, and only once I did a delivery abroad, but I stopped because it didnt go well, that drug delivery."

"When I was in primary school, I mainly studied and worked in coca on the weekends. As I grew older, I helped in preparing the coca leaves in bags to take them to the processing centers."

"I started working in the business when I dropped out of school at the age of 14 to earn money. I liked that life and I stayed since then. I ended up having my own plot at an early age where I could harvest and also process part of the coca into cocaine."

Table A28: Dropout rates (%)

Sample	All	Illegal stages
Primary (1 grade)	2.86	1.56
Primary (2 grade)	1.90	3.13
Primary (3 grade)	4.76	7.81
Primary (4 grade)	0	0
Primary (5 grade)	0.95	1.56
Primary (6 grade)	16.19	23.44
Secondary (1 grade)	8.57	12.5
Secondary (2 grade)	14.29	23
Secondary (3 grade)	0.95	1.56
Secondary (4 grade)	0	0
Secondary (5 grade)	43.8	21.88
University	5.71	3.13
Total observations	105	48

Table A29: Activities per age range (%)

	6-10	11-14	>14
Main activity			
Study only	5.66	7.55	0
Work and study	91.51	66.98	50.94
Work only	2.83	25.47	49.06
Main work activity			
Collecting coca	88.99	44.76	36.89
Transforming coca	11.01	21.90	29.13
Transporting coca/cocaine		23.81	33.01
Non-coca related		9.52	0.97