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

(Job Market Paper)

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Abstract

This paper shows that exposing children to illegal labor markets makes them more likely to be criminals as adults. I exploit the timing of a large anti-drug policy in Colombia that shifted cocaine production to locations in Peru that were well-suited to growing coca. In these areas, children harvest coca leaves and transport processed cocaine. Using variation across locations, years, and cohorts, combined with administrative data on the universe of individuals in prison in Peru, affected children are 30% more likely to be incarcerated for violent and drug-related crimes as adults. The biggest impacts on adult criminality are seen among children who experienced high coca prices in their early teens, the age when child labor responds the most. No effect is found for individuals that grow up working in places where the coca produced goes primarily to the legal sector, implying that it is the accumulation of human capital specific to the illegal industry that fosters criminal careers. As children involved in the illegal industry learn how to navigate outside the rule of law, they also lose trust in government institutions. However, consistent with a model of parental incentives for human capital investments in children, the rollout of a conditional cash transfer program that encourages schooling mitigates the effects of exposure to illegal industries. Finally, I show how the program can be targeted by taking into account the geographic distribution of coca suitability and spatial spillovers. Overall, this paper takes a first step towards understanding how criminals are formed by unpacking the way in which crime-specific human capital is developed at the expense of formal human capital in "bad locations."

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I was raised on a ranch called La Tuna, in an area that did not have and still does not have job opportunities. 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 marginalized areas of rich countries, as exemplified by the impact of the drug-trade from Peru and Colombia to the inner cities of the U.S.[1] While research in this area has mainly focused on enforcement measures, there has been little success in pinpointing root causes that are within the reach of policy. Understanding how criminal careers begin is especially important since once an individual embarks on a criminal career, he or she is unlikely to turn back.[2]

Crime is geographically concentrated, and recent evidence documents the lifelong consequences of growing up in a bad neighborhood (Chetty et al. 2015; Chetty and Hendren 2015; Damm and Dustmann 2014).[3] Another literature has shown how parental decisions, particularly those related to human capital investments, can have long-term consequences (e.g., Cunha and Heckman 2007; Heckman 2006; Brooks-Gunn and Duncan 1997; Becker 1981). Might location-specific factors during childhood and parental responses catalyze criminal careers?

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 children on a criminal life path. Using an exogenous shock 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. This in turn increases 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, have lower earnings, and are less likely to trust state institutions. However, 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 thus, drug production in coca suitable areas. This policy addresses an underlying cause of future

[1] There is a growing awareness that crime and illicit drugs are major impediments for development (UN 2012). Crime may affect development by driving away business, eroding human capital, and undermining democracy (UN 2007). This has been pointed out by several international organizations that 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 (see `http://homicide.igarape.org.br/`).

[2] See e.g. Bell et al. (2014)

[3] A large body of research demonstrates that crime is unevenly distributed across space. The high variation in crime rates across states, cities, and neighborhoods represents what Glaeser et al. (1996) called "the most puzzling aspect of crime." For example, in Newark metropolitan area in the U.S., 85% of homicides were concentrated in only a few municipalities (O'Flaherty and Sethi 2014). Similarly, violence and narco-trafficking activities tend to be geographically concentrated in specific municipalities in Mexico (Ajzenman et al. 2014).

criminality by limiting the formation of criminal capital while simultaneously increasing formal human capital.

To isolate causal channels, 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 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.[4] This resulted in higher prices and expanded coca production in Peru, where production doubled in districts with the optimal agro-ecological conditions. By 2012, Peru had become the largest producer of cocaine in the world.[5]

This setting yields three useful sources of variation: i) cross-district or cross-school/village variation in coca-growing suitability, ii) over-time variation in coca prices, and iii) differential exposure to coca growing across cohorts (during sensitive ages) within location-time cells.[6] I measure coca suitability in three ways: coca production in 1994 (prior to the events examined in my analysis), satellite image data showing where coca is grown, and a coca suitability index constructed based on the optimal conditions to grow coca.[7] Time variation comes from changes in the black market price of coca induced by the U.S.-supported eradication program in Colombia. I thus define age-specific shocks by interacting coca suitability measures and prices. Differential exposure arises since children within a district or village experience the coca boom at different ages and due to variation in coca suitability across districts, villages, and schools.

To observe these sources of variation, I build a detailed panel of administrative data for a variety of labor market, schooling, and crime outcomes.[8] First, I use a geo-coded school panel and satellite images of coca fields that allow me to link each school to a particular coca geographic cell and isolate how human capital accumulation is affected in the short-run. Second, to examine the long-run effects on criminality, I take advantage of confidential administrative data on the 2015 and 2016 universe of inmates in Peruvian prisons, which includes information on village of birth, date of birth, length of sentence, education, family characteristics, and previous occupation. Furthermore, black market prices of coca are obtained from United Nations surveys. These data allow me to track cohorts that were exposed to high coca prices during key ages across areas with different coca suitability. In this way, I am able to analyze whether exposed children are more likely to be incarcerated in adulthood.

I first show that investments in children's human capital are affected by the cocaine industry.

[4]During the period of analysis, coca production decreased by 60% in Colombia.

[5]See "National Drug Control Strategy," Office of National Drug Control Policy, U.S. Department of State, 2012. Also see `https://www.whitehouse.gov/ondcp/news-releases-remarks/`.

[6]I use cross-district variation when examining labor and crime outcomes (there are 1,839 districts). I use cross-school/village variation since schooling outcomes are geo-coded. There are about 100,000 villages and 50,000 schools in Peru.

[7]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.

[8]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.

The increase in coca prices induced by Colombia's anti-drug policy leads to a large and significant increase in child labor in areas suitable for coca production. Children between the ages of 6 and 14 are most affected, with largest effects for those between 12 and 14.[9] Consistent with an impact on child labor, when coca prices double, test scores decline by 0.3 standard deviations for primary school students located in high coca areas. The probability that affected students failed a grade increase by more than 20%. In addition, the relatively high earnings in the cocaine industry induce some secondary school-aged children to drop out of school. In particular, there is a 27% increase in the dropout rate for students beginning secondary school. 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 or migration.

I then ask how early-life exposure to illegal labor markets affects children's long-run outcomes at the ages of 18 to 40.[10] 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 and have 20% lower earnings 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 among children who experienced high coca prices in their early teens, the ages when child labor increases the most.[11] The fact that long-term effects are only driven by specific cohorts provides further evidence that results are not confounded by other factors such as increased enforcement in coca districts. In addition, I use coca satellite images 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 fixed effects. This controls for political decisions, such as the level of enforcement, that are made at the district level.

The second focus of this paper is to understand the mechanisms driving criminal careers. There are two potential mechanisms. First, exposed children have lower formal education. Previous literature has found that lower formal human capital can lead to crime.[12] Second, individuals

[9] Empirical results are consistent with qualitative evidence that children aged 6 to 14 are particularly affected by the increase in prices. Most of the work is unskilled, making children an attractive input. The International Labor Organization reports that a large percentage of children are involved in the production of drugs in Peru (for more information see "Ninios en zonas cocaleras. Un estudio en los valles de los rios Apurimac y Alto Huallaga.", Technical Report, United Nations, 2006). This has also been extensively reported by news outlets. See, for example, "The Mochileros: High stakes in the high Andes - the young backpackers risking their lives in cocaine valley," BBC News, November 24, 2015. Since contracts are hard to enforce, participants in the industry often rely on family and friends for different types of labor (Balbierz 2015; Beriain 2014; Pachico 2012; Van Dun 2012). In addition, children are often used because they cannot be legally prosecuted (Mejía Fritsch 2003).

[10] These are the ages for which I am able to construct the whole history of prices during childhood.

[11] In addition, previous literature has suggested that it is at these ages when children begin to interact more with their peers and are susceptible to becoming involved in crimes (Damm and Dustmann 2014; Ingoldsby and Shaw 2002). Furthermore, I find no effect for individuals that had high coca prices when they were older than 14, consistent with the fact that children above these ages are more likely to be at school. The lack of long-term consequences for older cohorts is also in line with the previous literature studying the effects of neighborhood exposure during childhood in the U.S.

[12] See e.g. Lochner and Moretti (2004) who show that schooling reduces the probability of incarceration, Anderson (2014) who shows that dropping out of school increase juvenile criminal behavior, and Deming (2011) who finds that access to better schools reduces criminal behavior. In a similar way, Aizer et al. (2015) shows that juvenile incarceration

may acquire skills specific to the illegal sector. For example, they may develop human capital specific to the drug trade such as knowledge about transforming coca into cocaine, knowledge about smuggling, or connections to buyers.[13] The criminal capital acquired during childhood may be complimentary with future criminal capital.[14]

I find evidence that the increase in criminality is mainly driven by human capital specific to the illegal drug industry. First, those that are affected by the shock are more likely to be convicted of violent and drug-related crimes, but not other types of crimes such as property crime, sexual assault, or white collar crime. Second, I find that similar price shocks that affect legal commodities such as coffee and gold increase child labor, yet have no effect on the likelihood of future criminality. I also show that individuals from districts where most of the coca is grown for traditional medicine and religious purposes are not involved in crime later in life even though they have lower schooling. Third, I show that these negative effects are found not only for those from coca areas who remain in coca growing districts as adults, but also for those who move to districts without coca production. This implies that the long-term effects are not caused by contemporaneous exposure to the cocaine industry during adulthood but rather to exposure during childhood.[15] Finally, by characterizing compliers, I find that an overwhelming majority of individuals who are in prison due to the shock report that they were involved in illegal activities before the age of 18. Moreover, most of the affected individuals reported farming as their last occupation, indicating that they likely started their criminal career growing coca.

These results also have broader implication in terms of state legitimacy. In line with the criminal capital channel, individuals involved in the illegal industry may learn to navigate an industry that operates outside of the rule of law, and consequently lose trust in public institutions. I find that children affected by the expansion of the illegal industry are less likely to believe democracy works well and have lower trust in the police and the national government when they are adults. This has important implications for state capacity, and may limit the government's ability to combat organized criminal groups and drug cartels.

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 attend school on a daily basis. Since the program was targeted based on poverty measures and not coca suitability I am able to examine how the CCTs interact with high coca prices in suitable coca areas.

Consistent with the hypothesis that parental responses during childhood matter, I find that conditional cash transfers can mitigate the negative effects of growing up during the expansion of

increases future criminal behavior by interrupting social and human capital accumulation during a critical period.

[13] 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).

[14] This is similar to the canonical model of human capital development (e.g. Cunha and Heckman (2007)).

[15] These results also provide further evidence that effects are not driven by an increase in enforcement in coca areas.

the cocaine industry. I show that coca areas that implemented the program experienced a significant reduction in coca production and child labor. This leads to better schooling outcomes even when prices are high. Moreover, I show suggestive evidence that effects are mainly driven by the conditionality rather than income effects.[16]

These results suggest that CCTs should be targeted toward coca-suitable districts in order to mitigate the effects of high coca prices. However, policy makers must also account for the fact that there may be a "balloon effect"—if illegal production drops in one area, it may expand in nearby areas. I show that reducing coca production by incentivizing schooling in one district leads to an increase in child labor in neighboring districts if those districts are also suitable for producing coca, mirroring the shift of coca production to Peru when eradication increased in Colombia. Using a simple algorithm, I show how a budget constrained social planner would optimally assign CCTs across districts taking into account these spillover effects. I find that if CCTs have to be allocated to only a given number of districts, the reduction in child labor and coca production can be maximized by allocating the policy to districts that have no neighboring districts with high coca suitability. These results indicate that accounting for location-specific factors and geographical spillovers when targeting a policy can increase its total impact on future crime considerably.

Overall, I provide new evidence that childhood environment and parental responses can affect criminality later in life. I argue that the formation of human capital is important for understanding the perpetuation of illegal industries and the geographic concentration of crime. In contrast, much of the previous literature on crime has mainly focused on enforcement, which can often lead to increased violence.[17] Moreover, there is a growing consensus that enforcement alone often can explain little of the variation in crime (O'Flaherty and Sethi 2014; Fisman and Miguel 2007; Levitt 2004). In this paper, I find that location-specific factors and parental responses are a root cause of crime. Furthermore, I show that policies that target parents taking into account location-specific factors reduce the development of criminal careers. 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.

The remainder of the paper is organized as follows. In the next section, I discuss the previous literature in more depth. Section 3 presents the setting and Section 4 describes the data. Section 5 presents the empirical strategy and results for child labor and schooling outcomes. Section 6 presents the long-run results. Section 7 show the general equilibrium effects of a specific policy

[16]Results are robust to district poverty time trends suggesting that the effect of CCTs is not mainly driven by an income effect. Moreover, if income effects were large we would expect to see a decrease in adult labor. In contrast, I find an increase in adult labor, providing evidence that coca producers substitute away from child labor when the opportunity cost of child labor increases. Moreover, I find that policies that only increase resources, such as mining transfers, do not mitigate the cocaine industry effects.

[17]Dell (2015) shows how drug enforcement caused a large increase in homicide rates in Mexico. Also, Abadie et al. (2014) finds that aerial eradication exacerbated armed conflict and violence in Colombia, by reducing guerrillas' main source of income. Castillo et al. (2014) show how changes in drug enforcement in Colombia generated an increase in violence in Mexico. In the same line, Vargas (2014) shows how violence spiked in Chicago after the arrest of a important gang leader, by generating violent competition among gangs over market share. For a review on drug enforcement measures and violence see Werb et al. (2011) and Miron (1999), which document a positive relationship.

targeting the mechanisms behind the effects. I return to the policy implications in the final section.

2 Related Literature

This paper connects several literatures. First, by looking at the long-term effects of location-specific labor markets, this paper is related to the recent literature examining the long-term effects of "place" in developed countries (Damm and Dustmann 2014; Chetty and Hendren 2015; Chetty et al. 2015). In the context of developing countries, I contribute to this question by presenting causal evidence that place based inputs matter for whether individuals start on a criminal path. In particular, I provide new evidence that the presence of illegal labor market opportunities during childhood affects adult incarceration, earnings, and trust in institutions. I argue that the effect of place is particularly important in the context of the illegal drug industry given that it generates large externalities and regions with narco-trafficking often suffer from weak institutions.

Second, a growing number of theoretical and empirical studies have analyzed how early childhood conditions and parental investments affect later outcomes (e.g., Currie and Almond 2011; Heckman 2006; Brooks-Gunn and Duncan 1997). Much of this empirical literature has analyzed how negative shocks early in life affect adult outcomes through human capital.[18] In this paper, I focus on the development of one type of industry-specific human capital, namely criminal skills specific to the drug industry. While much of this literature has focused on early childhood—before the age of five—I provide evidence that long-term outcomes can be affected during late childhood and early adolescence when individuals in developing countries are exposed to local labor markets.

By drawing insights from the literature on the effects of place and early childhood environment, this paper contributes to the literature by providing new evidence on the root cause of crime in developing countries. Individuals may be pushed into criminal careers by location-specific factors and parental decisions during childhood, highlighting the importance of location-specific policies that target these incentives.

This paper also provides evidence on how criminal behavior responds to changes in the private return to committing a crime. In a recent literature review, Draca and Machin (2015) observe that previous studies do not address such a channel, as they focus on how crime is affected by changes in the return to legal labor market opportunities and enforcement (e.g., Buonanno and Raphael 2013; Di Tella and Schargrodsky 2004; Levitt 1997).[19]

This paper is also related to the previous research studying the determinants of criminality by looking at particular attributes such as age, gender, education, military service, and peers (e.g., Deming 2011; Galiani et al. 2011; Lochner and Moretti 2004; Glaeser et al. 1996).[20] While most of the research has focused on concurrent factors during young adulthood or conditions during early

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

[19] See also Freedman and Owens (2014).

[20] A related literature focusing on developed countries also examines whether criminality is affected by early childhood conditions such as lead exposure (Reyes 2007) and pre-schools programs. For a review see Lochner (2011).

childhood, there is no empirical evidence about whether early exposure to illegal markets affect criminal careers. This mechanism potentially sheds light on why criminal activities are persistent over time and geographically concentrated.

This paper is also related to the growing literature studying how human capital investment decisions are affected by plausibly exogenous changes in legal labor market opportunities (Atkin 2012; Shah and Steinberg 2013). In addition, recent research has examined how changes in the return to legal activities affect drug supply (Dube et al. 2015). I complement this literature by examining labor market returns in an illegal sector, which also generates effects on crime and state legitimacy. For comparison, I examine shocks to coffee and gold, which are legal commodities, and find that, although the shocks reduce human capital in the short-run, they do not effect adult criminality. This paper also contributes to the literature examining the effect of child labor (e.g., Bandara et al. 2015; Cogneau and Jedwab 2012; Edmonds 2007). While the previous literature has focused on how child labor effects schooling and earnings, this paper provides evidence that child labor can have broader long-term effects.

This paper also relates to the literature studying the unintended consequences of drug enforcement policies and production (Dell 2015; Rozo 2014; Mejía and Restrepo 2013; Evans et al. 2012; Angrist and Kugler 2008; Dammert 2008). I provide evidence of international spillover effects from Colombia's drug enforcement policies and within-country spillover effects from a social program that was not intended to reduce drug production. While this literature has mainly focused on the effects of the drug industry on violence and conflict, I provide evidence on human capital development and long-term individual outcomes, highlighting the organizational structure of the industry. In addition, since Peru was not affected by rural insurgent activity when coca expanded, I can rule out any confounding factors related to civil conflicts.[21] These results are particularly important for drug policy. Since effects are driven by exposure during childhood, policies that increase the opportunity cost of child labor may reduce drug production. I provide new evidence that policies that indirectly reduce the incentive to engage in illegal activities can be more cost effective than increased enforcement.

Finally, this paper sheds light on how weak institutions may perpetuate themselves. My evidence supplements studies that consider the determinants of trust in institutions and how it may affect economic development (e.g., Nunn and Wantchekon 2009; Alesina and Ferrara 2002). I show that measures of state legitimacy can be affected by exposure to illegal activities at a young age.

3 Institutional Context

In this section, I provide background information relevant to my analysis. First, I provide an overview of the cocaine industry and describe the anti-drug policy that I exploit for identification. This paper focuses on the increase in coca and cocaine production in Peru due to eradication ef-

[21] Although important in the 1980s and 1990s, civil conflict diminished sharply when the leader of the main terrorist group was captured by Peruvian authorities in 1999.

forts in Colombia. Second, I review qualitative evidence indicating that children are an attractive input in the production of cocaine. Children are often used to pick coca leaves, although they are also used for other stages of the production process. Third, I also summarize my own conversations with coca farmers, school administrators, police officers, and government officials in Peru in order to better understand the potential long-term consequences of child labor in the cocaine industry. This anecdotal evidence is largely consistent with correlational evidence, as well as the more rigorous causal evidence presented in Section 5.

3.1 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.[22] These are the only countries that have the optimal agro-ecological conditions to grow coca. 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: Coca production in the Andean region

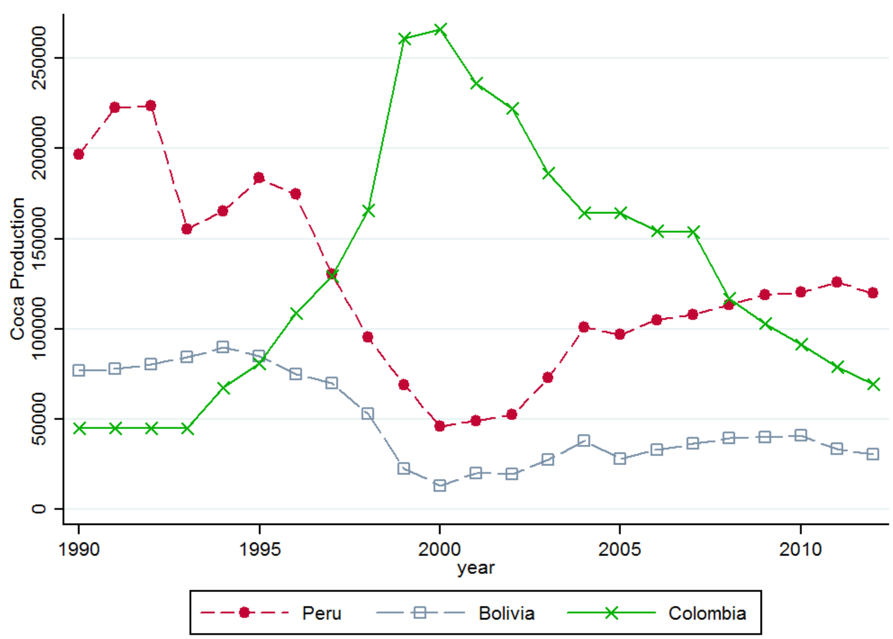


Figure 1 shows coca production in this region. I argue that the shift in coca production between countries was exogenous. In the beginning of the 1990s, most coca was produced in Peru. However, the closing of the air bridge used to transport drugs shifted production to Colombia. Then, in the 2000s, U.S. backed eradication efforts in Colombia shifted production back to Peru—an event

[22] In Peru, the remaining 10% is used in the traditional manner, 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.

which is the focus of this paper. 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.[23]

This paper primarily exploits the change in coca price in the 2000s induced by policies in Colombia, focusing on the period 1994 to 2014. I argue that this supply shock is uncorrelated with time-varying factors in Peru. In addition, I exploit the fact that this change in prices primarily affected those areas in Peru that were suitable for coca production.

Figure 2: Variation in coca production in 1994 across districts

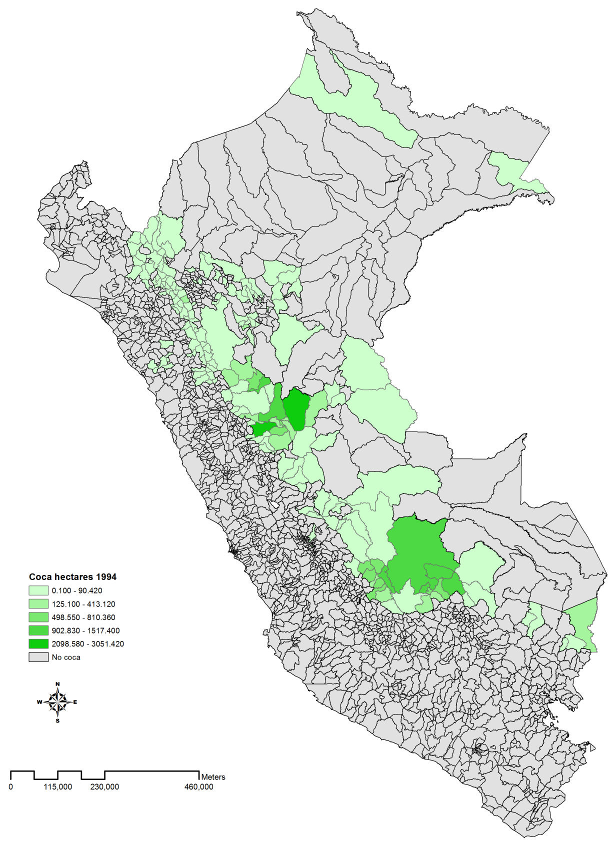


Figure 2 shows the 1994 distribution of coca production in Peru. There is substantial variation across districts in coca production. There are 1,839 districts in Peru and coca is grown in about 190 of these. While the Andes region in the south of Peru is highly productive, northern areas are less so. 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

[23] 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 (2013) 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.

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 2007). In general, local family-run organizations control production and domestic transportation of cocaine, while Colombian and Mexican intermediaries handle international trafficking.

3.2 The Use of Child Labor and Family Networks in the Drug Industry

Cocaine production primarily involves three phases: the collection of coca leaves, the transformation of coca into cocaine paste, and transportation. Children and adolescents an important input in every stage. There are two main reasons: children are ideally suited for the first stage of production which involves the farming of coca leaves. Also, family networks control each stage of the cocaine production and are unlikely to hire outsiders. Therefore, children are also commonly used to collect, transport, and process coca into cocaine. A qualitative survey carried out in one of the main coca valleys noted that about 90% of children who are born in coca areas work for the drug industry (Novak et al. 2011; UNICEF 2006). While young children often pick coca leaves, they often become involved with the transformation of coca into cocaine and transportation as they get older.

Most of the cited reasons for the use of children in the cocaine industry has to do with the production function in the first stages and the illegality of the sector. Harvesting coca requires relatively low-skilled workers; the plants grow close to the ground; hence, young children are well suited for collecting coca leaves. In addition, it is often thought that small children can more effectively hide from the police. And even if they do get caught, they face less harsh penalties than adults for similar crimes(Gastelumendi 2010; Mejía Fritsch 2003). A testimony from a municipal authority during my field work supports this view: "From the population, almost everyone grows coca and employs children. They are fast and they can hide from the authorities easily." Data from 2012 Agriculture Census also support the view that children are used in the production of coca.[24] Table A1 shows that the amount of coca is positively correlated with the fraction of child laborers within farms. This contrasts with other crops, such as coffee, where there is a negative correlation between production and the share of children.

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 stages of production. Since a high level of trust is necessarily, they rely on family and friend networks. Moreover, the higher-level individuals who control the organizations are often men who started

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

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).[25]

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. Moreover, children tend to work from 4am to 4pm, overlapping with school hours (usually 7am to 1pm). The harvest of an average size farm results in 125 kg of coca leaves, but only 0.3 kg of processed cocaine. Given that Peru produces 300 to 400 tones 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. Other students may drop out of school entirely, especially if they join other parts of the narco-trafficking process. School census data in Peru shows that about 10% of primary school students fail a grade and more than 25% have a higher age for the grade in coca producing areas.[26]

Although children may start by picking coca leaves, they are also likely to be exposed to other stages of the production process as they grow older. Once coca leaves are collected, the leaves are dried and manually crushed in maceration pits. The leaves are then processed into cocaine and transported. There is anecdotal evidence that as children grow older, they become involved in all of these stages of the production process.[27]

Childhood exposure to the cocaine industry may also affect the future probability that individuals are involved in the drug trade as adults. For instance, during my field work one participant involved in the industry stated that: "A child that grows up in a coca valley [in rural Peru] will follow an employment 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)." In a similar way, 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."

Consistent with the hypothesis that adult crime is due to exposure during childhood, the probability of incarceration is correlated with exposure to the drug industry during childhood. In particular, those born in high intensity coca districts are more than twice as likely to be incarcerated. This is especially true for drug related crime. About 33% of offenders born in coca areas were

[25] During my field work in the Alto Huallaga, one of main coca basins, one individual involved in the cocaine industry noted that there is a well defined system for alerting the community when the police or unknown people enter a coca area.

[26] A majority of primary school children during my field visits expressed that they spend most of their time working in coca fields. In interviews, teachers told me that older students were attracted to the potential for high earnings from working in the cocaine industry. I discuss further details on the qualitative-research methods in the Data Appendix.

[27] Several local and international newspapers have documented the fact 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." See "The Mochileros: High stakes in the high Andes - the young backpackers risking their lives in cocaine valley," BBC News, November 24, 2015.

arrested for drug trafficking versus 16% of offenders born in other areas. Moreover, about 20% of drug offenders were previously in a juvenile center, suggesting some path dependence in criminal behavior.

4 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 data 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 imagines that indicates 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 as well as trust in institutions. Finally, the incarceration dataset allows me to explore whether the young individuals exposed to the coca boom are more likely to be involved in criminal activities when they are adults.

4.1 Agro-ecological Data

The geographic variation in coca suitability that helps define the treatment group is drawn from two sources, an 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). In addition, 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.

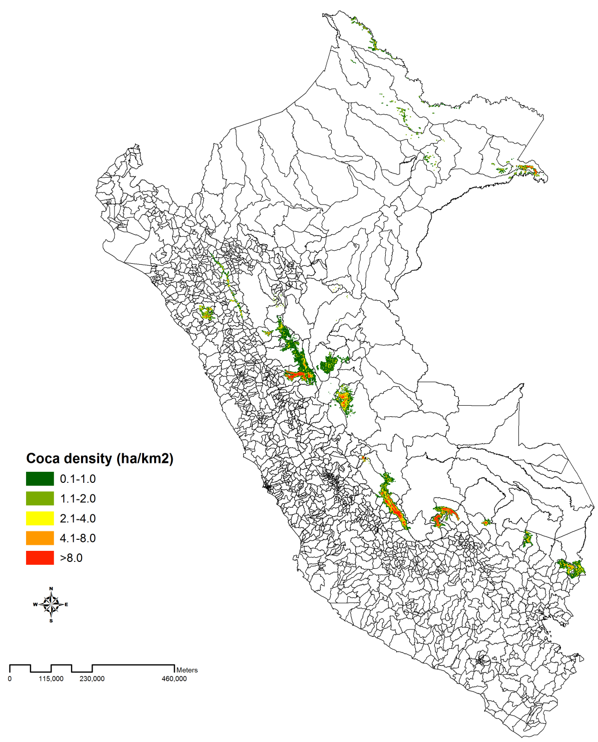
I use the Agriculture Census of 1994 to define historical coca production by the number of planted hectares of coca per district. I also use these data to create historical production of coffee by district for comparison. Given this measure is defined before the shock to Colombia, the short-run effects would not reflect endogenous production efforts in Peru.

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 images are verified by flying over randomly chosen areas each year. 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 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.

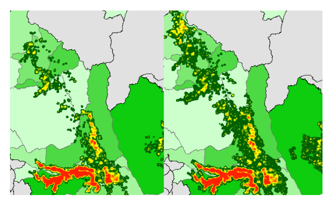
Figure 3 shows the coca satellite images during the 2000s. Most coca production was located in districts that also produced coca in 1994. This suggests that 1994 coca production is a good proxy for the areas that saw an expansion during the 2000s. Panel 3 presents the evolution of coca crops in one of 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 suitability index that shows which areas have ideal agro-ecological conditions to produce coca. I use information from the FAO Eco Crop system (see Figure A1a), which reports ideal ranges for precipitation, temperature, slope, altitude, and soil conditions. I define an area as "suitable" when it falls in the optimal range in every agro-ecological dimension. Figure A1b 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. The remaining suitable areas that do not produce coca after the expansion tend to be isolated areas.

Figure 3: Coca crops



(a) Coca satellite images during the 2000s

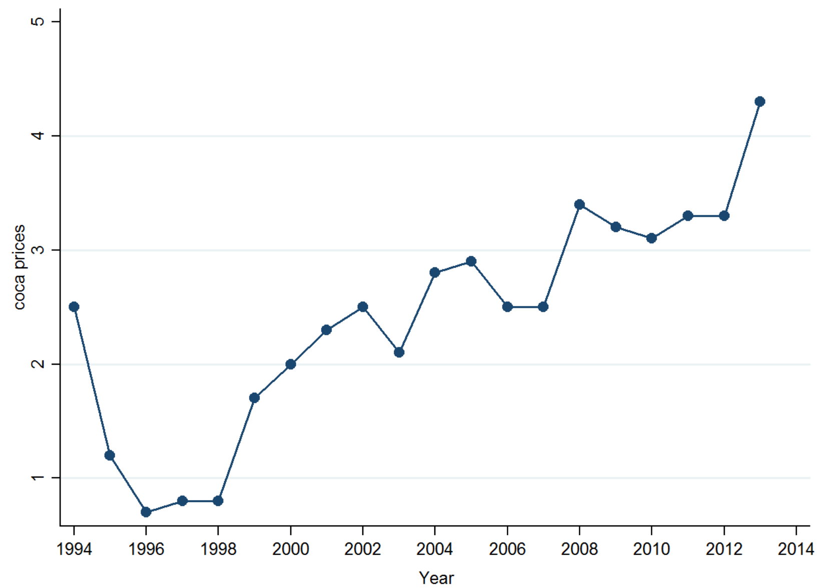


(b) Alto Huallaga region in Peru in 2002 and 2013

4.2 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 information 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. For the short-run analysis, I use prices for 1994, 1997, and 2001 to 2013 since these are the years when child labor outcomes are available. Figure 4 shows that during the expansion of the drugs industry in Peru in the 2000s, coca prices doubled.

Figure 4: Coca prices between 1994-2014



The prices reported by UNODC represent the price of coca on the international market. After 1994, prices decline due to an effective U.S-supported air interdiction. The main air bridge used to send coca paste from Peru to Colombia was disrupted. In 1999, Plan Colombia decrease coca production and increase cocaine seizures in Colombia. I argue that changes in the price of coca are primarily due to exogenously determined drug policies in Colombia that shifted production to Peru. I discuss this in more detail in Section 5. In particular, I use data on the number of coca hectares in Colombia provided by the Colombia Ministry of Defense to instrument for price.

4.3 Household Data

I examine the effects on child labor and other labor market outcomes as well as outcomes about state legitimacy using household data from the Peruvian National Household Survey (ENAHO) covering the period from 2001 to 2013. I complement these data with the Peruvian Living Standards Measurement Survey (PLSMS) for the years 1994 and 1997. Both surveys are nationally representative.[28] My final sample consists of 34,859 household-year and 16,172 children-year observations, distributed across 1,400 district-year observations.

I also use data from National Institute of Statistics (INEI) for baseline characteristics at the district level such as poverty, distance to the main city, area, number of classrooms, and fraction

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

of households exposed to violence during civil conflict in the 1980s. Table A2 shows summary statistics. Child labor is defined using the main activity reported by children between 6 and 14 years of age. Nationally, about 28% of children are working. It also shows that before the Colombian shock, the districts that are suitable for growing coca and the districts that specialize in other crops, such as coffee, have similar observable characteristics on average.

4.4 School Data

The school data I use are geocoded and cover the universe of schools in Peru during the period 1998 to 2014. The geographic coordinates allow me to combine these data with satellite image data on the location of coca production 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 examine the effect within schools.

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 enrollment by grade, but also measures of school achievement such as test scores, age for grade, and grade repetition.[29] I complement these data with the Census Evaluation, which is a national standardized test administered every year to all students in second grade in all primary schools.

Figure A2 in the Appendix shows distribution of schools across Peru. Of the approximately 50,000 primary and secondary schools in Peru, about 8,000 are located in coca-growing districts.

Table A3 presents the baseline characteristics of school located in areas with high coca suitability and low coca suitability when prices were low in 1998 (before the Colombian shock). With the exception of percentage of failed students and reading test scores, there are no statistical significant differences between baseline characteristics.[30]

4.5 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 drugs industry affects criminal behavior in later life. I compliment these data with a census of the incarcerated population from the first quarter of 2016 which contains additional information

[29] Many young children in rural areas attend some school even if they work. Therefore, primary enrollment may be less important than these measures of school achievement.

[30] Causal identification does not require baseline characteristics to be balanced given that I utilize difference-in-difference variation.

about the social and family environment of prisoners. I use this information to characterize the individuals that were affected by the shock.

The data contain 77,244 individuals incarcerated in Peru between the ages of 18 and 60 in 2015 (Figure A3 presents the age of arrest distribution). It contains information about their exact district and date of birth, their education, type of crime and main occupation (see FigureA4). 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.[31]

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. The final sample contains 64,298 individuals. I collapse these to the cohort and place of birth level. There are 4.7 offenders per cohort-district of birth cell on average.[32]

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 also 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 A2); in coca areas it is almost twice as high.

Figure A7 shows that when coca prices are high, incarceration rates are higher for individuals who grew up in coca districts. Moreover, there is no change for individuals from non-coca areas. This helps motivate my main empirical specification.

5 The Direct Effect of Drug Production on Child labor and Schooling

In this section, I examine the causal effect of coca production on short-run labor market and education outcomes. First, I describe the identification strategy which exploits plausibly exogenous variation in prices and geographic coca suitability. Using this identification strategy, I examine the relationship between the cocaine industry and child labor and schooling, as well as the economic mechanisms.

5.1 Econometric Specification

5.1.1 Baseline Econometric Specification

In order to estimate the causal effect of cocaine production on education and labor market outcomes I would ideally use data on who is producing cocaine. Unfortunately these data are unavailable since cocaine production is an illegal industry. As an indirect way to measure the effects of cocaine production, I combine a difference-in-difference strategy with an instrumental

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

[32] As a robustness check, I also construct a sample at the cohort-village of birth level.

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 identified from satellite images. Second, I exploit exogenous time variation in coca prices induced by an anti-drug policy in Colombia.

To estimate the effects of the expansion of the drugs industry on child labor I use a linear probability model in which the outcome is an indicator for whether the child 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. All specifications include district fixed effects, year fixed effects, linear trends by department, as well as controls for poverty, type of area, population, age, and gender.

Peru is a major coca producer and may affect the prevailing price. Thus, I instrument the coca price in Peru with the coca hectares in Colombia. Equation 1 presents the baseline specification:

$$Y_{i,d,t} = \beta \underbrace{(\textit{PriceCoca}_t \times \textit{Coca}_d)}_{PriceShock_{d,t}} + \alpha_d + \phi_t + \gamma X_{i,d,t} + \sigma_r t + \epsilon_{i,d,t} \tag{1}$$

where $\textit{Coca}_d$ 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. $\textit{PriceCoca}_t$ is the instrumented log price of coca in Peru in year t. It is instrumented by the log of the number of coca hectares in Colombia (per 100,000).[33] $Y_{i,d,t}$ is a dummy indicating whether the child in household i is working. The α_d are district fixed effect, ϕ_t year fixed effects, and $\sigma_r t$ department specific time trends.[34] 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. Note that the regressors $\textit{PriceCoca}_t$ and $\textit{Coca}_d$ are collinear to the year and district fixed effects. $X_{i,d,t}$ controls for poverty, type of area, population, age, and gender. To account for serial correlation of coca prices, I cluster the standard errors at the district level.

This strategy is similar to the standard difference-in-difference model, where the estimates 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.[35]

To test how the drug industry affects schooling outcomes, I use 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

[33] Ideally, I would like to have the share of coca hectares over all suitable land. However, I do not have access to these data. Nevertheless, the number of hectares is a good measure because my main assumption is that the more hectares of coca in a district, the more child labor is needed. In addition, as a robustness check, I control for the size of the district interacted with year fixed effects to ensure that results are not driven by larger districts.

[34] Peru is divided into 25 departments.

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

precise than estimation at the district level. I define $Coca_d$ with $DenCoca_s$ which ranges 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.

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

All specifications include school and year fixed effects and standard errors are clustered at the school level. I include a vector of school level varying controls which I construct by interacting time invariant characteristics with year dummies.

5.1.2 Addressing Potential Concerns

In this subsection, I show that districts that were producing in 1994 are the ones expanding their production in the 2000s. In addition, I discuss the exclusion, relevance, and common trends assumptions. I show that the instrument is not weak and that the shock did not impact other outcomes such as revenue, taxes, and transfers. Finally, I present a series of robustness checks that address the potential endogeneity of coca production and differential trends across districts.

In the above specification, I assume that only districts that produced coca in 1994 were suitable for coca and responded to the shock. One concern is that non-producing districts could have started producing coca after 1994 in response to booming prices during the 2000s. However, I find that only 10% of the growth in coca production is due to the expansion of coca in previously non-producing districts. 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 1). None of the intercepts are significant (suggesting no significant growth in the districts with no initial coca).

Table 1: Growing Status in 1994 and Coca Production Growth in 2002-2013

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	1,847	1,847
R-squared	0.093	0.15	0.06
Sample	All districts	High coca	Low coca

Notes: Standard errors clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

The results are in line with the intuition that areas with higher production in 1994 are suitable for coca and respond more to the shock from Colombia.[36]

Given that I use the number of coca hectares in Colombia as an instrument for prices, I also provide a formal test for the *relevance assumption* (Imbens and Angrist 1994) in Table 2. The Kleibergen and Paap F statistic is large, indicating that the weak instrument problem is not a concern. A 10% decrease in coca production in Colombia is associated with a 2.5% increase in prices in Peru.

The second 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 increases their enforcement or resources in coca areas when Colombia increased their drug enforcement policies. To address this concern, Table A5 presents evidence that rules out a violation of the exclusion restriction for covariates such as district's public income, taxes, and total transfers from the central to the district governments. The table shows the estimates of a regression of the instrument on these variables. None of the regressions shows significant coefficients.

The third main identifying assumption of the baseline specification is that there would be *common trends* across districts with different levels of coca suitability in the absence of price changes. This assumption could be violated if, for instance, child labor was increasing in suitable districts before the price shock. I address this concern by visually inspecting pre-trends and by including the years 1994 and 1997 in the main specification and controlling for coca area specific linear trends. I also include a vector of district baseline characteristics interacted with year (including classrooms, poverty index, childhood malnutrition level, the fraction of households exposed to violence during civil conflict in the 1980s, and kilometers to the main city) and coca area specific time trends. These interactions control for any potential differential trends across types of districts.

In addition, given that children beginning secondary education are more likely to drop out from school, I use a household fixed effects model to estimate the differential effect of coca prices across siblings (or other relatives) of different ages in the same household, thereby controlling for any household specific characteristics. Using this model, I can control for any differential trend across districts.

For schooling outcomes, since the data are geocoded, I also include an interaction of district-by-year fixed effects and compare schools within the same district in a given year. 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. This is especially relevant since most political decision are made at the district level. In particular, it rules out the concern that child labor and schooling results are

[36] 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.

driven by changes that vary by district and year such as an increase in political corruption or a decrease in district resources.

There are other potential concerns. To account for migration patterns, I check whether migration is affected by the expansion of the drug industry. Also, since the school treatment variable is constructed from 2002 satellite images—the beginning of the period of the expansion in Peru—it may be that the location of coca growing areas is endogenous to the shock. I address this concern by constructing a coca suitability index based on agro-ecological characteristics and check the robustness of the results using this index. Finally, to address whether the results are specific to the illegal industry, I estimate the effect of a legal commodity shock, coffee. Coffee is another important commodity in Peru and is produced in about 300 districts. I choose coffee since there is substantial variation across districts in coffee production and there is exogenous variation across time in coffee prices during the period of analysis. I construct the coffee shock by interacting the number of coffee hectares per district in 1994 with changes in the international coffee price. For schooling outcomes, since schools are geocoded, I use FAO-GAEZ coffee suitability index based on agro-ecological conditions that provides a finer measure. Table A4 shows that coca districts are similar to the districts that specialized in coffee production in 1997 when coca prices where low. Observable characteristics before the shock are mostly balanced across different areas.

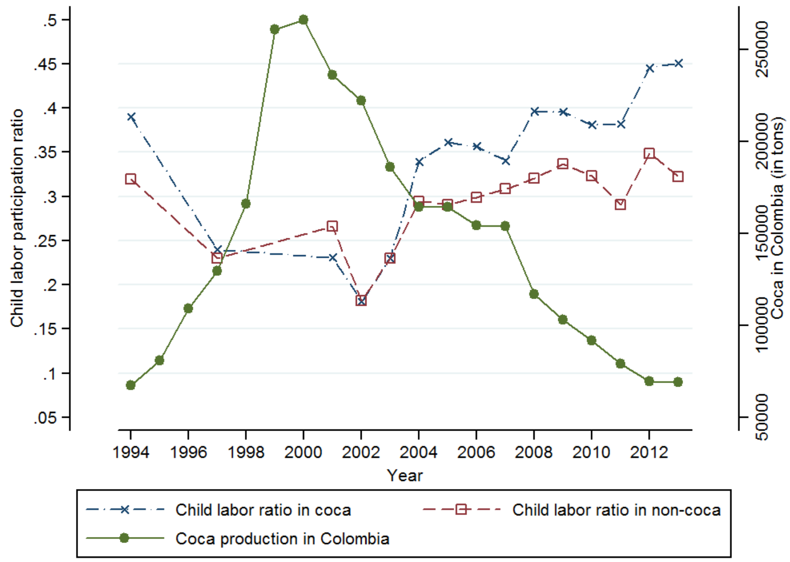
5.2 Results for Short-Run Effects

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

5.2.1 Child labor

Effect of Childhood Exposure to Illegal Activities on Child labor— Figure 5 shows the fraction of children working in coca and non-coca districts across time. 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 more children working.

Figure 5: Child labor in coca and non coca districts in Peru vs coca production in Colombia



Next, I turn to estimating the causal effect of coca prices on child labor. Table 2 shows the results from a linear probability model. Column (1) presents the results from a regression that includes all observations from the post period (2001-2013). 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 price doubled. The estimates suggest that this increase in coca prices led to an 8 percentage point increase in child labor in the average coca area (i.e. with a suitability of 0.5). This translates to a 30% increase relative to the mean. In Column (2) I estimate a similar specification to examine the effect of coffee production on child labor. The point estimate is statistically significant, but the magnitude is much smaller. For comparison, the estimates in Column (2) indicate that a similarly sized increase in coffee prices would increase child labor by only 5%.

Robustness Checks— The rest of Table 2 addresses some of the concerns presented in section 5.1.2. First, Column (3) presents the results with department trends and the results are very similar. Column (4) includes interactions of constant variables with year dummies such as the proportion of households exposed to violence in the pre-period, distance to main city, and malnutrition. This controls for potential biases coming from differential trends in places that have more violence in the past due to civil conflicts. When I include all these covariates the coefficient is similar to the baseline estimate and significant. Second, Columns (5)-(6) include 1994 and 1997 years from ENNIV surveys in order to be able to include coca specific time trends. The estimates are robust to these specifications. To account for pre-existing differential time trends, Columns (6)-(7) include coca specific time trends and interactions of department and year fixed effects. Finally, Column (8) tests whether changes in coca production affected migration within Peru. Since illegal industries require trust and rely on family and friend networks, they are unlikely to hire workers from other districts.

Table A6 in the Appendix presents the child labor estimates by age categories. I find that results are larger for those children who are 11 to 14 years old at the time of the shock and dissipate after age 14, with no effects for those older than 18. This is in line with the fact that older individuals can be legally prosecuted. Therefore, as an additional robustness check, I compare siblings of different ages within households. Panel (A) in Table A7 includes household fixed effects and still finds an increase in child labor for siblings who were 11 to 14 years of age compared to other ages. This result provides further evidence that results are not driven by differential time trends in coca districts. Any potential confounder needs to mimic the shock to coca prices and differentially affect children between 11 and 14 in high suitable coca districts.

To address the potential endogeneity of coca production in 1994, Panel (C) in Table A7 presents the results using the coca suitability index. Results are similar in magnitude and significance to using the 1994 coca production. Finally, another potential concern is that eradication efforts in Colombia are correlated with eradication efforts in Peru. If this is the case this would violate the exclusion restriction. Peru does not conduct aerial spaying eradication, instead they only engage in small-scale manual eradication. I check whether these eradication efforts in Peru are correlated with the eradication efforts in Colombia that form the basis of my identification strategy. I find a negative non-significant relationship over the period of analysis, providing additional evidence that the exclusion restriction is valid.[37] Table A8 in the Appendix also presents the reduced form results estimating the effect of Colombian coca hectares on child labor and results are of the same magnitude and significance. Moreover, results are robust to not instrumenting prices. This suggests that price endogeneity is not a concern.[38]

In sum, the child labor patterns are consistent with qualitative evidence presented in Section 3.2. I observe large effects since children are an important input in cocaine production. One limitation is that I cannot observe whether children that increased their labor participation belong to coca families and whether individuals switch between sectors. However, I do not find evidence of a decline in production of other cash commodities, such as coffee and cacao during the period of analysis. This is likely because when the returns to the illegal industry increase, this affected mostly farmers who have historically produced coca or have a relatives in the business.

[37]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.

[38]These results are not included for brevity but are available upon request.

Table 2: Effect of coca prices on child labor

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dep. Variable: Child labor							Dep. Variable: Migrate
$PriceShock_{d,t}$	0.165***		0.151***	0.147***	0.155***	0.149**	.149**	0.044
	(0.043)		(0.041)	(0.039)	(0.037)	(0.055)	(0.055)	(0.101)
$PriceCoffee_t \times Coffee\ int._{d,1994}$		0.011**						
		(0.004)						
	First Stage, Dep. Variable: $PriceShock_{d,t}$							
$CocaColombia_t \times Coca_d$	-.512***		-.512***	-.511***	-.513***	-.525***	-.521***	-.51***
	(.0189)		(.0187)	(.0174)	(.0186)	(.011)	(.012)	(.016)
Kleiberg-Paap F-stat	737.804		753.253	859.976	759.453	2132.827	1917.68	1004.626
Observations	233,824	233,824	233,824	228,446	234,465	242,580	242,580	230,205
Number of districts	1,431	1,431	1,431	1,412	1,436	1,436	1,436	1,412
District FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Department trends			✓	✓	✓			✓
Baseline trends				✓				✓
Covariates	✓	✓	✓	✓	✓	✓	✓	✓
Coca trends							✓	
Dep*Year FE						✓	✓	
Period	2001-2013	2001-2013	2001-2013	2001-2013	1997 2001-2013	1994,1997 2001-2013	1994,1997 2001-2013	2001-2013

Notes: This table presents the results of a linear probability model for the dependent variables: *child labor and migration*. The baseline specification is presented in Equation 1. Column (1) presents the results for the whole post period, 2001-2013 and includes controls for gender, age, poverty at the household level and population. Column (2) replace the coca interaction by the coffee interaction. Column (3) adds department time trends. Column (4) controls for baseline characteristics interacted by year such as the proportion of villages affected by conflict in the 1980s and malnutrition rates. Column (5) adds the year 1997. Column (6) adds department-by-year fixed effects. Column (7) includes coca specific linear trends as a regressor. Column (8) replicates the baseline specification with *migrate* as the dependent variable. Standard errors are clustered at the district level. Significant at *** p<0.01, ** p<0.05, * p<0.1.

5.2.2 Schooling

Effect of Childhood Exposure to Illegal Activities on Human Capital— I start by analyzing the effect on primary schools outcomes. Children attend primary schools between the ages of 6 and 11. Table 3 presents the results. Column (1) shows that there is no effect on enrollment. This is the case for all primary school grades, which is consistent with the fact that 96% of students are enrolled in primary school. In Columns (2)-(3), achievement measures are used as the dependent variable. The increase in coca prices during the period of analysis led to a 30% increase in the proportion of students with higher age for the grade, and a 28% increase in the probability of failing compared to the baseline levels. In addition, students in the second grade exhibit lower scores in math and reading. These results imply that children working in coca fields are technically enrolled but they are spending less time studying. Moreover, the fact that there is no effect in enrollment suggests that test scores results are not biased by selection of particular students taking the exams. I also find no evidence that the proportion of students that took the national exam over the number of scheduled students is affected when coca prices increase.

Table 3: The effect of coca prices on primary school students

	(1)	(2)	(3)	
	Enrollment	Age for grade	Failed	
$PriceShock_{d,t}$	0.027	0.020***	0.793***	
	(0.027)	(0.003)	(0.146)	
Mean of dependent	112.03	.20	8.35%	
Observations	433,696	433,696	425,905	
Number of schools	36,874	36,874	36,860	
	Math score	Lowest math level	Reading score	Lowest reading level
$PriceShock_{s,t}$	-12.353**	4.519*	-7.915*	-3.202
	(5.272)	(2.706)	(4.322)	(2.778)
Mean of dependent	515	50%	519	21%
Observations	95,039	70,847	95,034	70,759
Number of schools	13,581	11,853	13,581	11,843

Notes: This table presents the estimates from Equation 2 where $PriceShock_{s,t}$ is the interaction of prices with $DenCoca_{s,2002}$ which ranges from 1-5, 1 indicates 0.1-1 ha of coca per km^2, category 2 indicates 1.1-2 ha/km^2, 3 from 2-4 ha/km^2, 4 from 4-8 ha/km^2 and 5 more than 8 ha/km^2. All specifications include school and year fixed effects as well as department specific time trends. Standard errors are clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1.

Next, I analyze whether secondary school students are affected by the increase in coca prices. Table 4 presents the results on secondary school enrollment. There is a large decline in enrollment rates at 8th grade, suggesting that students may be dropping out of school at 7th grade when they are in the transition between primary and secondary education. These results are consistent with Census data that show that most dropouts occur when children are entering secondary education. Figure A5 shows a histogram of the educational attainment. There is a clear jump in 7th grade when students are about 12 and 13 years old: the probability of dropping out of school increases in this grade and decreases once students move to higher grades. [39] Therefore, this result suggests that students in the transition between primary and secondary education are dropping out to work full time in this industry and potentially working in the transformation and trafficking.

Table 4: Coca price shocks and secondary school students (enrollment)

	(1) All grades	(2) Grade 7 (Age 12)	(3) Grade 8 (Age 13)	(4) Grade 9 (Age 14)	(5) Grade 10 (Age 15)	(6) Grade 11 (Age 16)
$PriceShock_{d,t}$	-0.026	-0.011	-0.090***	-0.068*	0.019	0.037
	(0.027)	(0.021)	(0.029)	(0.041)	(0.058)	(0.064)
Mean of dependent	225.48	53.55	49.47	45.168	40.776	36.507
Observations	135,595	135,595	135,595	135,595	135,595	135,595
Number of schools	12,850	12,850	12,850	12,850	12,850	12,850

Notes: This table presents the estimates from Equation 2 where $PriceShock_{s,t}$ is the interaction of prices with $DenCoca_{s,2002}$ which ranges from 1-5, 1 indicates 0.1-1 ha of coca per km^2, category 2 indicates 1.1-2 ha/km^2, 3 from 2-4 ha/km^2, 4 from 4-8 ha/km^2 and 5 more than 8 ha/km^2. All specifications include school and year fixed effects as well as department specific time trends. Standard errors are clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1.

Robustness Checks— Table A9 presents several robustness checks. Panel (A) adds coca specific time trends and year effects interacted with baseline characteristic to the model. The estimates are robust to this specification. Panel (B) implements a more demanding comparison by controlling for district-by-year fixed effects. All coefficients reflect only differences within districts in a given year. Although the estimates for achievement measures are in some cases smaller, they are qualitatively similar. For enrollment, I find that results are similar in significance and in magnitude. These results rule out that schooling effects are driven by any changes over time at the district level. Second, given that coca production in 2002 can be endogenous, I check the robustness of the results by replacing the main treatment variable by my coca suitability index. Panel (C) shows that results do not change. Results are similar in significance and in magnitude, providing further evidence that previous results are not driven by endogenous coca production measures. Finally, Panel (D) redefines my treatment using the 1994 measure at the district level and results are similar.

[39]One concern with this specification is the lack of effects on enrollment at older ages given that some 9th to 11th graders were also exposed to high coca prices during grade 7th. However, since there are also 9th to 11th graders that were exposed to low coca prices during grade 7th, it is more difficult to find an effect on these grades. Nevertheless in the robustness check section I study the effects on the dropout rate rather than enrollment rate.

I further check the robustness of the results by replacing enrollment by the number of students who drop out of school as the dependent variable. This variable is only available for the years 2004 to 2014 and for a subset of schools. Again, I find that dropouts are concentrated in 7th grade. Finally, I analyze whether the achievement of secondary school children is affected by the increase in coca prices. I find positive but non-significant effects.[40] This suggests that while primary-school-age children are affected on the intensive margin, secondary-school-age children are affected on the extensive margin.

Taken together, these results show that the expansion of the drug industry in Peru had a large negative impact on children 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 schooling results are concentrated among 6 to 14 years old, which are the ages when child labor increases. Moreover, even within districts, effects are larger for schools located in high intensity coca cells, providing additional evidence on the child labor channel. Regression results are consistent with the qualitative evidence: younger children are harvesting coca leaves, attending school less often, or reducing their school effort. Older children who enter secondary school are likely to be involved in other parts of the cocaine industry as well, including production and transportation. The results imply that these are the students who drop out of school entirely.

5.2.3 Other Potential Mechanisms Behind Schooling Results

In this section, I provide evidence that schooling results are not driven by an increase in violence, cocaine consumption, or changes in the supply of education.

Changes in violence— Another possible pathway through which the expansion of the cocaine industry could impact schooling is by increasing the murder rate for young children, affecting returns to education. There is evidence that this mechanism is important for understanding the effect of the crack cocaine epidemic in the US (Evans et al. 2012). Expansion of coca production in Colombia in the 1990s also led to violence (Mejía and Restrepo 2013). However, if schooling results are driven by violence or murder rates we should also find that secondary students achievement would be affected. I find that this is not the case. Moreover, there is no reason to believe that violence would affect schools differentially depending on the intensity of the coca cells within each district. Nevertheless, using police data at the department level I visually inspect whether homicides and terrorism in these areas increased immediately after the Colombian shock.[41]

Figure A6 presents the number of homicides and terrorist events over time across both coca and non-coca areas and there is no increase after the shock in 1999. This is consistent with qualitative evidence suggesting that violence and terrorism have not increased in these areas. According to a coca farmer with whom I spoke during my field work "There is no need to use bullets when money can get the job done." Also news articles note that "Peru has also so far avoided the levels of bloodshed that have rocked Colombia and Mexico, with Peruvian traffickers apparently rely-

[40] Results are available upon request.
[41] Unfortunately, there is no data publicly available at the district level.

ing more heavily on bribes than bullets."[42] Finally, I also check whether affected cohorts are more likely to be affected by homicides using police record of victim's district of birth and age in 2011 and 2015. I find no evidence that individuals affected by high coca prices during childhood are also more likely to be victims of homicides.

Changes in the supply of education— It is possible that schooling results are driven by changes in educational resources in 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 changes that would affect the entire school. To rule out the possibility that teachers are directly affected by coca production, I check whether there is an increase in adult farm employment and find no effect. I also analyze whether there is a decrease in the number of teachers per school and find no effect. Finally, there is no effect on the quality of teachers as measured by the number of teachers with a post-secondary degree.

In addition, the effects I find are not driven by cocaine consumption. While it is possible that using cocaine affects student's schooling directly, most adolescents in Peru do not consume cocaine before the age of 16.[43] Moreover, during my sample period most cocaine consumption is concentrated in the main cities since it is an expensive product.

6 The Long-Term Consequences of Early Life Participation in the Illegal Industry on Crime and State Legitimacy

Thus far, the analysis has focused on how the expansion of cocaine 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 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 and trust in institutions by examining cohorts most affected by the increase in coca prices. Comparing the effects with other commodities and exploiting variation in districts where coca production is legal, I also show that effects are consistent with the development of industry-specific human capital, namely criminal capital.

6.1 Econometric Specification

6.1.1 Baseline Econometric Specification

In order to examine the long-term effects, I estimate the effect of high prices during childhood at relevant schooling ages. Identification comes from coca price variation at different ages and from coca suitability across districts of birth. For each adult individual at the time of the survey, I

[42] Source: Business Insider, 02/09/2016.

[43] For more information see *Estudio sobre prevencion y consumo de drogas en la poblacion general de Lima Metropolitana y El Callao*, Technical Report, 2014, Comisin Nacional para el Desarrollo y Vida sin Drogas, Public Health Department, Peru.

construct the full history of coca prices at different ages. In this way, I assess whether changes in prices during childhood have a long-term impact on adults who were born in districts with high coca suitability.

Equation 3 presents the specification:

$$Y_{d,c} = \beta^x \underbrace{(\mathit{PriceAge}_c^x \times \mathit{Coca}_d)}_{PriceShockAgex_{d,c}} + \alpha_d + \delta_c + \sigma_d c + \gamma_t + \epsilon_{c,d} \quad \forall x = 6, ..., 17 \tag{3}$$

where d indexes the district of birth and c the birth year. Coca_d is the number of coca hectares in the district of birth in 1994. $\mathit{PriceAge}_c^x$ is the log price of coca at different ages during childhood, where x ranges from age 6 to 17. For example, if we want to see an effect of prices at the age of 10 for an individual born in 1985, $\mathit{PriceAge}_c^{10}$ will be equal to prices in 1995. 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 control for time-invariant characteristics of the districts that may be correlated with both childhood exposure and future incarceration.

Control variables are not available for all years of birth. Therefore, to control for potential changes across districts of births I include district specific cohort trends, $\sigma_d c$. As a robustness check, I also include department-by-year fixed effects. District specific cohort trends account for the differential economic development and enforcement measures of each district through time. Furthermore, this isolates the deviation in the outcome from the long-run trend in a given district of birth. Given the spatial and time correlation in the error terms, I cluster standard errors by district of birth, allowing for an arbitrary variance-covariance structure within districts.

The parameter of interest is β, the effect of experiencing the boom in coca prices during childhood, 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. Given that schooling and child labor results were driven by children between age 6 and 14, there should be no long-run effect for cohorts that were affected at older ages. Therefore, as a falsification test, I also analyze whether there is an effect for older individuals.

For the earnings and trust outcomes, I use household surveys from 2011 to 2015. Therefore, I also controls for year of survey fixed effects, γ_t.[44] I also control for individual-level covariates including gender, poverty, migration status, population, and region. As in the main specification, I cluster standard errors by district of birth.

6.1.2 Addressing Potential Concerns

One potential concern is that increased enforcement may be correlated with exposure to the coca shock. I address this issue by comparing outcomes for individuals in different cohorts within

[44] Nevertheless, results are invariant to controlling for year of survey.

coca districts. In addition, for the sub-sample of individuals with village of birth information, I classify village of birth using the geographic cells from the satellite images.[45] This more granular classification allows for the inclusion of district-by-year fixed effects. 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. Given that most of the enforcement decisions are made at the district level, this helps rule out effects from differential enforcement.

Another potential concern is that the results are driven by adult exposure to criminal activity. To address this concern, I show that prices at older ages do not predict future incarceration. In addition, to directly control for adult exposure to criminal activity, I check the robustness of the results by restricting the sample to individuals that were in prisons located outside of coca districts. Identification comes from exposed individuals who move to a non-coca district, and therefore were not likely to be directly exposed to coca during adulthood.

As in the short-run analysis, areas that grew coca in 1994 are classified as suitable for coca. To address the concern that this may be endogenous, I check the robustness of the results using the coca suitability index based on agro-ecological variables and coca satellite images.

To control for the fact that incarceration may be trending upwards, but at different rates across Peru, I include department-by-year of birth fixed effects. In addition, since arrests of affected cohorts may be correlated with overall changes in policing in Peru, I control for year of arrest fixed effects. 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 experiences high coca prices at a particular age. For this specification, the data is aggregated so that there is one observation for each combination of year, district of birth, and year of arrest. Since there are individuals of the same age arrested in different years, I am also able to separate the age effects. Finally, I analyze whether effects are driven by differential mortality across cohorts and district of birth.

Peru was affected by intense civil conflicts between 1980 and 1993, including the rise of the Shining Path.[46] Although this is before my main period of analysis, it is possible that the oldest cohorts in the sample were affected during childhood. To control for the possibility that individuals affected by the coca shock could also be affected by civil conflicts, I control for the number of victims due to civil conflict per district per year of birth.

I also perform the following robustness checks. First, I check whether cohorts that were age 6 to 14 at the first peak of prices (in 2002) are most affected. In this specification, variation comes from their age in 2002 interacted with coca suitability measures. For instance, I can compare individuals who were 12 at the beginning of the coca boom versus individuals who were 17 at that time. Second, for the years that data are available I check the robustness of results by instrumenting prices by the number of coca hectares in Colombia. In Equation 3, I do not instrument prices

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

[46] Leon (2012) shows how human capital accumulation decreases due to civil conflicts in Peru.

given that historical data on the number of hectares in Colombia are not available. However, this is less of a concern because future incarceration rates are less likely to affect changes in coca prices during childhood. Moreover, short-term effects documented in the previous section are robust to not instrumenting coca prices. This is consistent with the view that changes in the price of coca are due to demand shocks from the U.S. and Europe and supply shocks in other source countries. Third, for comparison, I analyze the long-term effects of legal commodities which also increase child labor such as coffee and gold. Shocks to gold prices generated an increase in child labor of similar magnitudes as shocks to coca prices, making it a particularity relevant comparison.[47] In the case of gold, I define the shock as the interaction of mineral gold deposits per district in 1970s with international gold prices instrumented by gold exports of top producing countries.[48]

6.2 Results for Long-Run Effects

In this section, I provide evidence that adult criminal behavior is significantly affected by exposure to the drug industry during childhood. Cohorts born in coca districts who were exposed to high prices between age 11 and 14 are more likely to be incarcerated as adults.

Next, I examine the mechanisms driving these results by examining other outcomes as well as heterogeneous effects. Taken together, the evidence implies that exposure to the drug industry during childhood increase industry-specific human capital, leading to future criminality.

I show that incarceration effects are mainly driven by the increase in child labor. Moreover, I find the largest effects for violent and drug-related crimes with no effects on other crimes. In addition, the incarceration effects are concentrated in districts producing coca illegally, rather than districts producing coca for the legal section. I show that affected individuals are less likely to trust government institutions, which may affect state capacity in regions with a large illegal sector. Results are robust when examining only exposed individuals not currently living in the coca district. This implies that it is not adult exposure to the drug industry that affects adult outcomes but exposure during childhood. Moreover, there are no long-term effects for individuals who experience high coca prices after the age 14. Finally, results are not driven by an increase in violence and enforcement in coca areas.

6.2.1 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 they are exposed after age 14. These

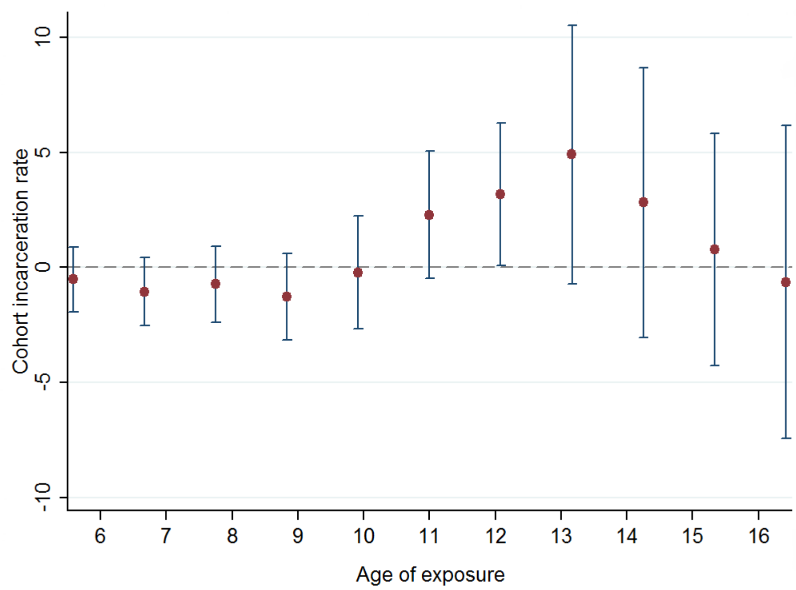
[47] Gold is an important commodity in Peru and children often work in gold production. For example, Santos (2014) finds that the boom in international gold prices increased child labor in Colombia.

[48] The international price of gold was obtained from World Bank (Global Economic Monitor Commodities Database). The volume of exports was obtained from `http://atlas.media.mit.edu/` and the gold deposits were obtained from the United States Geological Surveys Mineral Resource Database.

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. This finding is also consistent with previous literature showing that it is at these ages when children are more susceptible to neighborhood characteristics and criminal peers (Damm and Dustmann 2014).[49]

I then estimate Equation 3 but interacting coca suitability with the average prices between the ages of 11 and 14 for each individual. Table 5 presents the results. Results show that higher prices during the relevant ages lead to a statistically significant increase in the subsequent probability of being an offender in a district-cohort. The increase in coca prices after the eradication efforts in Colombia induces a 30% increase in the probability of incarceration of an individual who grew up in an average coca district in Peru. Column (2) presents the estimates for narco-trafficking crimes and the magnitude of the estimates double, which is consistent with an increase in industry-specific capital during childhood. Children who start working in this industry at an early age are more likely to be involved in the drug trade later on.

Figure 6: Incarceration rate effects by age



Notes: These graphs plot 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 and the X-axis shows the ages. Standard errors are clustered at the district level.

In the incarceration data I cannot observe individuals who entered the prison and were released before the beginning of my sample. This could bias my results if these individuals are not

[49]Previous research has also shown that exposure to adverse events during the transition between primary and secondary schooling can have a long-term effects on years of schooling and earnings (Shah and Steinberg 2013).

evenly distributed across treatment and control groups. Notwithstanding, most individuals in prison are serving sentences that average eight years. To address this concern, however, Column (3) in Table 5 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.

Table 5: Coca prices during childhood and subsequent criminal behavior

	(1) All	(2) Drugs	(3) Sentence length
PriceShock Age11to14$_{d,c}$	3.607***	2.127***	20.277
	(0.906)	(0.680)	(19.273)
Effect for avg district	+29%	+62%	+14%
Mean of dependent	4.5	1.2	98.37

Notes: *PriceShock Age11to14*$_{d,c}$ is the interaction between the coca suitability in the district of birth and the log average prices between the ages of 11 and 14. 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. Significant at *** p<0.01, ** p<0.05, * p<0.1.

Another potential concern with the results presented in Table 5 is that the time-series correlation in the exposure to illegal markets might be affecting my estimates. One way to indirectly test this is to include other age bins in the same regression. I do this in Table 6. Column (1) estimates the effects of childhood exposure to high coca prices on individuals who are between 18 to 30 years of age.[50] Results are consistent with the estimates of Figure 6. It shows that results are mostly driven by those who were below the age of 14. In particular, there are larger effects for those who experienced high prices at the critical period between the ages of 11 and 14. In Column (3), I estimate the effect for older individuals who are between 28 and 39 years old. In both samples, there are large increases in drug related crimes. This shows 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 their 30s). This suggests that affected cohorts remain on a criminal path well into adulthood. Moreover, higher prices between the ages of 15 and 19 do not affect the probability of being incarcerated, providing further evidence that results are driven by exposure prior to adolescence.

[50] 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 in 1993 to 2009 and thus were affected by the fall in prices and the expansion induced by Colombian policies.

Table 6: Coca prices during childhood and subsequent criminal behavior

	(1) All	(2) Drugs	(4) All	(5) Drugs
$PriceShock\ Age6to7_{d,c}$	1.239	0.543	-0.331	-0.008
	(0.817)	(0.601)	(0.932)	(0.502)
$PriceShock\ Age8to9_{d,c}$	1.409	0.734	1.654	1.613**
	(0.929)	(0.758)	(1.009)	(0.699)
$PriceShock\ Age10to11_{d,c}$	2.645**	1.604	1.609	1.720*
	(1.205)	(1.016)	(1.228)	(0.943)
$PriceShock\ Age12to13_{d,c}$	4.734**	2.820	1.962**	1.686**
	(2.182)	(1.767)	(0.831)	(0.748)
$PriceShock\ Age14to15_{d,c}$	5.003	1.097	1.393*	1.018*
	(3.284)	(2.616)	(0.756)	(0.583)
$PriceShock\ Age16to17_{d,c}$	-0.060	-1.286	0.271	0.036
	(2.844)	(1.955)	(0.429)	(0.369)
$PriceShock\ Age18to19_{d,c}$			0.566	-0.204
			(0.961)	(0.825)
Observations	23,853	23,853	22,028	22,028
Sample	18-30	18-30	28-39	28-39

Notes: $PriceShock\ Age6to7_{d,c}$ is the interaction between the coca suitability in the district of birth and log average coca prices at different ages. Results are robust to different ranges of bins. 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. Significant at *** p<0.01, ** p<0.05, * p<0.1.

Robustness Checks— To control for the fact that incarceration may be trending upwards, but at different rates across Peru, Panel (A) in Table A10 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 Panel (B), I control for year of arrest fixed effects.

To account for potential endogeneity of coca producing areas, Panels (C) and (D) present the results using the coca suitability index and instrumenting for coca prices during childhood using the number of hectares in Colombia. These specifications produce similar estimates.

Panel (E) employs district-by-year of birth fixed effects. Individuals from a village located inside a coca geographic cell (identified by satellite images) who experienced high prices at key ages are 50% more likely to be incarcerated for drug-related crimes. Any potential confounder needs to mimic the evolution of coca prices and differentially affect villages within a district that have higher coca suitability. The similarity with previous estimates at the district level 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.

To rule out that effects are not driven by civil conflicts, Panel (F) controls by the number of victims per year and district of births. Results do not change.

As an alternative approach, I compare cohorts who were between 6 and 14 years of age in the year of the first peak in prices versus cohorts who were older that year. The omitted category is those older than 16. Table A11 in the Appendix presents the results. The results are consistent with the previous estimates. Being between 11 and 14 years old at the time of the peak increases the chances of being an offender by 25% and it is significant at the 1% level. However, these results should be taken with caution because different ages at the time of the boom also reflect a change in the potential years of exposure to illegal labor market activities. Therefore, these estimates are a combination of the age at the time of the peak in prices and the years of exposure.

Finally, to check that results are not driven by differential mortality across cohorts and across regions with different coca suitability, I use homicide data from the police for the years 2011 and 2013.[51] These data contain information about the district of birth and age of 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 find no effect.

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 and schooling, 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:[52]

$$D_{c,d} = \phi \mathit{Treated}_{c,d} + \kappa_d + \nu_c + \pi_d c + \chi_t + \mu_{c,d} \tag{4}$$

$$X_{c,d} \times D_{c,d} = \beta D_{c,d} + \alpha_d + \delta_c + \sigma_d c + \gamma_t + \epsilon_{c,d} \tag{5}$$

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 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

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

[52]I calculate the proportion of compliers that had characteristic X as:

$$P(X_i = 1 | D_{1i} > D_{0i}) = \frac{E[X_i D_i | Z_i = 1] - E[X_i D_i | Z_i = 0]}{E[D_i | Z_i = 1] - E[D_i | Z_i = 0]}$$

where Z_i is a binary variable and takes value of 1 if the individual was induced to treatment and 0 if she was not induced to treatment D_i. D_{0i} is the value that D_i would have taken if $Z_i = 0$ and D_{i1} if $Z_i = 1$. In my case it indicates those cohorts who were induced to be in prison. X_i is an indicator for whether the individual has characteristic X.

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 7.

Table 7: Compliers Characteristics

	(1) Compliers	(2) Population
Has less than high school education	0.819***	0.585
	(0.219)	[0.493]
Has more than high school education	0.181	0.415
	(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]
Experienced violence in their family during childhood	0.434**	0.486
	(0.174)	[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 parenthesis. Standard deviations are presented in brackets. Significant at *** p$<$0.01, ** p$<$0.05, * p$<$0.1.

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 have 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 who were also affected by their schooling 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. I discuss this mechanism in more detail in the next section.

6.2.2 Mechanisms behind the Criminal Paths

There are two main mechanisms that could be driving the effects on adult criminal activity, an increase in criminal capital or decrease in formal human capital.

On the one had, it could be the case that illegal labor market opportunities increase criminal exposure during childhood and these investments in industry-specific criminal capital increase the benefit of future involvement in the industry.[53] This criminal capital may include 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, results could also be explained by a reduction in schooling during childhood. As children dropout of school, they may have fewer opportunities and lower wages in the formal sector, increasing future involvement in crime. I also examine other potential mechanisms such as exposure to violence and adult criminal exposure. In this section, I argue that the results are primarily due to the development of criminal capital during childhood.

Type of Crime—Table 8 presents the results by type of crime. The effect is concentrated on drug-related crimes, suggesting that crime-specific human capital is developed at the expense of productive human capital. I also find smaller significant effects for violent crimes and no effects for other crimes. These results are also consistent with the criminal capital channel. Children exposed to the drug industry continue to work in the drug trade as adults, leading to incarceration for industry-specific crimes such as drug trafficking and murder.

In addition, if I control for the average schooling of the offenders in the main specification, the magnitudes remain similar.[54]

Adult Criminal Exposure— An alternative hypothesis is that adult outcomes are driven by adult exposure to illegal industries rather than childhood exposure. To explore this, 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, which is a proxy for where they lived as adults.[55] Table 8 shows that there are significant effects for individuals who are incarcerated outside coca areas, implying that exposure during childhood affects adult criminality even if individuals are not exposed to the illegal sector as adults.[56] This finding suggests that individuals bring their criminal capital with them if they migrate to areas that do not produce coca.

[53]Previous literature studying the effects of incarceration (Mueller-Smith 2016; Bayer et al. 2009) suggest the development of criminal capital while in prison. Also, recent work has highlighted the importance of peers at schooling ages. Carrell et al. (2016) shows how exposure to disruptive peers in school affects adult earnings.

[54]This result is available upon request and should be interpreted with caution. Given that schooling is also affected by the drug industry, this specification could suffer from the *bad control* problem.

[55]In Peru, the location of imprisonment is usually close to the location of the crime.

[56]Figure A9 in the Appendix presents the results for different ages and I find similar results.

Table 8: Coca prices during childhood and subsequent criminal behavior

	(1) All	(2) Drugs	(3) Violent	(4) Sexual	(5) White collar	(6) Other
Panel A, All Prisons						
PriceShock Age11to14$_{d,c}$	3.607***	2.127***	1.304***	-0.107	0.046	0.237
	(0.906)	(0.680)	(0.397)	(0.193)	(0.103)	(0.355)
Effect for avg. district	+29%	+62%	+19%	-2.6%	+11%	+6%
Panel B, Prisons located in Non-Coca Districts						
PriceShock Age11to14$_{d,c}$	2.253***	1.275*	0.881***	-0.136	0.062	0.172
	(0.815)	(0.673)	(0.327)	(0.181)	(0.091)	(0.263)
Panel C, Women						
PriceShock Age11to14$_{d,c}$	0.384**	0.266**	0.062	0.000	-0.000	0.059
	(0.163)	(0.129)	(0.047)	(0.001)	(0.000)	(0.076)
Panel D, Legal Coca						
PriceShock Age11to14$_{d,c}$	4.091***	2.542***	1.379***	-0.305	0.030	0.445
	(1.055)	(0.812)	(0.425)	(0.215)	(0.124)	(0.343)
PriceShock Age11to14$_{d,c}$ × *Legal*	-3.749**	-2.654***	-0.965	0.151	0.049	-1.174
	(1.817)	(0.999)	(1.779)	(0.271)	(0.170)	(1.435)

Notes: *PriceShock Age11to14*$_{d,c}$ is the interaction between the coca suitability in the district of birth and the log average prices between the ages of 11 and 14. Standard errors clustered at the district of birth level. Significant at *** p<0.01, ** p<0.05, * p<0.1.

Women—Panel (C) in Table 8 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. Moreover, the fact that women are also affected by the drug-trade suggests that involvement in violence during childhood is not driving the results.

Coca production for the legal sector—I examine the differential effect for districts where most coca production goes to the legal sector.[57] In these districts, coca leaves are legally sold for medicinal and religious purposes.[58] Therefore, workers have less contact with the cocaine industry. I interact the shock with a dummy indicating whether the individual is from an area where coca is produced legally. For the fully saturated model in Panel (D), 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 to

[57] 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 sector.

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

the formation of industry-specific criminal capital and future criminality.[59]

Other commodities—Table A12 estimates the effects of price shocks for legal commodities--coffee and gold--on incarceration rates. Child labor is sensitive to price changes for both commodities. In the case of gold, the magnitude of the child labor shock is similar to that of coca. However, I find no evidence that early life participation in these sectors affects subsequent incarceration rates. This provides further evidence that it is child labor in *illegal activities* that drives the results, rather than child labor alone. This suggest that children acquire industry-specific criminal capital when working in the illegal sector, but not in the legal sector.

Other channels—I have argued that criminal capital develops during childhood from learning-by-doing through direct participation in the drug industry and 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). While I cannot completely rule this out, three pieces of evidence suggest that industry-specific criminal capital is developed by working in the illegal industry directly and not merely by general exposure. First, a 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 last occupation. Second, the incarceration effects are primarily driven by exposure during the ages when child labor increases the most. Third, even within a district-year, effects are larger for individuals who were born in a high coca density cell compared to individuals born in low coca density cells in the same district. If it was only general exposure, all children in coca districts would likely be affected. In Section 7, I provide further evidence that child labor in the illegal sector can play an important role for future criminality.

Another potential mechanism could be exposure to violence. It could be that children who grew up in a household with exposure to the drug industry may also be more exposed to violence, leading to future incarceration. Three pieces of evidence suggest that this is not the main mechanism driving the results. First, if exposure to violence was the main mechanism, violence should also affect older or younger individuals. Second, I do not find evidence that violence increased in the short-term in these areas, suggesting that individuals were not exposed to significant changes in violence. In addition, the complier analysis suggests that families of affected individuals were not more violent, as measured by self-reported family violence during childhood. Finally, exposure to violence would not explain why there are larger effects for drug-related crimes.

6.2.3 Trust and State Legitimacy

In the previous sections, I showed that affected cohorts gain industry-specific human capital and are more likely to follow a criminal life path. In line with the criminal capital mechanism, exposure to illegal industries may have broader implications for democratic values and state legitimacy. As individuals become more involved in the drug trade they may learn how to work under weak rule of law, changing their attitude towards the state. In particular, I examine satisfaction

[59]Table A12 in the Appendix presents the short-run effects on child labor and I find no differential effect in areas where most coca is produced legally.

with democracy as well as trust in various government institutions, including police, congress, judicial system, and political parties using data covering the period 2011 to 2014. These outcomes have been widely used to study state legitimacy in the context of developing countries.

Table 9 presents the results using the same specification as the previous section. Column (1) shows distrust in the regional government in general while Columns (2) to (4) show the coefficients for specific institutions as dependent variables. I find that individuals who were most exposed to the cocaine industry have more distrust in the police, regional government, and congress. This finding is consistent with the fact that during cocaine expansion, corruption increases, potentially affecting these institutions.[60]

Table 9: Coca prices during childhood and subsequent distrust in institutions

	(1) Government	(2) Police	(3) Congress	(4) Justice	(5) Democracy	(6) Politicians
$PriceShock\ Age6to14_{d,c}$	0.463**	0.324*	0.594**	-0.270	0.331*	0.482**
	(0.185)	(0.181)	(0.276)	(0.280)	(0.191)	(0.203)
$PriceShock\ Age15to18_{d,c}$	0.048	-0.004	-0.173	0.057	0.048	0.053
	(0.170)	(0.132)	(0.146)	(0.119)	(0.128)	(0.083)
Observations	30,253	30,253	30,253	30,253	30,253	30,253
District FE	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Department Trends	✓	✓	✓	✓	✓	✓

Notes: The dependent variable for columns 1-4 is a dummy that indicates whether the respondent does not trust the regional government (column 1), police (column 2), Congress (column 3), and Judiciary Power (column 4). Column (5) presents the results using a dummy that indicates whether the individual believes democracy does not work well in the country as the dependent variable. Column (6) is a dummy that indicates whether individuals think that democracy does not work well due to bad politicians. Standard errors clustered at the district of birth level. Significant at *** p<0.01, ** p<0.05, * p<0.1.

Column (5) shows the estimates using satisfaction with democracy as the dependent variable. Exposure to the drug industry during childhood increases the belief that democracy does not work. Column (6) shows that there is an increase in the belief that democracy does not work because of bad politicians. In addition, there are no effects for older cohorts.[61]

[60]While government may fight against the illegal drug business, they also often take a portion of profits. In interviews, one coca farmer noted that, "We can only trust locals, police take most of our merchandise [coca and cocaine] and re-sell it at higher prices." An NGO administrator working in the area said that "it is the police and people from outside the area who regularly steal cocaine." In addition, at least 115 local politicians have been prosecuted for involvement in drug-trafficking (Ministerio del Interior, 2015).

[61]Ideally, it would be possible to separately estimate the effect for each age. However, due to the lack of statistical power I rely on age bins.

Overall, the expansion of the drug industry reduced trust in institutions for those highly exposed to the illegal industry. This may have important implications for development. Distrust in institutions can lead to lower levels of social capital, which many view as a key ingredient for development (Horvth 2013; Baliamoune-Lutz 2011; Ahlerup et al. 2009).

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

So far I have shown how the expansion of the drug industry in Peru affected children, leading to long-term consequences for adult criminality and trust in institutions. 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 program (CCT) during the period of high coca prices. This second experiment helps further disentangle the mechanisms of the previous results and sheds light on the role of policy to mitigate the incarceration effects.

First, I examine the incentive to grow coca given the effect on the present value of lifetime earnings for parents and their children. In Section A.3, I estimate the short- and long-run effects on income using the same identification strategy as in Equations 1 and 3. In the short-run there are income gains from the shock to coca prices. However, individuals who are affected by high coca prices as children earn 30% less in the long-run. I use these estimates to calculate the change in the present discounted value of earnings across generations when individuals are exposed to the coca shock relative to those not exposed. Assuming a 5% discount rate, I find evidence that the present income gains from growing coca do not compensate the future income losses for children. This is true even though the calculation does not take into account the cost associated with the increased probability of incarceration when individuals grow coca.

In Section A.3, I develop a simple framework to analyze parents' choice to use child labor given the long-term effects for their children. In the model, parents choose whether to employ their children on the farm or send their children to school. Their utility is assumed to depend on the current earnings, as well as the present value of their children's future utility. Motivated by the empirical results, there are frictions that cause parents to not fully internalize the future cost of growing coca for their children. There are many potential reasons for these frictions such as credit constrains, myopia, or lack of information. The lack of information may be particularly important given that a survey from my field work shows that 65% of farmers do not believe that school is a better investment for children than working on coca farms.[62]

The model suggests that parents may decrease the use of child labor if there are additional incentives to send children to school. In the next section, I use the gradual rollout of a conditional cash transfer (CCT) to test to what extent results are driven by parental decisions in areas affected

[62] The survey was conducted on a sample of about 300 coca farmers. I describe the survey in more detail in Appendix A.6.

by the coca shock. In addition, I shed light on how to maximize the effects of the policy.

7.1 Direct Effects of Conditional Cash Transfer on Child Labor and Drug Production

In this section, I show that 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 and drug production, as well as improves schooling outcomes. I also provide suggestive evidence that the CCT reduces adult incarceration rates when children grow up in coca areas when coca prices are high.

The CCT program consists of a monthly lump-sum payment of about 30 dollars. 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: Rollout of CCTs

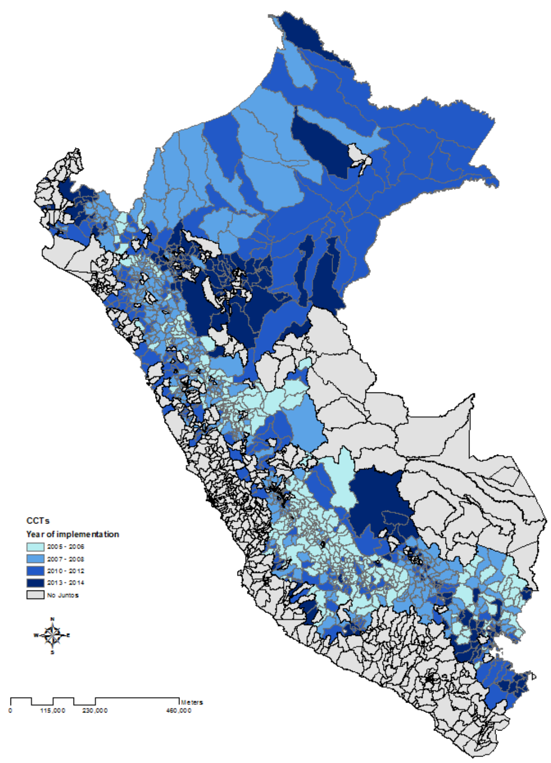


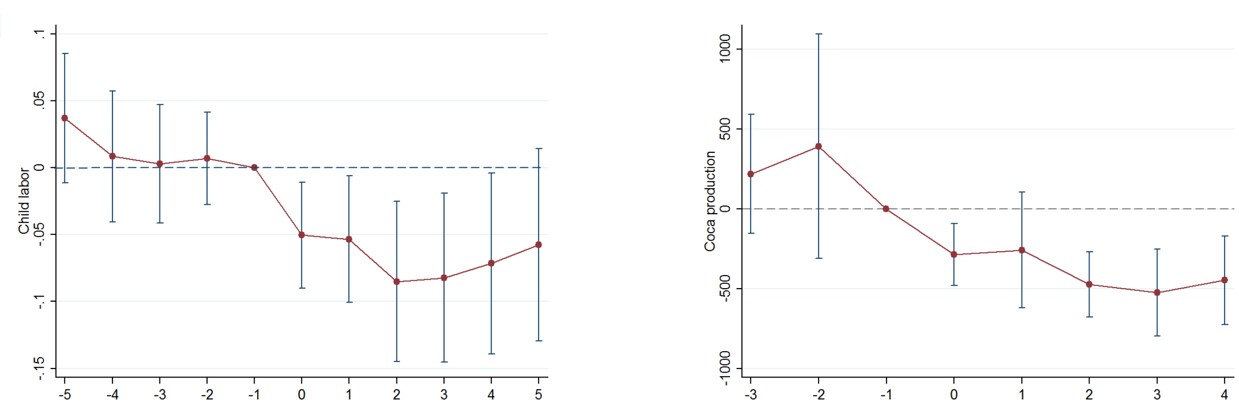
Figure 7 presents a map showing the rollout of the CCT program. There is substantial variation across districts and across years. By 2014, about 1,400 districts—covering 80% of the coca-growing districts—had CCTs. There were two large expansions in in 2007 and then in 2012. I find that average coca production was similar in both periods, suggesting that coca districts were not treated first. The selection of districts was based on an index that includes poverty and percentage of villages affected by violence during civil conflict. All regressions control for trends in this index. Notice that in the previous analysis, results did not change when controlling for this index. Thus, this suggests that the pre-trends assumption is satisfied. Nevertheless, using an event study analysis, I examine whether there are any pre-trends.

I start by estimating the effect of CCTs in an event study analysis:

$$Y_{i,d,t} = \alpha + \sum_{i=-4}^{5} \beta_i(\tau_{d,t} = i) \times Coca_d + \alpha_d + \phi_t + \sigma_r t + \epsilon_{i,d,t} \tag{6}$$

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 ($\tau = -1$). Figure 8 plots the event and year coefficients from estimating Equation 6 using child labor as the dependent variable. 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.

Figure 8: The effects of CCTs when coca prices are high



(a) Child labor relative to years with CCT

(b) Coca production relative to years with CCT

Table 10 presents a fully saturated version of Equation 1 including interactions with $CCT_{d,t}$, a dummy indicating whether the district d has a CCT in year t. I find that CCTs decrease child labor by 15% in coca areas. [63]

[63] The magnitude is consistent with experimental evidence in rural Mexico where CCTs decrease child labor by 22% (Skoufias et al. 2001).

Table 10: CCTs and coca price shocks on child labor

	(1)	(2)
	Child labor	Child labor
$PriceShock_{d,t}$	0.145***	0.237**
	(0.040)	(0.102)
$PriceShock_{d,t} \times CCT_{d,t}$		-0.116**
		(0.053)
Mean of dependent	0.25	0.25
Observations	233,824	233,824

Notes: This table presents the estimates of a fully saturated model of Equation 1 with interactions with $CCT_{d,t}$, a dummy indicating whether the district d has a CCT in year t and 0 otherwise. Results are robust to the inclusion of trends by the index for which they selected districts and differential trends by the stage of treated. Standard errors clustered at the district level are shown in parenthesis. Significant at *** p<0.01, ** p<0.05, * p<0.1.

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. Given that I only have data for years with high coca prices, I estimate a model excluding the price interactions. Panel (B) in Figure 8 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%.[64]

I assess whether the magnitudes are plausible by comparing the effects of the CCTs with the effects found from the increase in coca prices in the 2000s. During the boom in coca prices in the 2000s, I find that a 30% increase in child labor is associated with an 80% increase in coca production (this is the increase observed during the period of analysis). Assuming that there is no substitution between child and adult labor, a 15% decrease in child labor would then lead to a 40% decrease in coca production, close to the observed reduction of 34%.[65]

Table A17 presents the effect of CCTs on schooling outcomes. I find that the CCTs mitigate the negative effects on schooling. The exception is the age for grade outcome, where I find no statistically significant effect.

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 A18 suggests that incarceration effects are also mitigated when individuals have the CCTs in their early teens. There are no effects at older ages.

These findings have two implications. First, 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. Second, they shed light on the role of policy. Policy makers can actually solve some of the problems related to

[64]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.

[65]Moreover, if they are imperfect substitutes, one would expect coca production to decrease by less than 40 percent.

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.

7.1.1 What is Driving the Effects? Is it the Conditionality?

In this section I discuss two mechanisms that could explain these results: income effects and schooling-work substitution effects. Monetary transfers increase incomes, potentially reducing the incentives for those who are economically motivated to produce coca for the illegal market. Previous literature has showed how welfare transfers in the U.S. reduced economically motivated crimes (e.g., Jacob et al. 2015; Foley 2011). Also, Chioda et al. (2015) find that a CCT program in Brazil reduced youth crime by 18% and argue that the results are driven by income effects. CCTs may also affect drug production by incentivizing schooling. Children may be substituting time working on the farm and illegal activities with time spent in school. This is in line with the schooling incapacitation effect found in the crime literature. For example, Anderson (2014) finds that an increase in the minimum high school dropout age led to a reduction in juvenile arrest rates in the US. Similarly, the CCT program in Peru may increasing the time children spent in school, reducing the time for coca production.

To analyze the income component of CCTs, I check whether effects are driven by lower income areas. I also examine how adult labor responds to the introduction of the CCT. I find that results do not change when stratifying by poverty, suggesting that income effects are small. Moreover, if CCT effects were mainly driven by income effects, we would expect no effects on adult labor. However, Table A19 shows that adult labor increases after the introduction of the CCTs.

To shed additional light on the schooling-work substitution mechanism, I provide qualitative evidence showing that children have to work many hours in coca farming. Testimonies from my field work indicate that the coca harvest is done from 4 am to 4 pm during the week and from 6 am to 2 pm over the weekends. This implies that any increase in schooling is likely to reduce the available time for picking coca leaves.

7.2 Geographic Targeting of Conditional Cash Transfer Program

In this section, I explore the optimal geographic allocation of the CCT program. First, if the government objective is to reduce child labor and coca production, and thus future criminality, CCTs should be targeted toward coca districts where the likelihood of becoming a criminal is higher. Second, it is important to take into account spatial spillovers. In the same way that coca production spilled over from Colombia to Peru, CCTs can create spillovers across coca suitable areas in Peru. Previous research has found that increased enforcement can shift criminal or illegal activities to adjacent areas.[66] Therefore, I examine whether CCTs shift coca production and child

[66] For example, Dell (2015) shows that drug enforcement policy in certain municipalities in Mexico diverted drug trafficking to other municipalities.

labor to other suitable districts that did not have the policy and then use these estimates to provide an alternative allocation of CCTs that accounts for these potential spillovers.

7.2.1 Spillover Effects

In this subsection, I show that when a CCT program is introduced, child labor and coca production increase in neighboring coca districts where parental incentives for schooling are not provided.

In order to test whether the CCTs impact coca production in other districts without the policy, it is necessary to specify where spillovers are likely to occur. Using data from my field interviews, I assume that spillovers move to suitable neighboring districts since intermediaries may have specific contacts and resources such as trucks that are relatively immobile in a particular area. In addition, qualitative evidence suggests that when coca production decreases in one district, local intermediaries increase coca prices, generating an increase in coca production in nearby districts. In Peru there are about 13 coca/cocaine markets, each market containing several districts. Each market has intermediaries who supply the international market. These intermediaries have social capital (e.g. reputation with coca farmers) and physician capital (e.g. trucks) specific to each markets.[67] Therefore, if coca production decreases in one district, coca production is likely to move to neighboring coca district that are more suitable.

When CCTs are introduced in one district, child labor decreases, costs to produce increase, and therefore, production decreases in the district. Although there may be substitution to adult labor, it is more expensive. In response to the shift in supply, the intermediary increases the coca price in the area and the neighboring districts are now willing to produce more.[68] Although, I am not able to test the price mechanism, the qualitative evidence suggests the presence of spillovers effects. I empirically test for these spillover effects in the next section.

7.2.2 Empirical Strategy and Results

In order to estimate spillover effects of CCTs on neighboring coca areas, I first define the set of districts over which I expect the spillovers to be positive. These districts are those who are neighbors of at least one coca district based on the number of hectares produced in 1994. For these districts, I analyze the impact of neighboring districts with coca and CCTs. In other words, I study whether districts that neighbor a coca district that has the CCT program experience more child labor due to price shocks. I use the following specification to test spillovers:

[67] The intermediary can be a local family firm or a foreign drug cartel.

[68] Note that Rozo (2014) finds evidence that enforcement in Colombia shifted production internationally rather than to neighboring districts. This may be due to the fact that coca farmers in Colombia expected enforcement in all districts, whereas coca farmers in Peru were not affected by major drug enforcement policies.

$$Y_{d,t} = \beta_1 PriceShock_{d,t} + \beta_2 PriceShock_{d,t} \times \mathit{NeighborCCT}_{d,t} + \mathit{NeighborCCT}_{d,t} + \alpha_d + \phi_t + \sigma_r t + \epsilon_{d,t} \quad (7)$$

where $PriceShock_{d,t}$ is defined as the interaction of coca prices and coca production in 1994 instrumented by hectares in Colombia (see Equation 1) and $\mathit{NeighborCCT}_{d,t}$ is coded as 1 if the neighboring district has CCTs in year t.[69] The sample excludes years when district has CCTs themselves. For example if district d_1 has a neighbor d_2 that has the program in 2005 and district d_1 gets CCTs in 2009, district d_1 will only be coded as 1 for the period 2005 to 2009. The main regressor $PriceShock_{d,t} \times \mathit{NeighborCCT}_{d,t}$ is coded as 1 if district d has a neighboring district with both coca and CCTs in year t. I interact this dummy with the coca intensity and the logarithm of coca prices. β_2 measures how shocks to prices affect districts that are neighboring coca areas that have CCTs. A positive β_2 means that there is a larger impact for districts that are bordering a coca district with CCTs and also have a high share of coca compare to districts that are bordering coca but do not have CCTs.

Table 11 shows that coca districts that are bordering a district with CCTs experience a larger increase in child labor than those that are not bordering CCTs. β_2 is positive and significant, implying that there are positive spillover effects arising from coca districts that are bordering a district that receives the transfer. Child labor increases in neighboring coca districts by 7%. In an alternative specification, I keep the sample of coca districts that are bordering another coca area and estimates the effect of having CCTs. Column (2) shows that results do not change under this specification. I also test to what extent farmers may send their children to work in the neighboring districts that do not have CCTs. In Columns (3) and (4) I check whether there are spillover effects on migration of adults and children and I find no effect.

[69] I estimate the full saturated model that includes interactions with $\mathit{NeighborCCT}_{d,t}$. To simplify the exposition, these interactions are not shown in Equation 7.

Table 11: CCTs and child labor, spillovers in neighboring districts

	(1)	(2)	(3)	(4)
	Child labor	Child labor	Migration	Migration
$PriceShock_{d,t}$	0.200*		-0.090	-0.015
	(0.115)		(.110)	(0.113)
$PriceShock_{d,t} \times$ *Neighbor CCT*$_{d,t}$	0.046**	0.038**	0.0161	0.011
	(0.021)	(0.017)	(0.021)	(0.013)
Observations	170,814	46,581	170,814	998,647
Sub-sample of coca neighbors		✓		

Notes: *** p<0.01, ** p<0.05, * p<0.1. This table presents the estimates of a fully saturated model of Equation 1 that includes interactions with $NeighborCCT_{d,t}$, a dummy indicating whether the neighboring district d has a CCT in year t and 0 otherwise. Results are robust to the inclusion of trends by the index for which they selected districts and differential trends by the stage of treated. Standard errors clustered at the district level are shown in parenthesis.

Next, I conduct a falsification test. If spillover effects are driven by a reduction in coca production of neighboring districts due to CCTs, districts that are bordering a non-coca district with CCTs should not have spillover effects. I find that all the effects are driven by the districts that are bordering areas with CCTs but also had coca. There are no effect due to neighboring district with CCTs that are not producing coca. This suggests that it is not the direct effect of CCTs but the fact that the transfer program is reducing coca production in the bordering district.

In Table A20, using coca production from 2010 to 2014, I directly study the spillover effects on coca production and find that it increases in the neighboring districts by 19%. In this specification, I do not include the price interaction because I have no price variation. Results are robust to the inclusion of department and coca specific trends. Moreover, effects are robust to clustering the standard errors at the regional level.

7.2.3 Cost-Benefit Analysis of Using CCTs to Reduce Drug Production

The aim of the CCT program was to reduce poverty and increase human capital investments. In the previous sections, I show that it also has the benefit of reducing coca production by about 15% after taking into account the negative spillover effects. In 2012, the total cost of the program was about $212 million, providing CCT payments to about 600,000 households (the annual cost per household is about $340).[70] The average number of households in coca districts is 4,000. Even assuming that all households in coca districts are given the transfer, these estimates imply that it would cost an average of $1.4 million to implement the CCT in each coca district.

I can use these estimates to compare the cost of using CCTs to reduce coca production with the cost of increased enforcement. Spending $1.4 million on the CCT reduces coca production

[70] These figures come from Peru's Ministerio de Desarrollo e Inclusin Social.

by about 100 hectares. For comparison, Mejía et al. (2015) find that reducing 800 hectares of coca through an eradication program would cost between \$20 and \$27 million. Therefore, it costs about \$11 million to reduce coca production by the same amount through CCTs. Moreover, eradication programs have been shown to have unintended consequences by increasing violence and affecting local economic development (Abadie et al. 2014; Rozo 2014).

These estimates suggest that, relative to standard enforcement measures, CCTs can be a much more cost effective way to reduce production in the illegal drug market. Other policies that encourage schooling or limit the develop of criminal capital by promoting the legal sectors may also have positive returns. It is important to note that there may still be important interactions between increased enforcement and other policies that affect incentives for formal human capital.

7.2.4 Alternative Allocations of CCTs

In this section, I use my previous estimates to shed light on the optimal allocation of CCTs taking into account spillovers based on coca suitability. I assume that the objective function of the social planner is to reduce child labor in coca districts subject to a binding constraint that limits the number of districts with the CCT program. I develop an algorithm that maximizes this objective function. Results imply that that there are two potential strategies for a social planner. First, it may be optimal to allocate CCTs to districts with high suitability that neighbor districts with low suitability in order to reduce spillovers. Alternatively, it may be optimal to implement the CCT program in clusters of high suitable districts that all neighbor one another.

The idea of this exercise can be illustrated with the following example. Suppose we have two coca markets: coca market 1 is composed by two districts, A and B that are both very suitable for coca production, and coca market 2 where district C is very suitable and district D has very low suitability. Now given these markets, where is it better to implement CCTs if we could only choose one district? Given that spillovers occur in productive neighboring districts, it may be better to allocate CCTs to C since the elasticity of production with respect to price is low for the neighboring district. I formalize this idea in the following model.

The main assumptions in the model are: i) the government objective function is to minimize child labor in coca districts but can only choose a subset of districts, ii) spillovers can only occur in neighboring districts that can produce coca and are part of the same coca labor market, iii) if a district has the policy it does not receive spillovers from other districts, and iv) the spillover effects of each district are independent of whether other districts in the market have the policy.

Let $\mathcal{S} = \{1, 2, \ldots, S\}$ be the set of *districts* and A be an $S \times S$ matrix where each cell (i, j) is the spillover effect of *district* i on district j if the policy is implemented in i but not in j, and the diagonal elements of A ($[a_{ii}]$) is the effect district i gets when the policy is implemented in i, which depends on each district coca suitability.

We have two sets of binary decision variables: n_i ($i \in \mathcal{S}$) and m_{ij} ($i, j \in \mathcal{S}; i \neq j$). n_i is equal to one if the policy is implemented in i, zero otherwise, and m_{ij} is equal to one, if the policy is implemented in i but not in j, zero otherwise.

The objective is to maximize the effect of policy on districts:

$$\max \sum_{i\in\mathcal{S}} a_{ii}n_i + \sum_{i\in\mathcal{S}} \sum_{j\in\mathcal{S},i\neq j} a_{ij}m_{ij} \tag{8}$$

subject to three sets of constraints:

- *Spillover constraint*,

$$m_{ij} = \begin{cases} 1, \text{ if } n_i = 1, n_j = 0 \\ 0, \text{ otherwise} \end{cases}, \qquad i,j \in \mathcal{S}, i \neq j$$

which can be written in linear form as

$$2m_{ij} \leq 1 + n_i - n_j, \qquad i,j \in \mathcal{S}, i \neq j \tag{9}$$

$$m_{ij} \geq n_i - n_j. \qquad i,j \in \mathcal{S}, i \neq j \tag{10}$$

- *Budget constraint*,

$$\sum_{i\in\mathcal{S}} n_i \leq b. \tag{11}$$

where b is the maximum number of *Districts* to be selected for policy.

- the decision variables are binary,

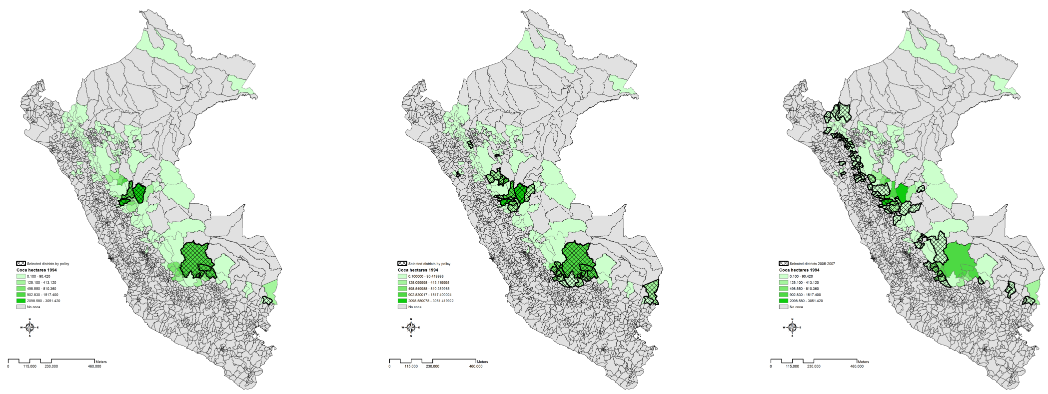
$$n_i \in \{0,1\}, m_{ij} \in \{0,1\}. \quad i,j \in \mathcal{S}, i \neq j \tag{12}$$

Therefore, the policymaker maximizes the following problem:

$$\begin{aligned} \text{min} \qquad & \sum_{i\in\mathcal{S}} a_{ii}n_i + \sum_{i\in\mathcal{S}} \sum_{j\in\mathcal{S},i\neq j} a_{ij}m_{ij} \\ \text{subject to} \qquad & 2m_{ij} \leq 1 + n_i - n_j, \ i,j \in \mathcal{S}, i \neq j \\ & m_{ij} \geq n_i - n_j, \ i,j \in \mathcal{S}, i \neq j \\ & \sum_{i\in\mathcal{S}} n_i \leq b, \\ & n_i \in \{0,1\}, \ i \in \mathcal{S} \\ & m_{ij} \in \{0,1\}, \ i,j \in \mathcal{S}, i \neq j \end{aligned}$$

Panel (A) in Figure 9 presents the results of this problem when the government can allocate the CCT to 10 districts (i.e. $b = 10$). We can see that the selected districts are those that are next to districts with low suitability or those that are next to other high suitability district with the CCT program. High suitable districts that are within a cluster of other high suitability districts are only given the CCTs if their neighbors also get the CCTs.

Figure 9: Targeting considering coca suitability



(a) Targeting 10 (b) Targeting 40 (c) Actual 2005-2007 allocation

If we increase the government constraint to 40 districts, it is optimal to target more clusters rather than individual coca districts. These results show that there are two reasons why policy may want to target specific places: i) to reduce spillovers to neighbors, the social planner should target districts that do not neighbor other high suitability coca districts, and ii) to reduce spillovers in the entire area, the social planner should target a cluster of suitable districts together.[71]

Next, in Panel (C) of Figure 9, I compare the optimal allocation of CCTs with the actual government selection between 2005 to 2007. During these years, the government implemented the policy in 84 coca districts based on their allocation rule. Most of the selected districts were those with low suitability or those with high suitability neighboring other high suitability districts, generating spillover effects. If the objective is to reduce child labor and reduce future criminality in these areas, these results suggest that there is significant room to improve outcomes by taking into account location-specific characteristics (i.e. the presence of illegal labor markets that are due to coca suitability).

8 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

[71]Notice that targeting all high coca suitable districts may generate international spillovers, which I am not considering in the analysis.

to the literature by showing that geographic conditions 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, undermining state legitimacy. 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.[72] 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.[73]

This paper also provides evidence that exposure to illegal industries generates distrust in state institutions, however there may be other important consequences related to state capacity. The presence of illegal labor markets may affect the quality and honesty of elected politicians. This is a particular concern since politicians in areas with large illegal sectors are often found to have connections to the narco-trafficking industry.[74] Relatedly, lower trust in government institutions may lead to substitution towards informal institutions, limiting the ability of the state to reduce drug trafficking. Understanding to what extent informal mechanisms of justice or informal groups may develop in areas exposed to illegal industries, as well as the determinants of politician quality in these areas, is an area for further research.

In the second half 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. In particular, I find that CCTs reduced drug production and future criminality by increasing the costs of child labor, one of the main inputs. This is relevant not only for developing countries where the expansion of drug production and trafficking has led to high levels of violence in the last decades, but also for international efforts to combat drug production. I argue that the judicious use of policies that decrease criminal capital can potentially be more cost effective than increased enforcement.

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.

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

[73]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.

[74]In Peru, at least 115 local politicians have been prosecuted for involvement in drug-trafficking (Ministerio del Interior, 2015).

References

Abadie, A., Acevedo, M. C., Kugler, M., and Vargas, J. (2014). Inside the war on drugs: Effectiveness and unintended consequences of.

Ahlerup, P., Olsson, O., and Yanagizawa, D. (2009). Social capital vs institutions in the growth process. *European Journal of Political Economy*, 25(1):1 – 14.

Aizer, A., Doyle Jr, J. J., et al. (2015). Juvenile incarceration, human capital, and future crime: Evidence from randomly assigned judges. *The Quarterly Journal of Economics*, 130(2):759–803.

Ajzenman, N., Galiani, S., and Seira, E. (2014). On the distributive costs of drug-related homicides. Technical report, National Bureau of Economic Research.

Alesina, A. and Ferrara, E. L. (2002). Who trusts others? *Journal of Public Economics*, 85:207–34.

Anderson, D. M. (2014). In school and out of trouble? the minimum dropout age and juvenile crime. *Review of Economics and Statistics*, 96(2):318–331.

Angrist, J. D. and Kugler, A. D. (2008). Rural windfall or a new resource curse? coca, income, and civil conflict in colombia. *The Review of Economics and Statistics*, 90(2):191–215.

Atkin, D. (2012). Endogenous skill acquisition and export manufacturing in mexico. Technical report, National Bureau of Economic Research.

Balbierz, P. (2015). Peru: the new king of cocaine.

Baliamoune-Lutz, M. (2011). Trust-based social capital, institutions, and development. *The Journal of Socio-Economics*, 40(4):335 – 346.

Bandara, A., Dehejia, R., and Lavie-Rouse, S. (2015). The impact of income and non-income shocks on child labor: evidence from a panel survey of tanzania. *World development*, 67:218–237.

Bayer, P., Hjalmarsson, R., and Pozen, D. (2009). Building criminal capital behind bars: Peer effects in juvenile corrections. *Quarterly Journal of Economics*, 124(1).

Becker, G. (1981). A treatise on the family harvard university press. *Cambridge, MA*, 30.

Bell, B., Bindler, A., and Machin, S. J. (2014). Crime scars: recessions and the making of career criminals.

Beriain, D. (2014). Los obreros de la cocaína.

Brooks-Gunn, J. and Duncan, G. J. (1997). The effects of poverty on children. *The future of children*, pages 55–71.

Buonanno, P. and Raphael, S. (2013). Incarceration and incapacitation: Evidence from the 2006 italian collective pardon. *The American Economic Review*, 103(6):2437–2465.

Carrell, S. E., Hoekstra, M., and Kuka, E. (2016). The long-run effects of disruptive peers. Technical report, National Bureau of Economic Research.

Castillo, J. C., Mejia, D., and Restrepo, P. (2014). Scarcity without leviathan: The violent effects of cocaine supply shortages in the mexican drug war. *Available at SSRN 2409268*.

Chetty, R. and Hendren, N. (2015). The impacts of neighborhoods on intergenerational mobility: Childhood exposure effects and county-level estimates. *Unpublished Manuscript*.

Chetty, R., Hendren, N., and Katz, L. F. (2015). The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment. Technical report, National Bureau of Economic Research.

Chioda, L., De Mello, J. M., and Soares, R. R. (2015). Spillovers from conditional cash transfer programs: Bolsa família and crime in urban brazil. *Economics of Education Review*.

Cogneau, D. and Jedwab, R. (2012). Commodity price shocks and child outcomes: The 1990 cocoa crisis in côte divoire. *Economic Development and Cultural Change*, 60(3):507–534.

Cunha, F. and Heckman, J. (2007). The technology of skill formation. *American Economic Review*, 97(2):31–47.

Currie, J. and Almond, D. (2011). Human capital development before age five. *Handbook of labor economics*, 4:1315–1486.

Damm, A. P. and Dustmann, C. (2014). Does growing up in a high crime neighborhood affect youth criminal behavior? *The American Economic Review*, 104(6):1806–1832.

Dammert, A. C. (2008). Child labor and schooling response to changes in coca production in rural peru. *Journal of development Economics*, 86(1):164–180.

Dell, M. (2015). Trafficking networks and the mexican drug war. *The American Economic Review*, 105(6):1738–1779.

Deming, D. (2011). Better schools, less crime. *The Quarterly Journal of Economics*, 126(4):2063–2115.

Di Tella, R. and Schargrodsky, E. (2004). Do police reduce crime? estimates using the allocation of police forces after a terrorist attack. *The American Economic Review*, 94(1):115–133.

Draca, M. and Machin, S. J. (2015). Crime and economic incentives. *Annual Review of Economics*, 7:389–408.

Dube, O., Garcia-Ponce, O., and Thom, K. (2015). From maize to haze: Agricultural shocks and the growth of the mexican drug sector.

Dube, O. and Vargas, J. F. (2013). Commodity price shocks and civil conflict: Evidence from colombia. *The Review of Economic Studies*, 80(4):1384–1421.

Edmonds, E. V. (2007). Child labor. *Handbook of development economics*, 4:3607–3709.

Evans, W. N., Garthwaite, C., and Moore, T. J. (2012). The white/black educational gap, stalled progress, and the long term consequences of the emergence of crack cocaine markets. Technical report, National Bureau of Economic Research.

Fisman, R. and Miguel, E. (2007). Corruption, norms, and legal enforcement: Evidence from diplomatic parking tickets. *Journal of Political economy*, 115(6):1020–1048.

Foley, C. F. (2011). Welfare payments and crime. *The review of Economics and Statistics*, 93(1):97–112.

Freedman, M. and Owens, E. G. (2014). Your friends and neighbors: Localized economic development and criminal activity. *Review of Economics and Statistics*.

Galiani, S., Rossi, M. A., and Schargrodsky, E. (2011). Conscription and crime: evidence from the argentine draft lottery. *American Economic Journal: Applied Economics*, 3(2):119–136.

Gastelumendi, M. (2010). Drogas, pobreza y derechos humanos: El impacto social del narcotrafico.

Glaeser, E. L., Sacerdote, B., and Scheinkman, J. A. (1996). Crime and social interactions. *The Quarterly Journal of Economics*, 111(2):507–548.

Heckman, J. J. (2006). Skill formation and the economics of investing in disadvantaged children. *Science*, 312(5782):1900–1902.

Horvth, R. (2013). Does trust promote growth? *Journal of Comparative Economics*, 41(3):777 – 788.

Imbens, G. and Angrist, J. (1994). Identification and estimation of local average treatment effects. *Econometrica*, 62(2):467–475.

Ingoldsby, E. M. and Shaw, D. S. (2002). Neighborhood contextual factors and early-starting antisocial pathways. *Clinical Child and Family Psychology Review*, 5(1):21–55.

Jacob, B. A., Kapustin, M., and Ludwig, J. (2015). The impact of housing assistance on child outcomes: Evidence from a randomized housing lottery. *The Quarterly Journal of Economics*, 130(1):465–506.

Leon, G. (2012). Civil conflict and human capital accumulation the long-term effects of political violence in perú. *Journal of Human Resources*, 47(4):991–1022.

Levitt, S. D. (1997). Using electoral cycles in police hiring to estimate the effect of police on crime. *The American Economic Review*, pages 270–290.

Levitt, S. D. (2004). Understanding why crime fell in the 1990s: Four factors that explain the decline and six that do not. *The Journal of Economic Perspectives*, 18(1):163–190.

Lochner, L. (2011). Nonproduction benefits of education: Crime, health, and good citizenship. *Handbook of the Economics of Education*, 4:183.

Lochner, L. and Moretti, E. (2004). The effect of education on crime: Evidence from prison inmates, arrests, and self-reports. *American Economic Review*, 94(1):155–189.

Mejía, D. and Restrepo, P. (2013). Bushes and bullets: Illegal cocaine markets and violence in colombia. Technical report, UNIVERSIDAD DE LOS ANDES-CEDE.

Mejia, D. and Restrepo, P. (2013). The economics of the war on illegal drug production and trafficking. Technical report, UNIVERSIDAD DE LOS ANDES-CEDE.

Mejía, D., Restrepo, P., and Rozo, S. V. (2015). On the effects of enforcement on illegal markets: evidence from a quasi-experiment in colombia. *The World Bank Economic Review*, page lhv051.

Mejía Fritsch, M. d. P. (2003). Condenados a la exclusin. nios que trabajan en las plantaciones de coca. Technical report, Instituto de Estudios Internacionales (IDEI)Pontificia Universidad Catlica del Per.

Miron, J. (1999). Violence and the u.s. prohibitions of drugs and alcohol. *American Law and Economics Review*, Fall(1-2):78–114.

Mueller-Smith, M. (2016). The criminal and labor market impacts of incarceration. Technical report.

Novak, F., Namihas, S., Huamn, M., and Garcia, L. (2011). Nios, nias y adolescentes en las zonas cocaleras del vrae y el alto huallaga. Technical report, Instituto de Estudios Internacionales (IDEI)Pontificia Universidad Catlica del Per.

Nunn, N. and Wantchekon, L. (2009). The slave trade and the origins of mistrust in africa. Technical report, National Bureau of Economic Research.

O'Flaherty, B. and Sethi, R. (2014). Urban crime. *Available at SSRN 2467297*.

Pachico, E. (2012). The evolution of the drug trade in peru's cocaine heartland.

PewResearchCenter (2014). Crime and corruption top problems in emerging and developing countries.

Reyes, J. W. (2007). Environmental policy as social policy? the impact of childhood lead exposure on crime. *The BE Journal of Economic Analysis & Policy*, 7(1).

Rozo, S. V. (2014). On the unintended consequences of enforcement on illegal drug producing countries. *Available at SSRN 2481400*.

Santos, R. J. (2014). Not all that glitters is gold: Gold boom, child labor and schooling in colombia. *Documento CEDE*, (2014-31).

Shah, M. and Steinberg, B. M. (2013). Drought of opportunities: contemporaneous and long term impacts of rainfall shocks on human capital. Technical report, National Bureau of Economic Research.

Skoufias, E., Parker, S. W., Behrman, J. R., and Pessino, C. (2001). Conditional cash transfers and their impact on child work and schooling: Evidence from the progresa program in mexico [with comments]. *Economia*, 2(1):45–96.

UNICEF (2006). Nios en zonas cocaleras. un estudio en los valles de los ros apurmac y alto huallaga. Technical report, UNICEF.

UNODC (2007). Drogas y delitos en el peru. situacion actual y evolucion. Technical report, United Nations Office of Drugs and Crime.

Van Dun, M. (2012). The drugs industry and peasant self-defence in a peruvian cocaine enclave. *International Journal of Drug Policy*, 23(6):442–448.

Vargas, R. (2014). Criminal group embeddedness and the adverse effects of arresting a gang's leader: a comparative case study. *Criminology*, 52(2):143–168.

Werb, D., Rowell, G., Guyatt, G., Kerr, T., Montaner, J., and Wood, E. (2011). Effect of drug law enforcement on drug market violence: A systematic review. *International Journal of Drug Policy*, 22(2):87–94.

A Online Appendix

A.1 Coca Index based on Agro-ecological Conditions

Figure A1: Coca suitability across Peru

Ecocrop

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Data sheet

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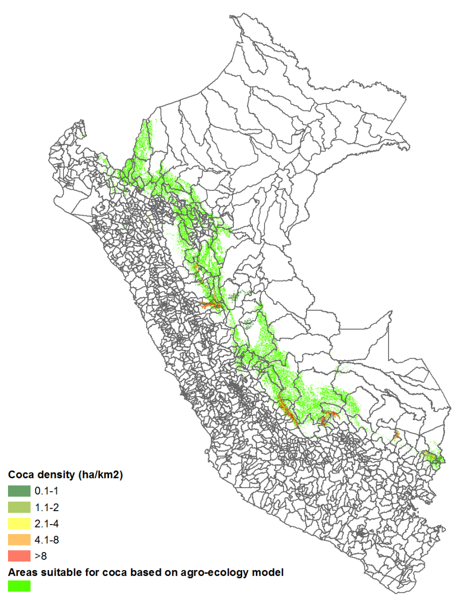
Erythroxylum coca

Description			
Life form	shrub, tree	Physiology	single stem, multi stem
Habit	erect	Category	medicinals & aromatic
Life span	perennial	Plant attributes	grown on small scale

Ecology	Optimal		Absolute			Optimal	Absolute
	Min	Max	Min	Max	Soil depth	deep (>>150 cm)	medium (50-150 cm)
Temperat. requir.	17	23	14	27	Soil texture	medium	heavy, medium, light
Rainfall (annual)	1000	2100	700	4000	Soil fertility	high	moderate
Latitude	-	-	40	40	Soil Al. tox		
Altitude	---	---	-	-	Soil salinity	low (<4 dS/m)	low (<4 dS/m)
Soil PH	5.5	6.5	4.3	8	Soil drainage	well (dry spells)	well (dry spells)
Light intensity	very bright	very bright	very bright	clear skies			

(a) Optimal ecological conditions for coca plants



(b) Coca suitability based on agro-ecological variables

A.2 Additional Summary Statistics and Results

Table A1: Correlation between fraction of children and coca and coffee production 2012

	Coca production/total arable land	Coca production/total arable land	Coffee production/ total arable land	Coffee production/ total arable land
No.children/No. total labor in farm	.013	.026	-.015	-.015
	(.004)***	(.004)***	(.005)***	(.005)***
District fixed effects		✓		✓
Observations	11,086	11,086	11,086	11,086
R^2	0.005	0.136	0.01	0.113

Notes:Coefficients of the fraction of children amongst total labor per farm. Data for coca and coffee production are from 2012 Agriculture Census. Standard errors clustered at the district level. Significant at *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Summary statistics of main variables

Variable	Unit	Obs	Mean	Std. Dev.
Panel level variables				
Child labor (6-14)	Individual	242,580	.283	.451
Adult labor (21-60)	Individual	522,887	.772	.412
Self-employment (21-60)	Individual	434,694	.438	.496
Population	District	11,785	19264.1	35790.9
Primary enrollment	School	434,309	112.032	178.54
Age for grade in primary	School	434,309	.199	.169
% Failed in primary	School	426,523	8.349	8.992
Secondary enrollment	School	136,083	225.475	317.544
Age for grade in secondary	School	136,083	.2305	.207
% Failed in secondary	School	132,342	6.19	7.624
Incarceration rate in non coca	District-cohort	40,196	.0034	.0205
Incarceration rate in coca district	District-cohort	40,196	.0055	.0146
District variables				
Coffee intensity, thousands of hectares, 1994	District	1441	.14	.821
Coca indicator, 1994	District	1441	.126	.332
Coca intensity, thousands of hectares, 1994	District	1441	.016	.014
Poverty index in coca districts, 2000	District	188	34.185	8.032
Poverty index in coffee districts, 2000	District	393	32.383	7.675
Population in coca districts, 2000	District	188	12970.64	20020.57
Population in coffee districts, 2000	District	393	12894.18	24279.97
Health posts, 2000 in coca districts, 2000	District	188	7.681	10.176
Health posts, 2000 in coffee districts, 2000	District	393	7.679	11.091
Classrooms, 2000 in coca districts, 2000	District	188	86.09	93.314
Classrooms, 2000 in coffee districts, 2000	District	393	82.97	109.759
% of coca villages affected by violence, 2000	District	188	1.356	3.986
% of coffee villages affected by violence,2000	District	393	1.225	3.404
Time-level variables				
Log international coffee price	Year	15	.959	.466
Log internal coca price	Year	15	1.06	.193
Eradicated coca hectares in Colombia, hundred thousands of hectares	Year	15	1.529	.467
Log coca hectares in Colombia, hundred thousands of hectares	Year	15	-.258	.304

Figure A2: Schools distribution

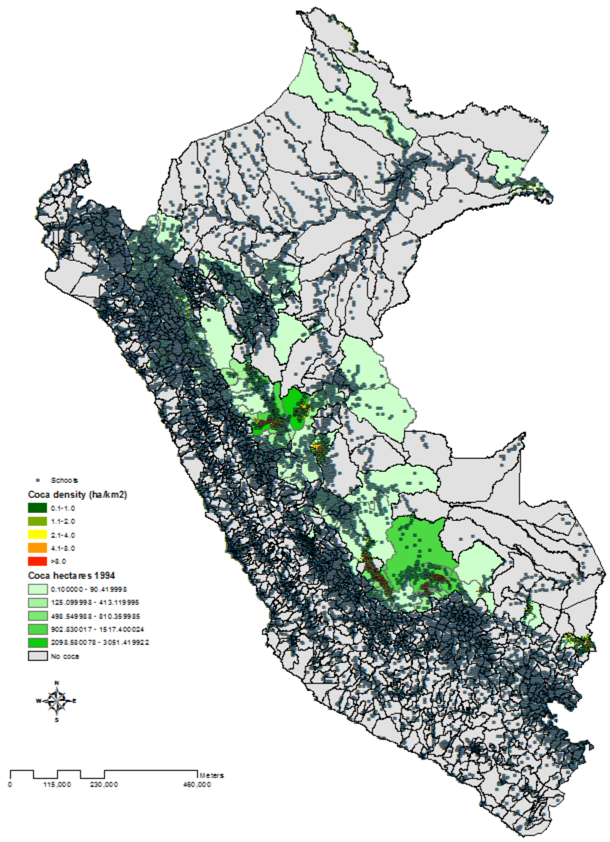


Table A3: Baseline 1998 schools located inside and outside coca geographic cells

Variable	Outside	Inside	Diff.	$\|t\|$	Pr($\|T\| >$ $\|t\|$)
Primary schools					
No of students	74.895	70.782	-4.113	1.00	0.3153
Age for grade	0.327	0.335	0.009	1.32	0.1861
% Failed students	13.856	11.476	-2.381	5.63	0.000***
No of teachers with degree	5.542	5.022	-0.520	0.81	0.4168
Math average (national exam second grade)	474.850	477.140	2.290	0.50	0.6190
Reading average (national exam second grade)	439.839	446.952	7.113	1.80	0.0715*
Secondary schools					
No of students	147.093	107.276	-39.817	1.28	0.2015
Age for grade	0.466	0.519	0.053	1.86	0.0635*
% Failed students	8.840	6.879	-1.961	1.59	0.1120
No of teachers with degree	19.101	23.649	4.548	0.78	0.4371

Table A4: Baseline 1997 coca and coffee districts

Variable	Coffee	Coca	Diff.	$\|t\|$	Pr($\|T\| >$ $\|t\|$)
Household characteristics					
Water inside hh	0.392	0.571	0.180	1.87	0.065*
Public drain	0.293	0.300	0.008	0.64	0.5234
Rural	0.477	0.453	-0.024	-0.23	0.816
Number of rooms	2.909	2.838	-0.071	-0.42	0.672
Male	0.504	0.511	0.007	0.55	0.5843
Age	23.542	23.469	-0.073	0.15	0.8842
Self-employed	0.439	0.451	0.012	0.87	0.3867
Years of education of household head	3.797	3.657	-0.140	-1.22	0.228
Married	0.283	0.292	0.009	0.61	0.5441
Household size	6.320	5.907	-0.414	-1.67	0.101
Children characteristics					
Male	0.506	0.508	0.002	0.06	0.9533
Age	9.418	9.253	-0.165	1.31	0.1902
HH work	0.808	0.814	0.005	0.24	0.8066
Hh work hours	1.493	1.474	-0.018	0.28	0.7780
Self-employed	0.224	0.232	0.008	0.36	0.7157
Self-employed days	3.965	3.629	-0.336	1.31	0.1904
Self-employed hours	3.445	3.776	0.331	1.43	0.1524
Read and write	0.845	0.812	0.033	1.58	0.1139
School enrollment	0.970	0.947	-0.023	2.15	0.0315**
Years of schooling	2.144	2.145	0.001	0.01	0.9941

Figure A3: Age distribution of incarcerated individuals

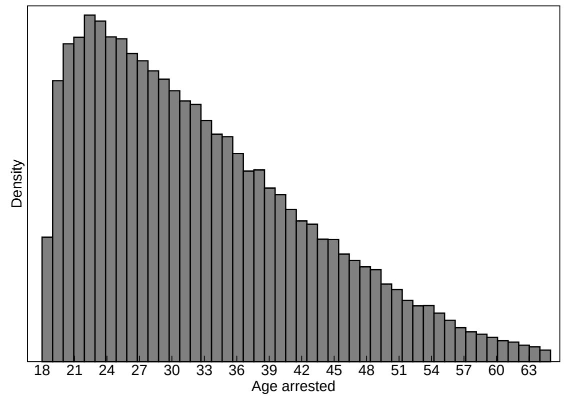
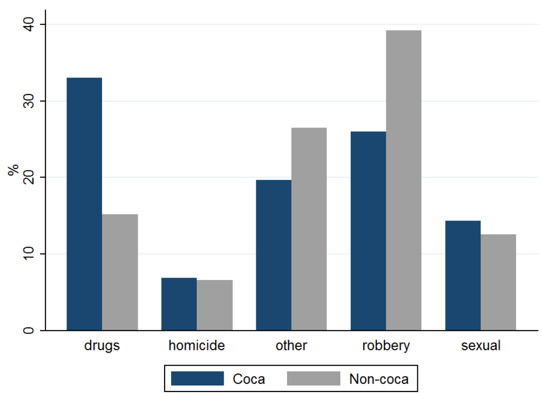
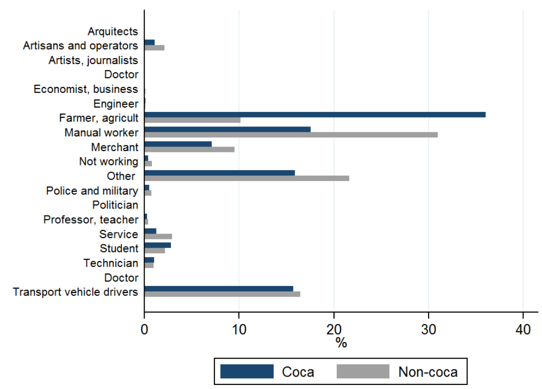


Figure A4: Incarceration data



(a) Type of crime



(b) Main occupation of incarcerated individuals

Figure A5: Histogram of educational attainment from 2007 Census

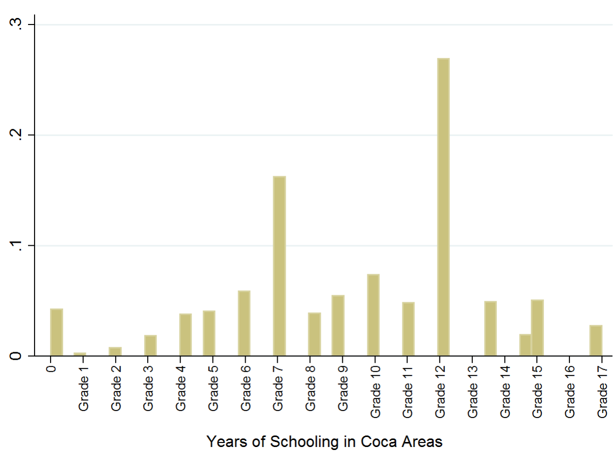


Table A5: Internal validity of the exclusion restriction

	(1) Taxes	(2) Income taxes	(3) Donations	(4) Income	(5) Canon	(6) Customs	(7) Special transfers	(8) Other transfers
$Coca_d \times CocaColombia_t$	-0.152	-0.181	0.005	0.182	4.382	0.024	0.181	0.524
	(0.138)	(0.136)	(0.010)	(0.114)	(3.826)	(0.016)	(0.239)	(0.479)
Observations	18,306	18,425	18,301	18,301	18,301	18,301	18,301	18,301
District FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: All variables are expressed in real values and come from the National Institute of Statistics (INEI). Canon corresponds to the tax income collected through natural resource exploitation. Transfers are made from the central to the local governments every year. Clustered standard errors at the district level are presented in parentheses. Significant at *** p<0.01, ** p<0.05, * p<0.1.

Table A6: The effect of coca prices on child labor in Peru, by age bins

	(1)	(2)	(3)	(4)
Ages	6-10	11-14	15-18	19-21
$PriceShock_{d,t}$	0.104***	0.276***	0.243**	0.204
	(0.038)	(0.089)	(0.12)	(0.193)
Effects for avg. district	21%	35%	26%	18.5%
Observations	126,414	107,410	102,756	62,026
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Department trends	✓	✓	✓	✓
Covariates	✓	✓	✓	✓

Notes: Column (1) presents the results for children who are between 6 to 11 years old. Column (2) presents the results for those between 11-14 years old. Column (3) and (4) presents the results for those between 15-18 and 19-21 years old respectively. I separate the sample between the ages that students are in primary and secondary school. Significant at *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Robustness checks, child labor

Panel A, Household Fixed Effects	
$PriceShock_{d,t} \times Age11x14_i$	0.073***
	(0.015)
Observations	161,746
Panel B, Coca Suitability Index	
$PriceShock_{d,t}$	0.309**
	(0.143)
Effects for avg. district	38%
Observations	233,753
Panel C, Controling for Violence	
$PriceShock_{d,t}$	0.163***
	(0.036)
Effects for avg. district	34%
Observations	233,727

Notes: All specifications control for district fixed effects, year fixed effects, department specific trends and covariates. Building upon the specification presented in Equation 1, Panel A adds a fully saturated model with interactions with *Age11x14*, a dummy indicating whether the individual is between 11 and 14 years old at the time of the survey, allowing for household fixed effects. Panel B defines $PriceShock_{d,t}$ using the coca suitability index instead of coca production in 1994. Panel C controls for trends by violence in 2000. Significant at *** p<0.01, ** p<0.05, * p<0.1

Table A8: Reduced form estimates: the effect of hectares in Colombia on child labor in Peru

	6-14	6-14	6-14	6-10	11-14
$Coca_d \times CocaColombia_t$	-0.086***	-0.079***	-0.085***	-0.056*	-0.122*
	(0.022)	(0.020)	(0.024)	(0.028)	(0.060)
Observations	234,473	234,473	233,832	126,438	107,394
R-squared	0.295	0.295	0.323	0.318	0.327
District FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Department trends		✓	✓	✓	✓
Covariates			✓	✓	✓

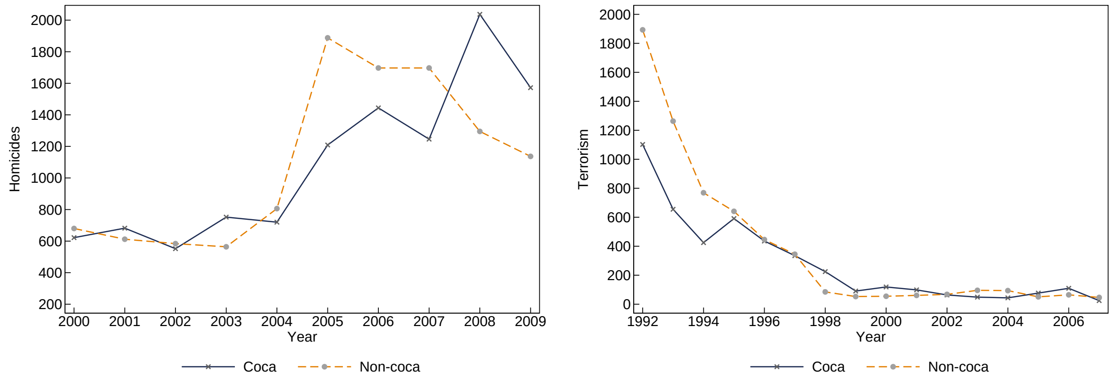
Notes: Standard errors clustered at the district level are shown in parenthesis. Significant at *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Robustness checks, schooling outcomes

	(1)	(2)	(3)	(4)
	Failed	Age for grade	Grade 8	Grade 9
Panel A, Including Baseline and District Trends				
$PriceShock_{s,t}$	0.706***	0.019***	-0.095***	-0.085**
	(0.163)	(0.003)	(0.030)	(0.042)
Effect for avg school	25%	28.5%	28.5%	25.5%
Observations	379,824	386,248	111,846	111,846
Panel B, Including District-Year Fixed Effects				
$PriceShock_{s,t}$	0.033	0.010**	-0.115**	-0.051
	(0.286)	(0.004)	(0.045)	(0.062)
Effect for avg. school	0.8%	15%	33%	15%
Observations	424,638	432,421	128,790	128,790
Panel C, Coca Suitability Index				
$PriceShock_{s,t}$	3.534***	0.071***	-0.298**	-0.311*
	(0.687)	(0.013)	(0.129)	(0.185)
Effect for avg. school	41%	35%	30%	31%
Observations	425,862	433,634	135,593	135,593
Panel D, Coca 1994				
$PriceShock_{s,t}$	2.207***	0.044***	-0.203***	-0.171*
	(0.457)	(0.008)	(0.069)	(0.104
Observations	425,862	425,892	135,593	135,593
Panel E, Coffee Shock				
$PriceCoffee_t \times Coffee\ int._d$	0.090	-0.001	0.033**	0.061***
	(0.117)	(0.002)	(0.016)	(0.021)
Observations	382,603	389,502	123,400	123,400

Notes: All specifications include school and year fixed effects, and department specific trends. Standard errors are clustered at school level. Significant *** p<0.01, ** p<0.05, * p<0.1.

Figure A6: Is violence driving the schooling results?



(a) Number of homicides

(b) Number of terrorist events

Figure A7: Differences in incarceration rates by period

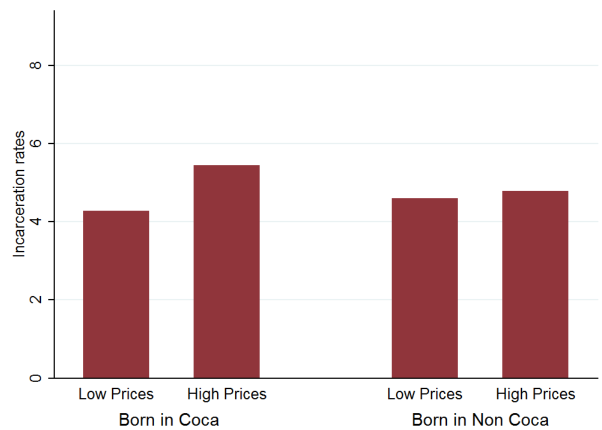


Figure A8: Effects on victims of homicides by age using police data

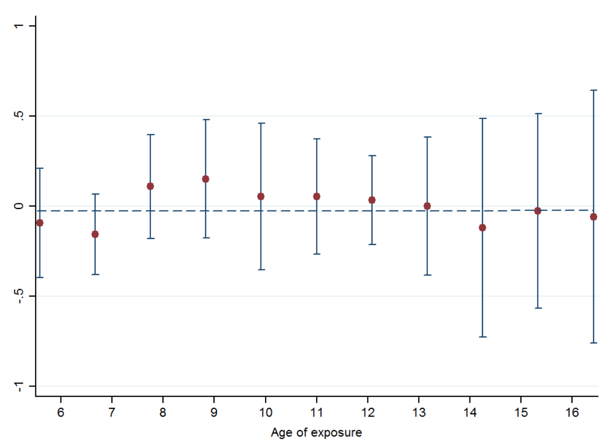


Figure A9: Incarceration rate effects by age using prisons located in non-coca districts

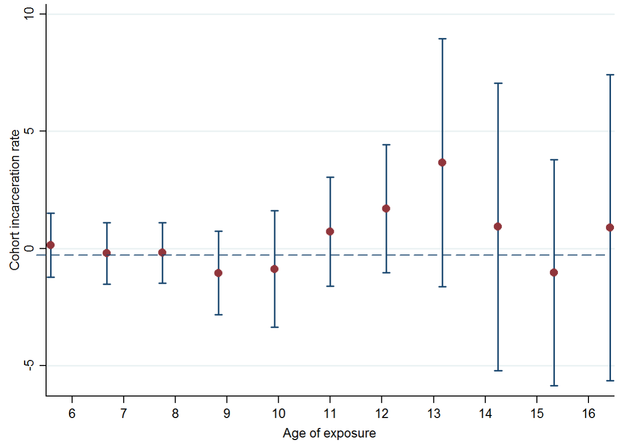


Table A10: Robustness checks, incarceration outcomes

	(1) All crimes	(2) Drugs	(3) Sentence length
Panel A, Including Department by Yob Fixed Effects			
PriceShock Age11to14$_{d,c}$	3.405***	2.160***	22.956
	(0.903)	(0.661)	(19.506)
Panel B, Including Year of Arrest Fixed Effects			
PriceShock Age11to14$_{d,c}$	0.129***	0.076***	-23.140
	(0.031)	(0.023)	(23.058)
Panel C, Instrumenting Prices			
PriceShock Age11to14$_{d,c}$	2.586***	1.482**	-24.282
	(0.654)	(0.645)	(46.932)
Panel D, Coca Suitability Index			
PriceShock Age11to14$_{d,c}$	2.217***	0.863**	19.897
	(0.597)	(0.337)	(13.284)
Panel E, Including District by Yob Fixed Effects [1]			
PriceShock Age11to14$_{v,c}$	0.006***	0.004***	
	(0.001)	(0.001)	
Panel F, Including Number of Victims During Civil Conflicts			
PriceShock Age11to14$_{d,c}$	2.888***	2.064***	23.433
	(1.061)	(0.691)	(19.021)
District FE	✓	✓	✓
Year FE	✓	✓	✓
Cohort FE	✓	✓	✓
District Trends	✓	✓	✓

Notes: *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. [1] Panel E uses 2016 census to obtain information of the village of birth but does not have information on the length of the sentence. Standard errors clustered at the district of birth level. *** p<0.01, ** p<0.05, * p<0.1.

Table A11: Age at time of the coca boom and subsequent criminal behavior

	(1)	(2)	(3)	(4)
Coca boom $Age6x7_c \times Coca_{d,1994}$	0.097	0.231**	0.227*	
	(0.080)	(0.093)	(0.125)	
Coca boom $Age8x9_c \times Coca_{d,1994}$	0.419	0.578*	0.572	
	(0.296)	(0.306)	(0.369)	
Coca boom $Age10x11_c \times Coca_{d,1994}$	0.551***	0.737***	0.728**	0.484***
	(0.207)	(0.253)	(0.293)	(0.182)
Coca boom $Age12x13_c \times Coca_{d,1994}$	0.551***	0.762***	0.751**	0.532**
	(0.187)	(0.218)	(0.291)	(0.218)
Coca boom $Age14x15_c \times Coca_{d,1994}$		0.556**	0.543*	0.349
		(0.276)	(0.285)	(0.222)
Coca boom $Age16_c \times Coca_{d,1994}$			-0.034	-0.209
			(0.493)	(0.412)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
District Trends	✓	✓	✓	✓

Table A12: Shocks to other commodities

Short-run effects on child labor					
Coca					
$PriceShock_{d,t} \times Legal$	0.195**				
	(0.096)				
Effect for avg. district	33%				
Coffee					
$PriceCoff_t \times Coff\ int._{d,1994}$	0.011**				
	(0.004)				
Effect for avg. district	5%				
Gold					
$PriceGold_t \times Gold\ int._{d,1975}$	0.019**				
	(0.008)				
Effect for avg. district	30%				
Long-term effects on incarceration					
	All	Drugs	Violent	Sexual	White collar
$PriceCoff\ Age11x14 \times Coff\ int._{d,1994}$	-0.414	0.047	-0.328**	0.091	-0.069**
	(0.260)	(0.058)	(0.165)	(0.217)	(0.033)
$PriceGold\ Age11x14 \times Gold\ int._{d,1975}$	-0.041	0.020	-0.052	0.010	0.000
	(0.121)	(0.033)	(0.084)	(0.030)	(0.005)

A.3 Does Coca Production Generate Large Income Effects?

Although coca production may have negative effects for children in the future, it is possible that present income gains may compensate the long-term negative effects. In this section, I show that the lifetime income for these individuals is negative.

To explore this, first I estimate whether income increases when coca price increases in the short-run. The household surveys record the total income and the earned income. I replace the dependent variable in Equation 1 for these income measures. Table A13 presents the results. Columns (1) and (2) present the results with the log of total income and log of earned income among adults. Columns (3) to (4) present the results for youth. All four coefficients are positive although only significant for earned income. Earnings increase by 10% for adults and 25% for youth. This implies that there are immediate income gains from the increase in coca prices. Moreover, the fact that I find effects only for youth is consistent with the story that coca prices increased wages of younger individuals.

Next, I explore how future income is affected for individuals who have high coca prices during childhood. I start first by analyzing whether children exposed to high prices at the ages of 6 to 14 experience lower income using household surveys from 2011 to 2014. Then, I check whether future income is particularly affected when children are exposed at a particular age.

Table A14 presents the results. Column (1) shows that cohorts affected by the coca boom when they are schooling age have lower income. The rest of the table provides robustness checks. For example, Columns (2) and (3) separates the sample by migration status and results are similar. Column (4) adds coca specific cohort trends. Given that some adult individuals who are 17 may still be at school, I check the robustness of the results by analyzing the effects on adults over the age of 18. Columns (5) and (6) show that results are robust to different sample sizes. Finally, in Column (7) I present the results with more dissaggreated bins. The coefficients are negative for all ages but stronger and significant for those between 11 and 14 years of age.

I also analyze whether the earnings results are driven by children who experienced high prices at specific ages during childhood. Table A15 presents the results with more dissaggreated bins. Although, the estimates lose some precision, most of the effects are concentrated among adults that experienced high coca prices at the age of 12. This is the age of most students in 7th grade, which is the grade where most dropouts occur.

Table A13: The effects of coca prices on present income

	(1) log income	(2) log earned income	(4) log income	(5) log earned income
$PriceShock_{d,t}$	0.204	0.286*	0.476*	0.603**
	(0.264)	(0.153)	(0.256)	(0.265)
Observations	340,560	166,449	128,322	89,456
R-squared	0.060	0.094	0.158	0.216
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Department trends	✓	✓	✓	✓
Covariates	✓	✓	✓	✓
Ages 21-60	✓	✓		
Ages 14-21			✓	✓

Notes: Standard errors clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table A14: Coca prices during childhood and adult earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PriceShock Age6to14$_{d,c}$	-0.601**	-0.604*	-0.556	-0.487**	-0.554*	-0.461*	
	(0.244)	(0.339)	(0.593)	(0.240)	(0.285)	(0.276)	
PriceShock Age15to16$_{d,c}$	0.160	0.288	-0.021	0.148	0.118	0.113	
	(0.360)	(0.416)	(0.695)	(0.347)	(0.386)	(0.371)	
PriceShock Age6to10$_{d,c}$							-0.317
							(0.245)
PriceShock Age11to14$_{d,c}$							-0.791**
							(0.389)
Observations	64,300	37,199	27,101	64,300	56,209	56,209	56,209
R-squared	0.060	0.087	0.048	0.058	0.056	0.054	0.049
District FE	✓	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓	✓
Year of the survey FE	✓	✓	✓	✓	✓	✓	✓
Department trends	✓	✓	✓		✓		✓
Coca time trends				✓		✓	
Sample	All	Movers	Non Movers	All	All	All	All
Ages	16-30	16-30	16-30	16-30	18-30	18-30	18-30

Notes: The baseline specification is presented in Equation 3. Column (1) presents the results for the whole sample and includes controls for gender, age, department trends, cohort fixed effects and year of the survey fixed effect. Columns (2) and (3) present the estimates for the sample of movers and non movers. Column (4) includes coca specific time trends. Column (5) and (6) replicates Columns (1) and (4) for adults who are more than 18 years old at the time of the survey. Column (7) presents the results with more dissaggreated bins. Standard errors are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1.

Table A15: Coca prices during childhood and adult earnings

	(1)	(2)
$PriceShock\ Age6_{d,c}$	0.297	0.279
	(0.345)	(0.332)
$PriceShock\ Age7_{d,c}$	-0.081	-0.044
	(0.384)	(0.372)
$PriceShock\ Age8_{d,c}$	-0.310	-0.277
	(0.265)	(0.251)
$PriceShock\ Age9_{d,c}$	0.522*	0.497
	(0.306)	(0.309)
$PriceShock\ Age10_{d,c}$	-0.405	-0.441
	(0.527)	(0.492)
$PriceShock\ Age11_{d,c}$	0.251	0.325
	(0.601)	(0.560)
$PriceShock\ Age12_{d,c}$	-0.557***	-0.595***
	(0.172)	(0.203)
$PriceShock\ Age13_{d,c}$	0.702	0.744
	(0.605)	(0.587)
$PriceShock\ Age14_{d,c}$	-0.625	-0.547
	(0.464)	(0.442)
$PriceShock\ Age15_{d,c}$	0.958	0.789
	(0.698)	(0.609)
$PriceShock\ Age16_{d,c}$	-0.915	-0.961
	(1.144)	(1.081)
Observations	56,203	56,203
R-squared	0.050	0.056
District FE	✓	✓
Cohort FE	✓	✓
Department time trends	✓	✓
Year of the survey FE	✓	✓
Department*year FE		✓
Coca time trends		✓
Ages	18-30	18-30

Notes: The specification is presented in Equation 3. Standard errors clustered at the district level.*** p<0.01, ** p<0.05, * p<0.1.

Table A16 addresses some concerns such as under-reporting of income and I find no evidence that affected cohorts are reporting no or lower income. Column (1) uses an indicator for whether the individual has completed high school as the dependent variable. I use this specification to test whether using pooled household surveys leads to an accurate measure of the long-term effect. I find that the probability is increased by 30% for affected cohorts which is similar to the results found using school census data in Section 5.2.2.

Another potential concern is that income may be under-reported for those individuals who are more likely to be in the illegal sector. I test this by estimating the same model but replacing the dependent variable by the probability of reporting a low or no income. Columns (3) and (4) report the results and there is no evidence that affected cohorts have incentives to under-report.

Finally, I examine whether these results are driven by the reduction in education. I recover the returns to schooling by dividing my earnings estimates by the schooling estimates. If I expect students who stay in school after age 12 to get 4.2 more years of education on average, this implies the return to an extra year of education is about 18%.

Table A16: Coca prices during childhood and adult earnings

	(1) High School drop out	(2) High School drop out	(3) Missing earnings(=1)	(4) Low earnings(=1)
PriceShock Age6to14$_{d,c}$	0.110**	0.105*	-0.042	0.037
	(0.054)	(0.055)	(0.098)	(0.035)
PriceShock Age15to16$_{d,c}$	-0.024	-0.027	0.083	0.008
	(0.043)	(0.042)	(0.058)	(0.051)
Observations	56,203	56,203	56,203	56,203
R-squared	0.037	0.038	0.078	0.050
District FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Department trends	✓			
Coca time trends		✓	✓	✓
Sample	All	All	All	All
Ages	18-30	18-30	18-30	18-30

Overall, these results suggest that individuals affected by coca prices during childhood are experiencing higher earnings in the short term at expenses of lower earnings when they are adults. Using these estimates and assuming that each household has a discount rate of 0.95, I calculate the present discounted life income of households. I calculate that individuals have present income gains for 4 years which is the average number of years individuals in my sample were exposed. I find that the present discounted income of households is negative.[75] In the next section, using a simple framework I discuss how these results are consistent with a model of parental incentives.

A.3.1 Theoretical Framework to Understand the Role of Parental Incentives

In this section, I provide a model in which parents are not able to internalize the costs of child labor. This could be because they are credit constraint or present low inter-generational altruism or misguided beliefs about schooling as well as they may discount the future more heavily. However, I show that once the social planner introduces a transfer to parents with the condition that children have to attend school, all the negative effects are mitigated even if coca prices are high.

I build on qualitative evidence from my field work suggesting that many parents do not internalize the future costs of children working in coca farms. In particular, parents do not believe that school is a better

[75] Note that in Table A5 I also rule out the existence of income gains coming from local development at the district level.

investment for children than working on coca farms. From about 300 farmers, 65% of coca farmers reported that school is not more important for their children future than working in coca farming (I describe more about this survey in Appendix A.6).

I present a two-period model in which parents choose whether their children work or go to school.[76] In the first period, parents receive income if their child works growing coca. In the second period, children are grown and returns to schooling are realized. Using this simple framework, I examine the effect of a conditional cash transfer that incentivizes schooling.

In particular, when parents put children to work in coca fields they get the following utility:

$$U_i^l = U(I_i + P_t h_c) + \beta\delta_i U(H - h_c)$$

If parents decide to invest in their children's schooling:

$$U_i^s = U(I_i) + \beta\delta_i U(H)$$

In the first period, parents have exogenous income I. I assume I is distributed with CDF $F(I)$ and positive support over $[\underline{I}, \bar{I}]$. In addition, parents receive additional income from coca that depends on the price of coca, P_t, and number of hours children work, h_c . If children do not work, then they attend school and parents receive no additional income.

In the second period, children are grown and have earnings that depend on the amount of human capital accumulated in the first period. If children worked in the first period, they receive earnings $H - h_c$, where H is the maximum amount of human capital. Therefore, if they do not work in the first period, earnings are H.

Parents have discount rate δ_i, which is distributed with CDF $G(\delta_i)$ and positive support over $[\underline{\delta}, \overline{\delta}]$. In addition, β is the degree to which parents internalize the future utility of their children. It can also be a measure of inter-generational altruism.[77] Note that $\beta = 1$ if their children's earnings are fully internalized. If parents place less weight on their children's utility or do not believe working will effect their children's future utility, then $\beta < 1$.

Parents will decide to invest in schooling if:

$$U_i^s > U_i^l$$

$$U(I) + \beta\delta U(H) > U(I + P_t h_c) + \beta\delta U(H - h_c)$$

[76]In this model, I study the effects of prices and transfer on the extensive margin of child labor. This is mainly because in my data I do not have access to number of hours worked by children. A potential concern is that I am not being able to identify income effects (whether when prices increase, households reduce the number of hours children are working). While previous literature has found mixed effects, in the coca areas it is more likely for substitution effects to operate. This is mainly because children are an important input in the production process. Moreover, if income effects were dominating, schooling outcomes would improve and I find no evidence of this.

[77]Also it could be that parents may discount the future more heavy than the children or that interest of parents are not so well align with interest of children. In addition, β could also represent some measure of present biased beliefs. It is possible that parents decisions hold persistently misguided beliefs about either the nature of the process of investments in child education or the subsequent returns to these investments. For instance, parents may believe that earnings respond to education less elastically than they actually do. In addition, β can be define by $\frac{1}{1+r}$ and we could think that parents who are credit constraint face a high interest rate.

$$\delta > \delta^* = \frac{U(I + P_t h_c) - U(I)}{\beta[U(H) - U(H - h_c)]}$$

Note that δ^* is defined as the threshold and households with $\delta < \delta^*$ children will work. $G(\delta^*)$ is the proportion of parents that are doing child labor.

When P_t increases,

$$\frac{\partial \delta^*}{\partial P_t} = \frac{U'(I + P_t h_c) h_c}{\beta[U(H) - U(H - h_c)]} > 0$$

The threshold increases $\delta^*(P') > \delta^*(P)$ when $P' > P$ and a larger proportion of parents choose child labor. The opposite happens when exogenous income I increases.

When $\beta < 1$, the equilibrium outcome is inefficient since parents do not fully internalize the cost of child labor. As β decreases, a larger proportion of parents will choose child labor, increasing the inefficiency.

The social planner fully internalizes the cost of child labor, setting $\beta = 1$. Therefore, the δ^{SP} threshold set by the social planner is

$$\delta^{SP} = \frac{U(I + P_t h_c) - U(I)}{U(H) - U(H - h_c)}$$

When $\beta < 1$, this is lower than δ^*.

Now if we add a transfer conditional on schooling, T, parents will decide to invest in schooling if:

$$U(I + T) + \beta\delta U(H) > U(I + P_t h_c) + \beta\delta U(H - h_c)$$

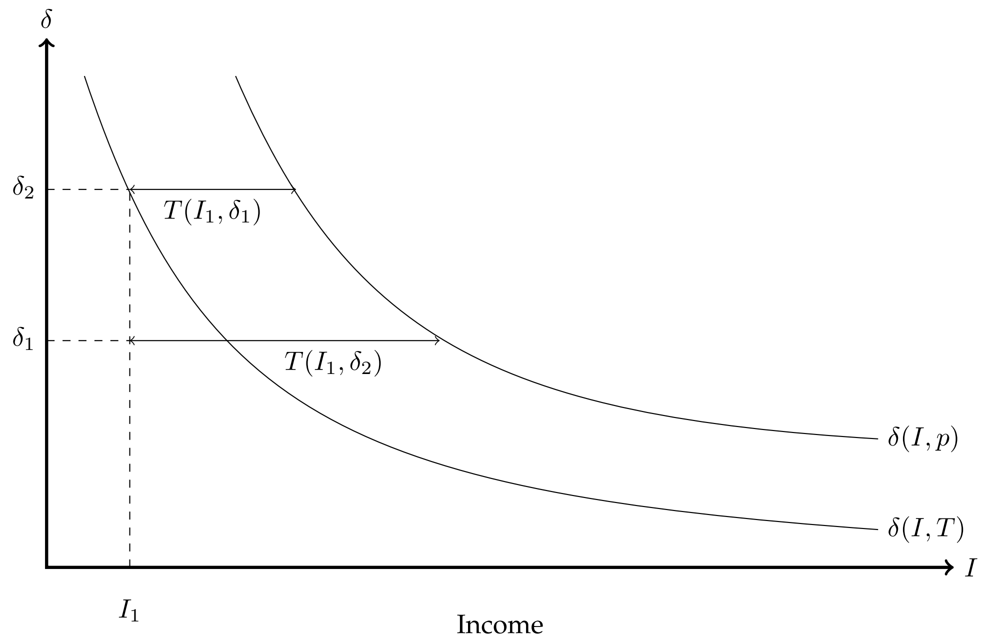
Then the threshold for child labor becomes:

$$\delta^*(T) = \frac{U(I + P_t h_c) - U(I + T)}{\beta[U(H) - U(H - h_c)]}$$

When T increases,

$$\frac{\partial \delta^*(T)}{\partial T} = \frac{-U'(I + T)}{\beta[U(H) - U(H - h_c)]} < 0$$

the threshold decreases ($\delta^{P'} > \delta^P > \delta^T$) moving the indifference curve to the left. In this way, the transfer can compensate for an increase in coca prices and correct the market failure by reducing the proportion of parents choosing child labor (the type of parents between $\delta(I, p)$ and $\delta(I, T)$).



Prediction 1: a conditional cash transfer will induce some parents to not use child labor even when coca prices are high.

Moreover, at higher prices a larger transfer is needed to mitigate the effects. To see this result note that the the social planner chooses T^* such that the threshold under $\beta = 1$ is equal to the threshold with transfer:

$$\frac{U(I + P_t h_c) - U(I)}{\beta[U(H) - U(H - h_c)]} = \frac{U(I + P_t h_c) - U(I + T)}{[U(H) - U(H - h_c)]}$$

$$U(I + T^*) = (1 - \beta)U(I + P_t h_c) + \beta U(I)$$

Using implicit function theorem, I calculate $\frac{\partial T^*}{\partial P}$:

$$\frac{\partial T^*}{\partial P} = -\frac{(1 - \beta)U'(I + P_t h_c)h_c}{U'(I + T)} > 0$$

Similarly, when parents do not internalize the cost of child labor and have a low β, a larger transfer is needed to compensate for high prices:

$$\frac{\partial T^*}{\partial \beta} = -\frac{U'(I + P_t h_c)h_c}{U'(I + T)} > 0$$

Even though I did not formally introduce a parameter measuring the land suitability for coca, it is clear that the effect is similar to an increase in coca prices and a larger transfer may be needed to get to the social planner solution when districts are more suitable for coca.

Prediction 2: when coca price or coca suitability increases, a larger transfer is needed to incentivize parents to not do child labor. [78]

[78] The model could also be extended by assuming that coca production also leads to an increase in crime, generating an additional externality. In this case, parents do not only internalize the cost of future crime in addition to the future effect on children's earnings. This model would have similar implications.

A.4 Additional Results, CCTs

Table A17: CCTs and coca price shocks on schooling

	(1) Failed	(2) Age for grade	(3) Grade 8	(4) Grade 9
$PriceShock_{d,t}$	0.600**	0.023***	-0.162***	-0.180***
	(0.238)	(0.005)	(0.038)	(0.061)
$PriceShock_{d,t} \times CCT_{d,t}$	-0.381***	-0.001	0.042**	0.063**
	(0.114)	(0.002)	(0.020)	(0.025)
Observations	424,096	431,790	135,123	135,123

Notes: This table presents the estimates of a fully saturated model of Equation 2 with interactions with $CCT_{d,t}$, a dummy indicating whether the district d has a CCT in year t and 0 otherwise. Results are robust to the inclusion of trends by the index for which they selected districts and differential trends by the stage of treated. Standard errors clustered at the district level are shown in parenthesis. Significant at *** p<0.01, ** p<0.05, * p<0.1.

Table A18: CCTs and coca price shocks on incarceration, drug-related crimes

	Affected Cohorts	Unaffected Cohorts
PriceShock Age11to14$_{d,c}$	2.003***	
	(0.896)	
PriceShock Age11to14$_{d,c}$ $\times$ *CCTs Age11to14*	-0.355*	
	(0.200)	
PriceShock Age15to16$_{d,c}$		-0.073
		(1.488)
PriceShock Age15to16$_{d,c}$ $\times$ *CCTs Age15to16*		0.141
		(0.204)

Table A19: CCTs and coca price shocks on adult labor

	(1) Hours worked	(2) Hours worked	(3) Self-employment	(4) Self-employment
$PriceShock_{s,t}$	-4.803**	-8.183**	0.052	-0.010
	(1.951)	(3.428)	(0.054)	(0.045)
$PriceShock_{s,t} \times CCT_{d,t}$		3.564***		0.031
		(1.097)		(0.027)
Observations	430,574	430,574	522,409	522,409
R-squared	0.038	0.038	0.087	0.087
Number of District	1,440	1,440	1,440	1,440
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Department trends	✓	✓	✓	✓
Covariates	✓	✓	✓	✓
Ages 21-60	✓	✓	✓	✓

A.5 Spillover Effects

Table A20: CCTs and coca production 2010-2014, spillovers in neighboring districts

	(1)	(2)
$Coca_d \times Neighbor\ CCT_{d,t}$	248.057***	251.664***
	(69.540)	(75.463)
Observations	3,455	688
Mean coca	671	671
District FE	✓	✓
Year FE	✓	✓
Valley Trends	✓	✓
Sub-sample of coca neighbors		✓

Notes: This table presents the estimates of Equation 7, a fully saturated model of Equation 1 with interactions with $NeighborCCT_{d,t}$, a dummy indicating whether the neighboring district d has a CCT in year t and 0 otherwise. The dependent variable is the number of coca hectares between 2010 and 2014. Results are robust to the inclusion of trends by the index for which they selected districts and differential trends by the stage of treated. Standard errors clustered at the district level are shown in parenthesis. Significant at *** p<0.01, ** p<0.05, * p<0.1.

A.6 Qualitative Data Appendix

This research project developed from a set of interviews that I conducted during the months of April and July of 2015 to understand what factors influence child labor decisions in coca areas in Peru. In this Appendix, I describe the interview methodology.

I conducted structured interviews in 11 districts in Peru: Monzon, Rupa-Rupa, Daniel Alomia Robles, Mariano Damaso Beraun, Jose Crespo y Castillo, Tocache, Pichari, San Francisco, Llochegua, Otari, and Catarata. These districts are part of two main cocaine basins: Huallaga and the valleys of the rivers Apurimac, Ene and Mantaro (VRAEM). The total population in these areas is about 1.1 millon. Both regions have about 30 narcotraffic organizations with a production of between 200 and 500 kg of cocaine per month. Research participants were drawn from an arbitrary and convenient sample found in fields: households (parents and children), farmers, schools (principals, teachers, and children), NGOs, and government officials. In the VRAEM regions, the sample included 50 private individuals (farmers, fieldworkers, parents, children), 10 government officials, and 10 school officials. The research participants in the Huallaga area were 32 private citizens and 4 school officials. In addition to the interviews, I helped designing a survey given to 270 farmers in the district of Mariano Damaso Beraun. These farmers were part of an Alternative Development Project to substitute coca production for coffee and cacao. The survey included questions about production, earnings from coca and other activities, and beliefs about education.

Interview lengths ranged from 30 minutes to two hours. Participants answered questions about working and schooling decisions. The interviews were usually conducted in participants' homes, offices, classrooms, and farms. For children, the questions included: whether they attended school, whether they liked school and why, what they wished was different about school, what were the reasons they did or did not attend school, what were their main activities after school, and what were the main difficulties they faced finishing their studies. For parents and farmers, the questions included whether children attend school and why, whether they used child labor, farming decisions such as how and when they decided to grow coca or other crops, whether prices influenced their choices, and main sources of employment (family, friends, external labor, etc.). For school teachers and headmasters, the questions included why they think children do not attend school, their satisfaction in their jobs, and whether children dedicated time to activities related to drug production. For government officials, the questions included: what they thought were the main problems in drug producing areas, why they think children did or did not attend school, and their understanding of the local environment.

I also conducted less-structured interviews in which I embedded myself in the community. I also accompanied government officials on the Alternative Development in Mariano Damaso Beraun project, in which ex-coca farmers traveled to villages to teach skills and encourage farmers to grow legal crops. This included living with local families during the visits and understanding their production and labor decisions.