# School or Crime: A Teenager's Choice [*]

Andrea Franco
University of Wisconsin-Madison
*Job Market Paper*

Christian Posso
Central Bank of Colombia

November 1, 2025

*Click here for most recent version*

**Abstract**

This paper studies how exposure to organized crime affects teenagers' educational choices and how public policy responds in such contexts. We focus on the 2008 extradition of Medellín's top gang leader, after which a gang war erupted and created neighborhood-level variation in criminal activity. Using rich administrative data from Medellín, Colombia, we find that dropout rates among boys increased in affected neighborhoods, while girls were unaffected, consistent with heightened gang recruitment rather than general violence. We then examine how Conditional Cash Transfer (CCT) programs shaped educational outcomes and find that they effectively reduced dropout rates, with stable impacts even amid increased gang activity. To further understand criminal involvement and evaluate policy responses, we develop and estimate a dynamic discrete choice model of schooling, crime, and labor market decisions from middle school through early adulthood. Leveraging design-based results, we identify shifts in the criminal payoff and assess the effectiveness of CCTs in offsetting dropout. The model evaluates three policy interventions: (i) expanding CCT coverage, (ii) increasing law enforcement, and (iii) combining both. Expanding subsidies reduces teenage crime and arrests during school years and raises higher-education enrollment, though with limited post-school effects. Stronger law enforcement curbs post-school crime but raises arrests among teenagers. Combining both policies yields the largest crime reduction but smaller educational gains than CCTs alone. A back-of-the-envelope cost-benefit analysis shows that while the combined policy delivers the highest net benefits, expanding CCT coverage achieves nearly comparable gains at lower implementation costs and with clearer fiscal implications.

[*]Franco: francohernan@wisc.edu. Posso: cpossosu@banrep.gov.co. Franco is grateful to her committee members Chao Fu, Jesse Gregory, and Chris Taber. We also thank Jeff Smith, Naoki Aizawa, and Laura Schechter for their useful feedback. This research has benefited from comments from seminar participants at the public workshop at UW-Madison. We also thank the Central Bank of Colombia for allowing us to use the data to conduct this research. The opinions expressed in this document belong to its authors and do not reflect the views of the Central Bank of Colombia or its Board of Directors.

# 1 Introduction

Crime participation often begins in early adolescence and is concentrated among boys from disadvantaged backgrounds living in high-poverty neighborhoods (Merlo and Wolpin, 2015; Lochner, 2004; Lochner and Moretti, 2004; Deming, 2011). As a consequence, these individuals accumulate less human capital and face more difficult school-to-work transitions (Imai and Krishna, 2004; Fu et al., 2022; Salazar, 2023; Sviatschi, 2022; Leon, 2012; Foureaux Koppensteiner and Menezes, 2021). Moreover, social interactions within neighborhoods, particularly exposure to criminal peers, schoolmates, and educators, play a central role in shaping criminal trajectories (Damm and Dustmann, 2014; Bayer et al., 2009; Billings et al., 2014; Rose et al., 2022). This paper examines how exposure to organized crime influences teenagers' educational decisions and evaluates the capacity of social programs to mitigate these effects. Combining a dynamic structural model of schooling and crime decisions with design-based evidence, we provide new insights into the mechanisms through which gang recruitment increases school dropout and use counterfactual simulations to assess the effectiveness of alternative policy responses.

Our analysis focuses on Medellín, Colombia, where an unexpected shock in the balance of criminal power created quasi-experimental variation in exposure to gang recruitment across neighborhoods. The empirical setting exploits the 2008 extradition of Diego Fernando Murillo, known as "Don Berna," the leader of the city's dominant mafia organization. Don Berna had consolidated control over Medellín's criminal networks, sustaining a fragile equilibrium that limited open violence (Duncan, 2014). His sudden removal triggered a violent reorganization of gangs and a struggle for territorial control throughout the city. The timing and nature of this event were unanticipated by residents, generating plausibly exogenous increases in exposure to organized crime in some neighborhoods but not others.

We link this shock to rich administrative records that allow us to track a wide range of outcomes: secondary school enrollment and dropout for the universe of public-school students, tertiary education enrollment, detailed crime and arrest records from law enforcement, and eligibility and participation in Colombia's national Conditional Cash Transfer (CCT) program.

We begin by analyzing the consequences of the criminal shock on schooling. The extradition of Don Berna intensified competition among gangs and created a sudden surge in demand for adolescent recruits,

raising the opportunity cost of staying in school. We exploit quasi-experimental variation generated by the extradition shock, interacting it with pre-2008 gang presence to construct a shift-share exposure measure. Following Goldsmith-Pinkham et al. (2020); Borusyak et al. (2022), this specification is equivalent to a Difference-in-Differences design in which the common shock provides the exogenous source of variation and gang presence determines treatment intensity.

The results show that the shock increased neighborhood criminal activity and reduced law enforcement effectiveness. Consistent with targeted recruitment, dropout rates rose sharply among boys aged 13-15, with no comparable effect on girls, who serve as a natural counterfactual group. This divergence suggests that the mechanism operates through increased recruitment incentives rather than general exposure to violence. Dynamic specifications confirm the absence of differential pre-trends and reveal sharp increases in dropout immediately after the shock, concentrated in younger cohorts. The effects persist beyond high school, boys exposed to the extradition are less likely to enroll in tertiary education, suggesting long-term losses in human capital accumulation. Robustness checks, including synthetic DiD estimators and placebo shocks, support the validity of the identification strategy.

We then turn to the role of Conditional Cash Transfer (CCT) programs, which may mitigate the rise in dropout by increasing the relative returns to schooling during periods of heightened criminal demand. We estimate specifications with individual fixed effects and detailed controls for eligibility and continuous vulnerability scores, ensuring that identification relies on within-student changes in participation rather than differences in household vulnerability. Across cohorts, CCT participation reduces high school dropout by 12-16 percentage points, representing 25-40 percent of the average dropout rate. The effects are stable across neighborhoods regardless of pre-shock gang presence. To strengthen inference, we implement complementary approaches, a synthetic DiD that enforces parallel pre-trends and an instrumental variables strategy exploiting the eligibility threshold within a Regression Discontinuity framework. The IV estimates are larger in magnitude, consistent with higher returns among marginal households near the eligibility cutoff. Taken together, these findings show that CCTs sustained school enrollment even under conditions of intense gang recruitment, offsetting the increased opportunity cost of education created by the criminal shock.

While the design-based results credibly establish that crime shocks increase dropout and that CCTs

mitigate some of these effects, the structural model complements this analysis by providing a deeper understanding of the behavioral mechanisms and enabling policy evaluation beyond the scope of reduced-form methods. The model formalizes teenagers' forward-looking decisions regarding schooling and criminal participation in the presence of gangs (Imai and Krishna, 2004; Fu et al., 2022). By estimating the value adolescents place on future outcomes, the model allows us to characterize the adulthood transition, the long-term decisions that depend on cumulative outcomes from the school stage.[1] Linking early choices to later outcomes is essential for quantifying how middle-school decisions, such as dropping out or being arrested, affect higher education, formal and informal employment, and adult criminal participation.

We develop and estimate a dynamic model of schooling, crime, and labor market choices from middle school through early adulthood. Following Fu et al. (2022), we incorporate two core sources of heterogeneity: (1) differences in endowments, reflecting family background and elementary school quality, and (2) stochastic shocks that influence choices and, through dynamic linkages, have long-term effects on individual trajectories. We extend this framework along two dimensions. First, we introduce neighborhood-level variation in gang presence, which captures how changes in organized crime recruitment shape teenagers' paths. Second, we incorporate CCT participation into the utility from schooling, allowing us to evaluate social programs in the presence of crime. We also extend the adulthood stage to include four labor market options—higher education, formal employment, informal employment, and crime—enabling a richer characterization of life-cycle choices. The model is estimated using indirect inference to recover parameters governing preferences, grade progression, and unobserved heterogeneity. Using the design-based results, we estimate changes in criminal payoffs and the impact of CCTs on schooling incentives.

We use the model to investigate the importance of two key factors shaping teenagers' decisions in the presence of gangs: family background and policy support. We compare the outcomes of individuals across three environments, neighborhoods with and without gang presence, and counterfactual scenarios without CCTs. We find that both CCT programs and family endowments are crucial determinants of educational outcomes. CCTs are particularly effective in neighborhoods with gangs, where they help

[1] Most economics papers on crime build on the framework of Becker (1968), in which individuals make rational decisions about engaging in criminal activity.

offset the elevated risks and opportunity costs associated with recruitment.

Finally, we conduct a series of counterfactual policy simulations targeting disadvantaged teenagers, who are most likely to be drawn into criminal activity. We simulate the effects of scaling up CCT generosity, intensifying law enforcement, and combining both strategies. The results reveal that expanding CCTs substantially reduces dropout in gang affected neighborhoods and increases higher education enrollment. While stricter enforcement modestly affects educational outcomes, it reduces criminal participation by increasing the expected cost of arrest. Combined strategies generate the largest long-run reductions in crime among both teenagers and adults, though the gains in human capital are smaller than those from CCT expansion alone, as higher arrest rates discourage schooling. These counterfactual yield important policy insights: while enforcement may be politically salient, social transfers appear to be a more effective instrument for sustaining education in violent contexts.

Back-of-the-envelope cost-benefit calculations suggest that both CCT expansion and enhanced law enforcement generate positive net benefits, with the combined approach delivering the highest returns, though very similar to CCT expansion alone. These findings underscore the potential of social programs to mitigate the long-term consequences of early-life exposure to criminal environments and to prevent the emergence of poverty traps. CCT programs are more cost-effective than law enforcement alone, yet the combination can create complementarities that enhance overall effectiveness.

This paper contributes to several strands of the literature. First, we add to research linking human capital formation, labor market outcomes, and crime (Lochner and Moretti, 2004; Lochner, 2004; Fella and Gallipoli, 2014; Imai and Krishna, 2004; Fu et al., 2022; Freeman, 1996; Foureaux Koppensteiner and Menezes, 2021; Sviatschi, 2022; Sickles and Williams, 2008; Salazar, 2023; Mancino, 2022; Deming, 2011). We make two contributions to this body of work. First, we provide new causal evidence on how organized crime affects educational outcomes by exploiting neighborhood-level variation in gang presence. Second, by combining design-based and structural approaches, we go beyond reduced-form estimates to evaluate counterfactual policies and quantify how targeted interventions can mitigate the adverse effects of crime on schooling and long-term outcomes.

Second, we contribute to the literature on social programs and the intergenerational transmission of poverty (Angrist et al., 2002; Attanasio et al., 2010, 2015, 2025; Todd and Wolpin, 2023, 2006; Djeb-

bari and Smith, 2008). We examine the interaction between CCT programs and exposure to organized crime, showing that school subsidies can offset the educational costs of gang recruitment. This finding underscores the potential of social policy to prevent the long-term consequences of early-life exposure to criminal environments and the formation of poverty traps. Through counterfactual simulations, we further illustrate how the effectiveness of social programs depends on local criminal dynamics.

Relatedly, this paper adds to the literature on the importance of place and neighborhood conditions for long-term outcomes (Chetty et al., 2016; Chetty and Hendren, 2018; Kling et al., 2005; Damm and Dustmann, 2014; Bayer et al., 2009; Billings et al., 2014; Rose et al., 2022) and to work on early-life and adolescent shocks (Currie and Almond, 2011; Heckman, 2006; Heckman et al., 2013). We show that exposure to organized crime during adolescence shapes teenagers' educational trajectories and long-term outcomes, with persistent effects on higher-education enrollment and formal employment probabilities.

Finally, we contribute to the structural labor and human capital literature by developing and estimating a dynamic discrete choice model linking schooling, crime, and labor market decisions from middle school through early adulthood. Building on the forward-looking behavior framework (Imai and Krishna, 2004; Fu et al., 2022; Salazar, 2023; Merlo and Wolpin, 2015; Mancino et al., 2016), we incorporate heterogeneity in neighborhood criminal environments and explicitly model human capital depreciation following criminal involvement, capturing the lasting labor market penalty of prior arrests. The model extends existing frameworks by allowing a richer adulthood transition with four possible choices—higher education, formal employment, informal employment, and crime—offering a comprehensive view of how early-life shocks and adolescent decisions jointly shape long-term trajectories.

The remainder of the paper is organized as follows. Section 2 provides background on organized crime in Medellín. Section 3 describes the data sources and descriptive statistics. Section 4 presents the design-based empirical strategy and results. Section 5 introduces the model, estimation strategy, and results. Section 6 discusses counterfactual policy simulations and cost-benefit analysis. Section 7 concludes.

# 2 Background and Data

## 2.1 Background

In this section, we provide background information about the city of Medellín, Colombia, and the context of organized crime. We first describe the criminal shock, explaining how organized crime operated in the city. We then introduce the Conditional Cash Transfer (CCT) program implemented in Colombia, which we use to analyze how public policy can mitigate the effects of criminal shocks on teenagers.

### 2.1.1 Organized Crime in Medellín

Medellín is Colombia's second-largest city, with a population of approximately 2.6 million. The city is divided into 21 districts (*comunas*) and 256 neighborhoods. Figure 1 depicts the distribution of household income and teenage criminal activity across the city in 2008. Panel (a) shows that the wealthiest districts are located in the southeast, where teenage arrest rates are relatively low (Panel (b)). In contrast, the downtown and northeastern districts exhibit higher crime rates. These areas are characterized by lower income levels and have historically been associated with drug cartels since the 1980s and 1990s, continuing to experience a strong gang presence today.

Organized crime began to emerge in Medellín in the late 1970s and early 1980s, primarily driven by the rise of drug cartels. During that period, the city gained a reputation as one of the most violent in the world. Violence peaked in the early 1990s during the war with the Medellín Cartel.[2]

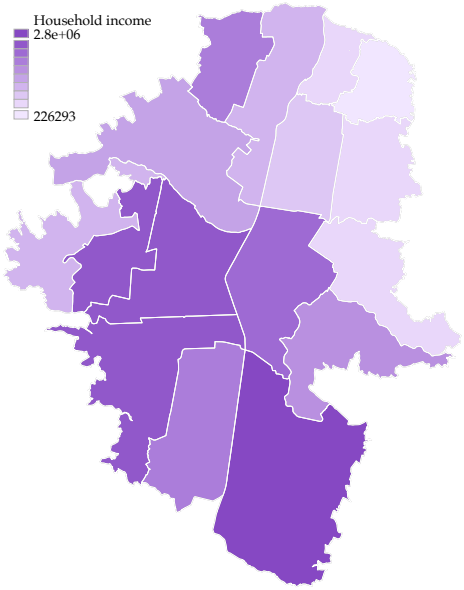
Pablo Escobar created *La Oficina* in the 1980s as the first *"oficina de cobro"* (criminal debt-collection agency). He used it to enforce payments from drug traffickers and other criminals, often through violent means. Those who fell behind on payments risked threats, beatings, or assassination by Escobar's *"sicarios"* (hitmen). After Escobar's death in 1993, Diego Fernando Murillo, known as "Don Berna," took control of *La Oficina*, which rose from the ashes of the Medellín Cartel.

Don Berna inherited Escobar's drug trafficking empire and established a system of criminal governance over Medellín's street gangs, known as *"combos"*. He demanded a share of their earnings in exchange

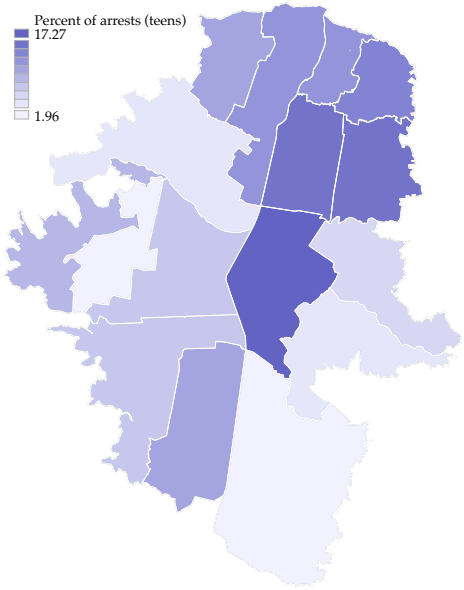
[2] In recent years, the homicide rate has declined substantially, falling from 87 homicides per 100,000 inhabitants in 2010 to approximately 32 in 2015 (Figure 2). For comparison, in 2015, the homicide rates in Baltimore and St. Louis were 55 and 59 per 100,000 inhabitants, respectively.

Figure 1: Distribution of Income and Criminal Activity by District, 2008

(a) Household income




(b) Teen arrests

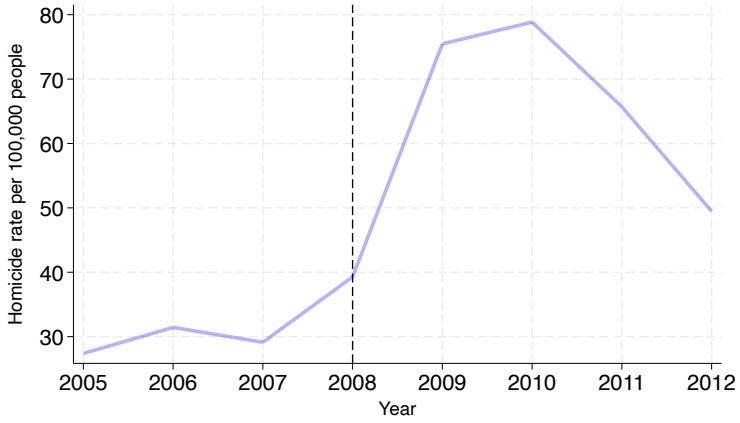



*Notes.* Panel A shows household income per comuna, darker colors indicate higher income levels. Panel B shows the percentage of arrests of teenagers (ages 12-17) per comuna relative to the total arrests. Darker colors indicate higher arrest rates.

for allowing them to extort, steal, and sell drugs. Through this centralized control, Don Berna reduced inter-gang violence, leading to a sharp decline in homicides. This period of relative peace became known as *"Donbernabilidad,"* a cynical play on the Spanish word for "governability" (Martin, 2012).

In 2008, Don Berna was extradited to the United States, creating a power vacuum that triggered a violent struggle for control among Medellín's gangs. Within *La Oficina*, two factions emerged—one led by Maximiliano Bonilla ("Valenciano") and the other by Erick Vargas ("Sebastián"). Between 2008 and 2011, these groups fought for territorial dominance, sparking widespread violence across neighborhoods. The intensity of the conflict varied geographically, depending on the presence of gangs affiliated with each faction. Figure 2 shows how the city's homicide rate nearly doubled following the onset of this gang war.

Figure 2: Homicide Rate in Medellín

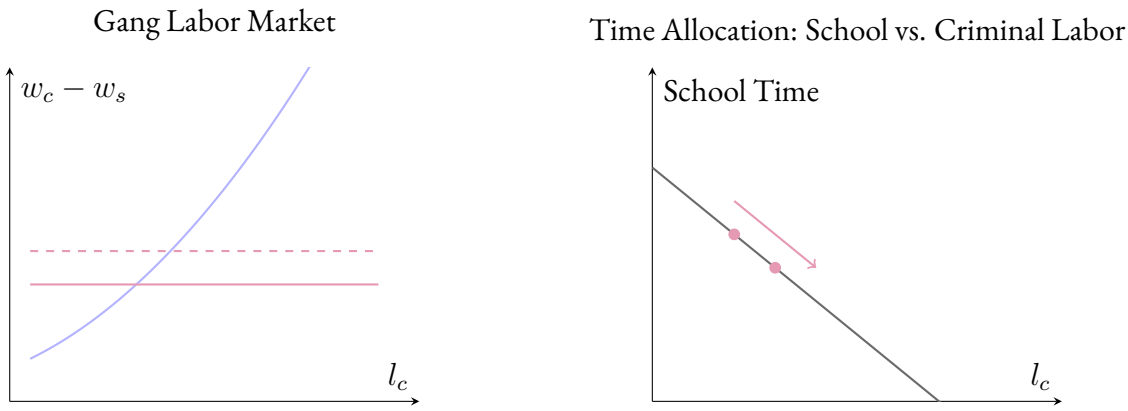



*Notes.* The figure shows the homicide rate (per 100,000 inhabitants) in Medellín from 2002 to 2015. The vertical dashed line indicates the year of Don Berna's extradition (2008).

We interpret the 2008 conflict as a demand shock to the criminal sector. Similar to other labor markets, an external shock can shift the demand curve for labor, in this case, for criminal labor. The gang economy in Medellín relies heavily on teenagers and young adults, who represent the majority of gang members. This framework allows us to view the conflict as an exogenous increase in the demand for teenage criminal labor. Because illegal labor markets are generally unobservable, we analyze the consequences of this demand shock through changes in schooling behavior. Specifically, we model schooling and crime as substitutes in teenagers' time allocation: when the returns to crime rise, the opportunity cost of schooling increases, leading to higher dropout rates. Figure 3 illustrates this mechanism conceptually, a rightward shift in criminal labor demand increases participation in crime and reduces schooling time.

Figure 4 presents the change in homicide rates per 10,000 inhabitants (Panel (a)) and the change in male dropout rates (Panel (b)) before and after 2008, by neighborhood. The dots in each map indicate gang presence. The maps show that the intensity of violence varied across neighborhoods, with the highest increases in areas where gangs were active. Furthermore, there is a clear spatial correlation between increases in violence and school dropout rates, consistent with the demand-shock mechanism illustrated in Figure 3. We detail the empirical identification of the causal effect of the criminal shock on dropout rates in Section 4, and later use this information to construct the structural model in Section 5.

Figure 3: Criminal Labor Market and Time Allocation




*Notes.* The left panel illustrates a simplified labor market for gang members, where the demand curve shifts rightward due to increased gang competition after Don Berna's extradition. The right panel shows how this shift leads to higher criminal labor participation ($l_c$) and reduced schooling time, as indicated by the movement along the time allocation line.

To identify neighborhoods affected by the 2008 Don Berna extradition, we use historical records from Medellín's Security Department and complement them with archives from *El Colombiano*, the city's largest newspaper. We classify a neighborhood as treated if, prior to the extradition, it was controlled by gangs affiliated with either Sebastián or Valenciano.

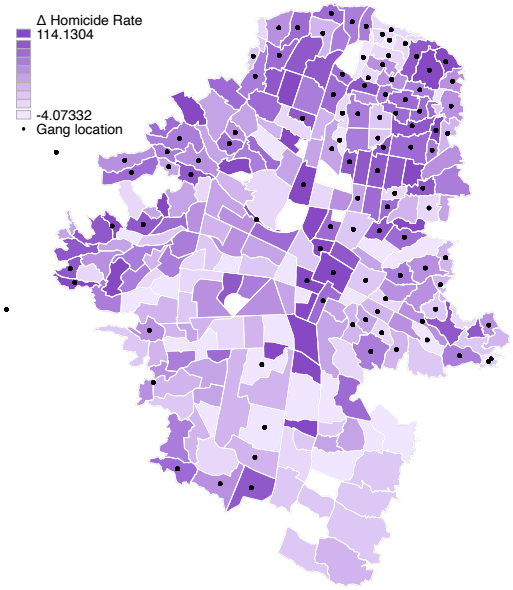
### 2.1.2 Conditional Cash Transfer Program

*Familias en Acción* is a Conditional Cash Transfer (CCT) program launched in Colombia in 2002. Initially targeted to low-income households in rural areas, the program was expanded to urban areas in 2007, focusing on the poorest 20% of households. It provides subsidies to families with children, conditional on school attendance and health checkups, aiming to improve health and nutrition among children under seven and to foster human capital accumulation among those aged 7-17 (Attanasio et al., 2010, 2025, 2015). In this paper, we focus on the school-attendance component of the program to study how the CCT policy interacts with criminal shocks. Conceptually, the CCT increases the opportunity cost of engaging in crime by making schooling more financially attractive.

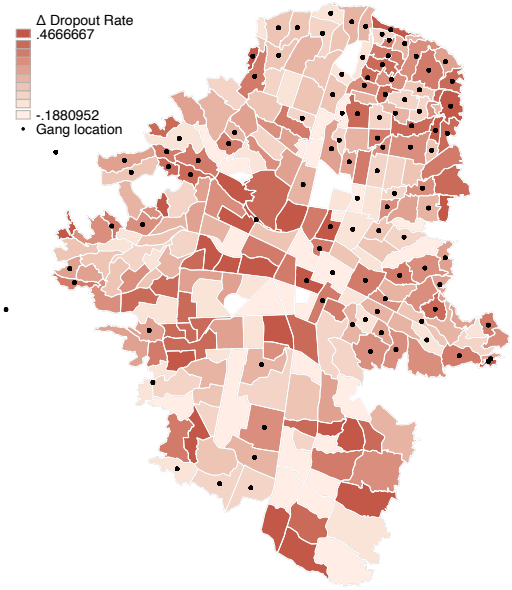
Eligibility for *Familias en Acción* is determined using a proxy for vulnerability based on the *Sistema de Identificación de Potenciales Beneficiarios de Programas Sociales* (SISBEN), which is constructed from

Figure 4: Changes in Homicide and Dropout Rates Before and After 2008

(a) Change in Homicide Rate




(b) Change in Dropout Rate




*Notes.* Panel A the change in the homicide rate (per 10,000 inhabitants) by neighborhood between the periods 2004-2007 and 2008-2011. Panel B shows the change in the dropout rate for males by neighborhood between the same periods. The dots indicate neighborhoods with gang presence before 2008.

household characteristics such as demographics, income, economic activity, assets, sanitation, and housing quality. During the 2007 urban expansion, the government used the SISBEN II index (introduced in 2005), which assigns each household a score between 0 and 100 according to socioeconomic conditions. Households scoring 11 or below (extreme poverty) with children aged 7-17 enrolled in school were eligible for the program.[3] The subsidy amount varied by grade level: COP 15,000 (USD 4) per month for primary school, COP 25,000 (USD 6.4) for lower secondary, COP 35,000 (USD 9) for most high school grades, and COP 40,000 (USD 10.2) for the final grade of high school. By 2009, *Familias en Acción* covered about 40% of eligible households, and in our sample approximately 8% of children were enrolled in the program.

[3] Households displaced by the Colombian civil conflict or belonging to minority groups were also eligible.

# 3 Data and Descriptive Statistics

## 3.1 Data Sources and Linkage

This paper combines multiple administrative datasets at the individual, household, and neighborhood levels, allowing us to follow students, families, and local conditions in Medellín over time. The resulting panel links students' educational trajectories to their household background, neighborhood exposure to organized crime, and subsequent educational and labor-market outcomes. The linkage is possible through Colombia's unique national identification number (*cédula de ciudadanía*), complemented by names and dates of birth.

**Education Records.** Student-level records come from the *Secretaría de Educación de Medellín*, covering the universe of students enrolled in public middle and high schools between 2004 and 2015. These administrative data track enrollment, grade progression, and dropout decisions annually and include each student's residential address and school identifier. School-level characteristics—such as total enrollment, school type, and location—are obtained from DANE's annual School Census. This comprehensive set of school and student records forms the core of our empirical analysis and serves as the foundation for linking with the additional administrative datasets described below.

**Conditional Cash Transfer (CCT) Program.** Participation in *Familias en Acción*, Colombia's national Conditional Cash Transfer (CCT) program, is measured using administrative data from the *Departamento Nacional de Planeación*. Medellín was the first large urban area to implement the program in 2007, providing a valuable setting to study how social policy interacts with localized violence. Eligibility for *Familias en Acción* is determined using a proxy for vulnerability based on the *Sistema de Identificación de Potenciales Beneficiarios de Programas Sociales* (SISBEN). We use data from SISBEN II (2005), which assigns each household a score between 0 and 100 according to socioeconomic and living conditions. Households with scores of 11 or below (extreme poverty) and with children aged 7-17 enrolled in school were eligible for the program.[4] These data allow us to identify both program participation and the underlying eligibility cutoff, providing rich demographic information at the household level.

[4] Households displaced by the armed conflict or belonging to recognized minority groups were also eligible. The program also includes a health and nutrition component for children under seven, which we do not analyze here.

**Crime and Delinquency Data.** We obtain detailed arrest records for teenagers and young adults from the *Seccional de Investigación Criminal* of the Metropolitan Police of Medellín. These administrative files represent a near-census of arrests between 2004 and 2015 and include information on offense type, date, and location. This dataset allows us to track criminal involvement for all individuals in our sample. We complement it with homicide data from Colombia's Vital Statistics and with official crime reports from the *Secretaría de Seguridad de Medellín*. Together, these sources provide comprehensive coverage of violent and non-violent crimes, enabling the construction of neighborhood-year indicators of homicide rates, total criminal activity, and arrest probabilities—defined as the ratio of arrests to reported crimes. Information on the presence and affiliation of gangs is drawn from the *Secretaría de Seguridad* and historical intelligence reports, cross-checked with local newspaper archives. These sources allow precise identification of neighborhoods under gang control before the 2008 Don Berna extradition.

**Postsecondary Outcomes.** To examine longer-term outcomes, we link students to three additional administrative systems:

- *The Ministry of Education's Higher Education Database (SNIES)* records enrollment in all accredited tertiary institutions, allowing us to track students' transitions into higher education.
- *The Planilla Integrada de Liquidación de Aportes (PILA)* provides universe-level information on formal employment, wages, and firm characteristics for all registered workers contributing to social security. These data allow us to follow formal labor-market trajectories.
- Informal employment is identified through self-reported data in SISBEN III among individuals not appearing in PILA.

**Linkage and Sample Construction.** We construct a longitudinal dataset that tracks students from middle school through early adulthood by linking administrative records via the unique national identification number, cross-verified with names and dates of birth. The main analysis focuses on boys attending public schools who entered sixth grade in either 2005 or 2006, which allows us to observe their full secondary school trajectories. These cohorts were directly exposed to the 2008 Don Berna extradition, when they were approximately 13-15 years old.

Labor-market outcomes are available for students who began high school in 2004 or 2005, enabling us

to observe their early employment histories between 2009 and 2012. These transitions are used to estimate the model's terminal value and identify parameters associated with each choice-specific payoff. However, these data do not allow for causal identification of the criminal shock's effect on labor outcomes within the reduced-form design.

Exposure to the 2008 criminal shock is measured at the neighborhood level, based on the pre-existing presence of gang organizations. Neighborhoods that were under the control of a single gang before 2008 are classified as gang-dominated, while the remaining neighborhoods serve as controls. This classification is fixed over time and exogenous to post-shock outcomes.

The merged dataset includes approximately 240 public schools and 54,756 students. Prior to 2008, the average annual dropout rate was about 4 percent. Following the Don Berna extradition, homicide rates nearly doubled citywide. By 2009, the *Familias en Acción* program covered roughly 40 percent of eligible households, providing variation to examine how conditional cash transfers mitigated the educational consequences of the criminal shock. In our sample, approximately 8 percent of children were enrolled in the program. The combination of universe-level microdata, detailed geographic identifiers, and credible temporal variation provides a unique setting to analyze how organized-crime shocks affect human capital accumulation and how social policy can buffer these effects.

## 3.2 Descriptive Statistics

Table 1, presents descriptive statistics for two cohorts of students (2005 and 2006), disaggregated by neighborhood type, those with and without gang presence. The table is organized into three panels: dropout probabilities, student characteristics, and boys' high-school outcomes.

Panel A shows the probabilities of dropout for boys and girls. We measure these variables at the year-student level during middle and high school. For both cohort 2005 and 2006, girls have a lower dropout rate compared to boys. In the cohort 2005, boys have an average dropout probability of 16% and girls have a probability of 12.5%. In cohort 2006, boys have a dropout probability of 17.5% and girls have a probability of 14.1%. Across both cohorts, dropout rates are higher in neighborhoods with gangs compared to those without. For example, in the 2005 (2006) cohort, boys in gang neighborhoods have a dropout probability of 16.4% (18.1%), compared to 15.5% (16.8%) in non-gang neighborhoods.

Panel B summarizes key student characteristics. Students with parents who have higher education is 10% in gang neighborhoods and 14.3% in non-gang areas in 2005 cohort ( 10.0% vs. 14.8% in 2006). Nearly 77% of students in the 2005 cohort coming from low SES backgrounds, compared to 67% in non-gang areas (79% vs. 67% in 2006). Around one third of the students attendance to high-quality schools, and the share of students in private-voucher schools is 9.2% in gang neighborhoods and 8.4% in non-gang areas (9.3% vs. 11.1% in 2006).

Panel C focuses on boys' high-school outcomes. High-school graduation rates are lower in gang neighborhoods for both cohorts, 61.3% (54.5%) in neighborhood without gangs and 58.8% (51.4%) in gang areas, in the 2005 (2006) cohort. College enrollment is also reduced 16.2% (14.3%) in gangs areas and 20.8% (19.1%) in non-gang areas in the cohort 2005 (2006). The proportion of boys ever arrested in school is around 1.7% in both cohorts.

# 4 Design-Based Strategy

In this section, we present our design-based empirical strategy to identify the impact of criminal shocks on teenagers' schooling decisions. Our objective is to estimate how an increase in criminal labor demand affects school dropout, and to assess whether Conditional Cash Transfer (CCT) programs continue to support school enrollment in the presence of such shocks, attenuating the impact of sudden increases in criminal activity on educational choices, or whether their effectiveness diminishes when extreme conditions raise the opportunity cost of schooling.

## 4.1 Identifying the Effect of Criminal Labor Demand

To identify the causal effect of changes in criminal activities on teenagers' decisions, we exploit the extradition of Don Berna, Medellín's top gang leader in 2008. This unexpected event triggered a violent struggle for territorial control, generating a sudden positive shock to the demand for criminal labor. In this framework, schooling and crime are substitutes in the allocation of teenagers' time: as the expected returns to crime rise, the opportunity cost of remaining in school increases, leading to higher dropout. While we cannot directly observe criminal wages, schooling decisions provide a revealed alternative mar-

Table 1: Descriptive Statistics

| | Cohort 2005 | | | | Cohort 2006 | | | |
|---|---|---|---|---|---|---|---|---|
| | No gangs | | Gangs | | No gangs | | Gangs | |
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| **Panel A. Dropout Probability** | | | | | | | | |
| Dropout Probability Boys | 0.155 | 0.362 | 0.164 | 0.371 | 0.168 | 0.374 | 0.181 | 0.385 |
| Dropout Probability Girls | 0.120 | 0.325 | 0.128 | 0.334 | 0.135 | 0.342 | 0.146 | 0.353 |
| Observations | 56915 | | 75710 | | 61785 | | 79370 | |
| **Panel B. Student Characteristics** | | | | | | | | |
| Parents with Higher Education | 0.143 | 0.350 | 0.103 | 0.304 | 0.148 | 0.356 | 0.100 | 0.300 |
| Low SES Households | 0.665 | 0.472 | 0.768 | 0.422 | 0.669 | 0.470 | 0.789 | 0.408 |
| High-Quality School | 0.341 | 0.474 | 0.322 | 0.467 | 0.333 | 0.471 | 0.298 | 0.457 |
| Private-Voucher | 0.084 | 0.277 | 0.092 | 0.290 | 0.093 | 0.290 | 0.111 | 0.314 |
| Percent of Male (%) | 48.4 | | 47.8 | | 48.0 | | 47.3 | |
| Observations | 11383 | | 15142 | | 12357 | | 15874 | |
| **Panel C. Boys' High-School Outcomes** | | | | | | | | |
| High-School Graduation | 0.613 | 0.487 | 0.588 | 0.492 | 0.545 | 0.498 | 0.514 | 0.500 |
| College Enrollment | 0.208 | 0.406 | 0.162 | 0.368 | 0.191 | 0.393 | 0.143 | 0.351 |
| Ever Arrested in School | 0.016 | 0.125 | 0.017 | 0.130 | 0.020 | 0.141 | 0.014 | 0.117 |
| Observations | 5505 | | 7240 | | 5930 | | 7501 | |

*Notes.* Panel A shows the probabilities of dropout for boy and girls, at the year-student level during middle and high school. Panel B shows students characteristics at the student level sample includes both girls and boys. Panel C shows average outcomes at the end of high school for boys only.

gin of adjustment, since teenagers allocate their time between education and participation in the criminal sector.

Our empirical design builds on the intuition of shift-share strategies (Borusyak et al. (2022), BHJ hereafter). The Don Berna extradition represents a common shock to the criminal sector; while pre-existing gang presence provides exposure shares that determine the intensity of local treatment. Neighborhoods with gangs before 2008 were more exposed to the shock because those gangs faced sudden territorial disputes, creating an exogenous surge in demand for adolescent recruits.

We construct exposure as a binary share equal to one for neighborhoods with documented gang presence before 2008 and zero otherwise. Identification does not require gang exposure to be exogenous (BHJ

2022). Instead, what is crucial is that the shock itself is quasi-random: the timing of the extradition was an unforeseen policy event, orthogonal to local dropout trends. This shift-share framework converges to a standard Difference-in-Differences representation, as shown by BHJ (2022), who show that shift-share instruments can be equivalently expressed as a DiD design with shock-level variation providing the quasi-experimental source of identification. We implement this logic in a two-way fixed effects approach:

$$Y_{ilt} = \beta(Gangs_l \times DBE_t) + X_{ilt}\alpha + \theta_t + \theta_l + \epsilon_{ilt} \tag{1}$$

where $Y_{ilt}$ is an indicator for dropout of student $i$ in neighborhood $l$ at time $t$. $Gangs_l$ indicates pre-shock gang presence, and $DBE_t$ is a binary variable equal to one in the period after the Don Berna extradition. $X_{it}$ is a vector individual and household controls. $\theta_t$ and $\theta_l$ are time and neighborhood fixed effects, respectively. Fixed Effects capture permanent neighborhood differences and common year shocks.

In the shift-share framework, identification relies on the exogeneity of the shock rather than the exogeneity of exposure. Nevertheless, including rich controls can improve the credibility and precision of the estimates. In our setting, gang presence before 2008 may be correlated with student and household characteristics that also predict dropout. We therefore include controls for parental education, age, household socioeconomic status, school quality, and whether the school is public or private-voucher. These variables capture key dimensions of heterogeneity in educational outcomes, ensuring that our estimates reflect the additional effect of the criminal shock rather than baseline differences across neighborhoods and schools.

The coefficient of interest, $\beta$, captures the average effect of the criminal demand shock on dropout. Identification relies on a parallel trends assumption: absent the extradition, dropout trends in neighborhoods with and without gangs would have evolved similarly. This assumption is plausible because (i) gang presence was measured prior to 2008 and hence predetermined, and (ii) the extradition was an unexpected, externally imposed policy event.

While our primary focus is on boys, who are the main target of gang recruitment in Medellín, analyzing girls provides a useful counterfactual. If the increase in dropout following the Don Berna extradition reflects generalized violence, we would expect similar effects for both genders. By contrast, if effects are concentrated among boys, this points to recruitment into gangs as the operative mechanism rather than

a broad deterioration of local security conditions.[5] Evidence from Colombia and other conflict settings suggests that boys are disproportionately drawn into armed groups, while girls often experience violence in different, non-recruitment forms. Therefore, contrasting boys and girls allows us to sharpen identification of the mechanism through which criminal demand shocks affect schooling decisions.

### 4.1.1 Results at neighborhood level

We start by showing the effect of the shock at the neighborhood level. We estimate equation 1 using neighborhood-level data, where the outcome variables are the homicide rate per 10,000 people, the aggregate criminal rate per 1,000 people, and the arrest probabilities. The homicide rate captures the intensity of violent conflicts between gangs following the extradition. The aggregate criminal rate reflects overall criminal activity in the neighborhood, while arrest probabilities indicate law enforcement effectiveness. The results are shown in Table 2. Column (1) shows that the homicide rate increased by 16.6 per 10,000 inhabitants relative to the pre-event mean in control neighborhoods. Column (2) indicates that the aggregate crime rate rose by 1.8 crimes per 1,000 inhabitants in treated neighborhoods compared to controls. Finally, Column (3) shows that the probability of arrest decreased by 9 percentage points in treated neighborhoods. Taken together, these results suggest that the extradition intensified gang conflicts, fueling higher violence and criminal activity, while simultaneously weakening law enforcement effectiveness, as reflected in the decline in arrest probabilities.

### 4.1.2 Gang's recruitment effect on dropout

We next estimate how the criminal shock affected school dropout, exploiting heterogeneity both across gender and cohorts.To do so, we estimate equation (1) at the individual level, with the dependent variable indicating whether student $i$ in neighborhood $l$ dropped out in year $t$. The contrast between boys and girls is central to our interpretation. Boys were the primary target of gang recruitment, while girls were mainly exposed through generalized violence and community-level insecurity. If dropout rates rise for both genders, the mechanism is likely generalized violence. By contrast, if effects are concentrated

[5] Dell and Querubin (2018) use a similar logic in the context of U.S. military operations in Vietnam. They show that boys and men were disproportionately affected through recruitment and militarization, while outcomes for girls serve as a counterfactual capturing generalized exposure to violence rather than targeted recruitment.

Table 2: Neighborhoods Effects

| | Homicide Rate | Criminal Rate | Arrest Probabilities |
|---|---|---|---|
| $Gangs_l \times DBE_t$ | 16.61* | 1.76** | -0.09*** |
| | (10.05) | (0.77) | (0.03) |
| Observations | 1968 | 1968 | 1968 |
| Mean Dep. Var. | 23.12 | 16.49 | 0.26 |

*Notes.* All regressions includes time and neighborhood fixed effects. Control variables includes: share of men in the neighborhood, average SES in the neighborhood, proportion of formal worker, and education level at the neighborhood level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

among boys, this points to targeted recruitment as the key channel. In this sense, girls provide a natural counterfactual group to rule out explanations based solely on a general deterioration of neighborhood safety.

In addition, we explore heterogeneity across student cohorts, since the timing of exposure relative to the schooling cycle is critical. Recruitment is most intense during the middle school years, when adolescents are more likely to be convicted to engage in gangs. We therefore compare cohorts who were 13-14 years old (8th grade) and 14-15 years old (9th grade) at the time of the extradition. These groups were at the peak ages for recruitment, and thus most likely to show effects if the mechanism operates through increased demand for adolescent gang members.

Table 3 presents the overall estimates for boys and girls and the two cohorts. Consistent with the recruitment hypothesis, we find large and statistically significant effects on boys' dropout rates, whereas the estimates for girls are small and statistically indistinguishable from zero. Importantly, a formal test rejects the equality of coefficients across genders, reinforcing that the shock had markedly different effects on boys and girls. This divergence provides strong evidence that the main mechanism linking the shock to educational outcomes is targeted gang recruitment, rather than a broader deterioration of local security conditions.

To further explore the timing of exposure, we estimate a dynamic version of equation 1, restricting the sample to boys. Specifically, we replace the post-shock indicator with a set of leads and lags relative to

Table 3: Difference between Girls and Boys Dropout Effects

| | **Cohort 2006** | **Cohort 2005** |
|---|---|---|
| $ATT_boys$ | 0.024 | 0.024 |
| | (0.006) | (0.007) |
| $ATT_girls$ | -0.001 | -0.006 |
| | (0.006) | (0.007) |
| $Difference$ | 0.025 | 0.030 |
| $p-value$ | (0.000) | (0.000) |
| N | 141,155 | 132,625 |

*Notes.* All regressions include time and neighborhood fixed effects. Control variables includes: parental education, age, household SES, school quality and whether the school is public or private-voucher. Cluster standard errors by neighborhood in parentheses.

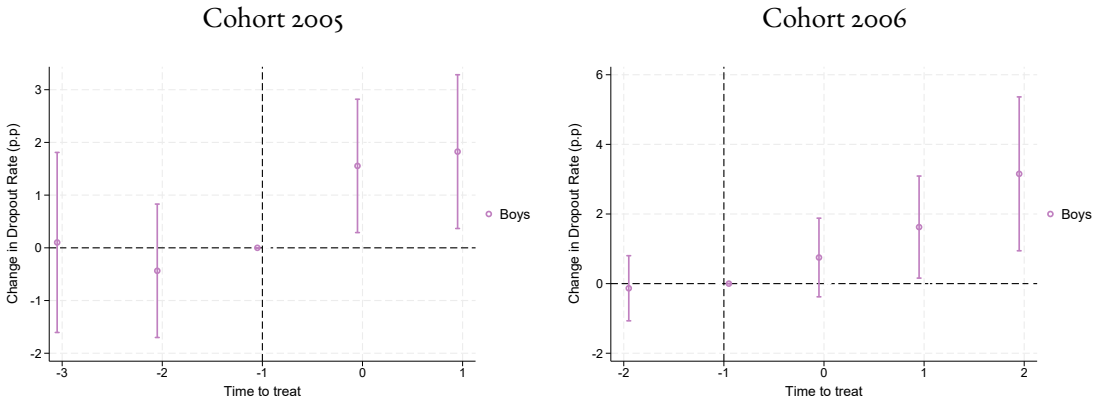
the year of the extradition, normalizing $t = -1$ as the reference period:

$$Y_{ilt} = \sum_{\tau \neq -1} \beta_\tau (Gang_l \times \mathbf{1}\{t = \tau\}) + X_{it}\alpha + \theta_t + \theta_l + \epsilon_{ilt} \tag{2}$$

Figure 5 plots the coefficients $\beta_\tau$ with 95% confidence intervals for the 2005 and 2006 cohorts. The estimates show no evidence of differential trends in dropout before the shock, pattern consistent with our identification assumptions. After the extradition, dropout among boys rises sharply, with effects concentrated in the younger cohorts. For the 2005 cohort (ages 14-15), dropouts increase by nearly 2 percentage points in the years following the shock. The effects are even larger for the 2006 cohort (ages 13-14), where dropouts rise by more than 3 percentage points within two years of exposure.

To assess whether the effects of the shock persisted beyond high school, we extend the analysis to transitions into higher education. We define a "dropout from the education system" as the probability of not enrolling in any postsecondary institution after completing high school. Figure 6 shows the dynamic effects for the 2005 and 2006 cohorts of boys, using the same specification as before but adding an additional period that captures the (no) transition to higher education. The estimates show that the dropout rate from the education system increased by about 4 percentage points in cohort 2006 and 2.3 percentage points in cohort 2005. These findings indicate that the shock's impact on schooling decisions

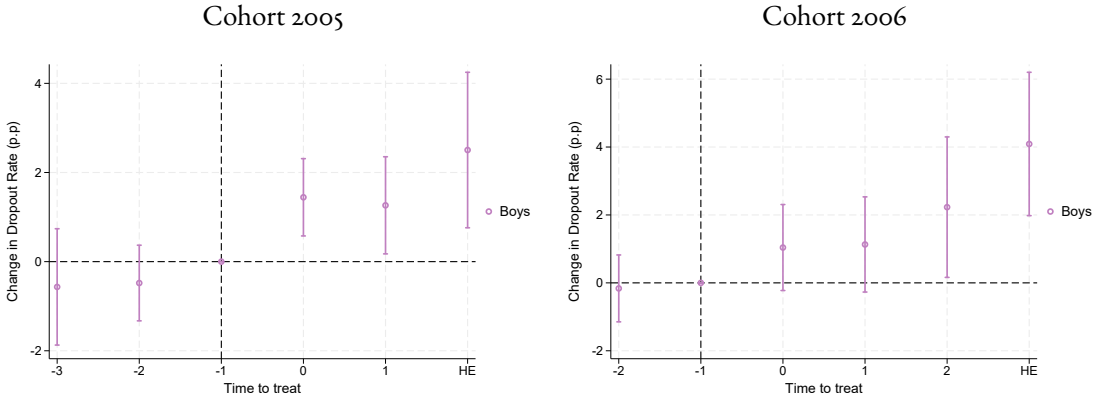
Figure 5: Event Study Dropout Rate




*Notes.* Figure shows the estimated coefficients $\beta_\tau$ from equation 2 with 95% confidence intervals. Cohort 2005 includes students who started 6th grade in 2005, while cohort 2006 includes those who started in 2006.

persisted beyond secondary education, consistent with a long-term reduction in human capital accumulation. In particular, the results suggest that the extradition shock not only increased the likelihood of leaving school during adolescence but also lowered enrollment in higher education institutions, with potential implications for future earnings and labor market trajectories.

Figure 6: Event Study Dropout Rate from the Education System




*Notes.* Figure shows the estimated coefficients $\beta_\tau$ from equation 2 with 95% confidence intervals. HE indicates the (no) transition to higher education after high school completion.

To assess the robustness of our findings and provide further support for our identification strategy, we conducted two complementary exercises. First, we implemented a synthetic difference-in-differences

approach (Arkhangelsky et al., 2021). This method constructs a weighted synthetic control for the treated cohort such that pre-treatment trends are forced to align, thereby relaxing the standard parallel-trends assumption and providing a more credible counterfactual. Appendix Figure 10 present the results for the 2005 and 2006 cohorts, showing that the synthetic control closely tracks the pre-treatment dynamics. Second, we conducted a placebo exercise in which we re-defined the timing of the treatment to 2006 and re-estimated our main specification (Table 3) for boys. Appendix table 10 reports the results, the estimated placebo coefficients are small and statistically indistinguishable from zero, suggesting that our findings are not driven by spurious shocks or differential pre-trends.

## 4.2 Do CCTs Sustain Enrollment When Criminal Labor Demand Rises?

Conditional Cash Transfer (CCT) programs have been widely documented as effective instruments to promote school attendance and human capital accumulation (Attanasio et al., 2010, 2025; Todd and Wolpin, 2006; Djebbari and Smith, 2008). Their role is particularly salient under conditions of extreme shocks. Following the framework of social insurance (Fiszbein and Schady, 2009), CCTs may attenuate the adverse effects of shocks by raising the relative return to schooling and offsetting sudden increases in the opportunity cost of education. In this setting, the critical question is whether CCTs continued to mitigate dropout during the surge in criminal recruitment following the Don Berna extradition, or whether their effectiveness diminished under these conditions.

To examine this, we estimate the following specification:

$$Y_{it}^{l} = \sum_{\tau \neq -1} \delta_{\tau}^{l}(CCT_i \times \mathbf{1}\{t = \tau\}) + \gamma_1 Eleg_i \cdot Post_t + \gamma_2 \, Sisben_i \cdot Post_t + \theta_i + \theta_t + \varepsilon_{it}, \quad \text{for } l \in \{\text{Gangs, No Gangs}\} \tag{3}$$

where $Y_{it}$ is an indicator for dropout of student i and year t, and $CCT_i$ denotes participation in the program. The specification includes individual fixed effects ($\theta_i$) which absorb all time-invariant differences across students, and year fixed effects ($\theta_t$) which capture common shocks. We also include an indicator for eligibility ($Eleg_i$), defined as having a SISBEN score $\leq 11$, as well as the continuous SISBEN

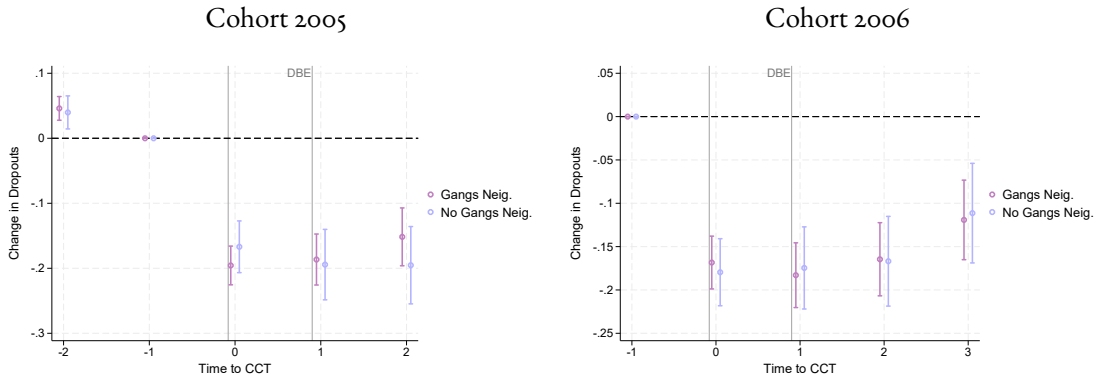
score ($Sisben_i$), interacted with $Post_t$, to flexibly capture continuous variation in household vulnerability. While identification with only individual and year fixed effects would rely on within-student changes in program exposure, including eligibility and SISBEN score is crucial in our context. Because program access is explicitly tied to the SISBEN threshold ($\leq$ 11), and because SISBEN captures time-varying household vulnerability, omitting these variables risks conflating the program's effect with underlying poverty dynamics. By conditioning on both eligibility and the continuous SISBEN score, we ensure that identification comes from within-student changes in participation around the eligibility rule, rather than from systematic differences in dropout risks across households. In the similar fashion as equation (3), we implement a synthetic DiD approach (Arkhangelsky et al., 2021) to impose parallel pre-trends (Appendix Figure 11). In all exercises, the estimated effects remain large and statistically significant.

The event-time coefficients $\delta_\tau$ in equation (3) capture dynamic effects relative to the year prior to program introduction. We estimate this specification separately for neighborhoods with and without pre-shock gang presence to compare the program's effectiveness in attenuating the criminal shock in gang and non-gang neighborhoods. Figure 7 presents the results. Across both the 2005 and 2006 cohorts of boys, CCT participation substantially reduces dropout rates. The estimated effects range between 12 and 16 percentage points, between 25 and 40 percent of the average dropout rate. Importantly, the estimated impacts are very similar across gang and non-gang neighborhoods in all years, including 2008 (period $t = 1$ in figure 7), the year of the extradition of Don Berna, suggesting that the effectiveness of the program did not diminish in the presence of increased demand for adolescent recruits.

Our identification assumption may fail if CCT participation is correlated with unobservables, time varying household characteristics that also affects dropouts. To address this concern, we complement our baseline estimates with an instrumental variables (IV) approach that exploits the program's assignment rule. Specifically, we implement a Regression Discontinuity Design (RDD), where we use program eligibility (the SISBEN threshold of 11) as an instrument for program participation into the program to correct for potential endogneity in take-up. We estimate this IV specification controlling by SISBEN score polynimials and on three symmetric score windows around the threshold: [0, 22], [3,19] and [6,16].

The IV parameters identify a local average treatment effect (LATE) for compliers at the SISBEN threshold within each badwidth. Identification requires that elegibility strongly predicts CCT take-up,

Figure 7: CCT Effects on Dropout Rate by Gang Presence




*Notes.* Confidence Intervals at 95%. Line at 0 indicates the year of CCT introduction, line at 1 label as DBE, indicates the year of the Don Berna Extradition.

which in our data is around 52% and highly statistically significant, and the elegibility affects dropout only through program participation.[6] The estimates, table 4, confirm that CCT participation significantly reduces dropouts, with effects ranging from 12 to 55 percentage points across cohorts and bandwidths. The results are also larger in magnitude than the above estimation, which is consistent with the IV capturing the impact on marginal households near the eligibility cutoff, that is, students at the dropout margin, who experience larger gains from program participation. These findings reinforce our main results, demonstrating that CCTs effectively sustain school enrollment even in the face of increased criminal labor demand that elevates opportunity costs of education.

## 4.3 From the Design-Based to the Structural Model

We find that the extradition of Don Berna had a significant effect on school dropout rates and that Conditional Cash Transfer (CCT) programs offer an effective mechanism to mitigate the impact of this shock on children's involvement in crime. While the design-based results credibly establish that crime shocks increase dropout and that CCTs alleviate part of this effect, the structural model serves as a necessary complement by providing a deeper understanding of the underlying behavioral mechanisms and en-

[6] The exclusion restriction is supported by the institutional rollout of the program. Medellín was one of the first cities included in the national expansion of CCTs, and households were not aware in advance that the program would be introduced. At the time, the SISBEN cutoff of 11 was used exclusively to determine eligibility for the transfer and was not tied to other social programs or benefits.

Table 4: Local Average Treatment Effect of CCT on Dropout (RDD/2SLS)

| | Cohort 2005 | | | Cohort 2006 | | |
|---|---|---|---|---|---|---|
| | Window [0,22] | Window [3,19] | Window [6,16] | Window [0,22] | Window [3,19] | Window [6,16] |
| **Panel A. First stage: CCT on Eligibility** | | | | | | |
| Below cutoff | 0.508 | 0.531 | 0.695 | 0.502 | 0.515 | 0.630 |
| | (0.031) | (0.035) | (0.077) | (0.030) | (0.035) | (0.078) |
| Observations | 33305 | 29375 | 20455 | 36345 | 32000 | 22635 |
| **Panel B. Reduced form: Dropout on Eligibility** | | | | | | |
| Below cutoff | -0.106 | -0.134 | -0.244 | -0.056 | -0.118 | -0.345 |
| | (0.033) | (0.043) | (0.081) | (0.032) | (0.042) | (0.079) |
| Observations | 33305 | 29375 | 20455 | 36345 | 32000 | 22635 |
| **Panel C. 2SLS: Dropout on CCT** | | | | | | |
| Effect of CCT | -0.209 | -0.253 | -0.350 | -0.112 | -0.229 | -0.548 |
| | (0.064) | (0.080) | (0.115) | (0.063) | (0.081) | (0.132) |
| Observations | 33305 | 29375 | 20455 | 36345 | 32000 | 22635 |

*Notes.* All regressions include time and student fixed effects. Panel A presents the first stage estimates. Panel B presents the reduced form estimates, using the elegibility directly into the dropout equation. Panel C presents the RDD/2SLS estimates, which identify the causal effect of CCT on dropout rates. Cluster standard errors by student in parentheses.

abling counterfactual policy analysis that the design-based approach alone cannot offer. The structural model provides a formal framework to analyze and estimate teenagers' forward-looking decisions regarding school enrollment and participation in criminal activities over time in the presence of gangs.

By modeling forward-looking behavior, we are able to estimate how teenagers value future outcomes and formally specify the adulthood transition—the final, long-term decision stage that depends on the cumulative outcomes of earlier schooling periods. Linking early choices to later outcomes is essential to quantify how middle- and high-school decisions shape long-term trajectories such as pursuing higher education, entering formal or informal employment, or continuing in crime as adults. Finally, a key advantage of the structural model is that it allows us to conduct counterfactual policy simulations that extend beyond the scope of design-based estimates.

# 5 Model

In this section, we describe a dynamic discrete choice model of teenagers' decisions to either enroll in school or participate in crime. The model is structured in two stages: the first covers the school years, and the second captures the transition to adulthood. It begins in middle school and spans the period leading up to the first transition into either the labor market or higher education. We build the model following the structure of Fu et al. (2022).

Our objective is also to estimate the value associated with gang presence in a neighborhood and how it affects school enrollment and criminal participation. Additionally, we model the effect of school subsidies by including them directly in the utility of schooling.

## 5.1 Primitives

There are $L$ neighborhoods. Each neighborhood, $l$, has different average household income, crime rates, arrest probability, and presence of gangs.

**Endowment.** A teenager, $i$, is endowed with a vector of family background $X_i$, neighborhood $l_i$, school characteristics $k_i$ and discrete type $\eta_i$. One knows his type but it is unobserved for the researcher. We model this as a logistic function, which depend on one's endowment, and neighborhood characteristics:

$$Pr(\eta_i|X_i, X_{k_i}, X_{l_i}) = \Psi(X_i, X_{k_i}, X_{l_i}) \tag{4}$$

**Choices.** In the school stage, expect when one is in jail which unable them to make choices, a teenager decides whether or not to enroll in school ($s_{it}$) and whether or not participate in crime activities ($c_{it}$): $(s, c) \in \{(0,0), (1,0), (0,1), (1,1)\}$. These choices represent: attending school only $(1,0)$, engaging in crime only $(0,1)$, or doing both simultaneously $(1,1)$ or doing neither of them $(0,0)$.

In the adulthood transition, which is the final period and the teenager is done with high school, either graduated or dropped out. Individual choices between attend to college, work in the formal sector, informal sector, or crime. This extension is important since it will allow us to analyze how early decisions affect the labor market path of young adults. We estimate the model using indirect inference to recover the parameters governing the distribution of preferences, grade progression, and unobservable types. Us-

ing the design-based estimates we can estimate changes in the criminal payoff and the impact of CCTs on schooling incentives.

### 5.1.1 Grade Progression and Human Capital Accumulation

If one decides to go to school, he will progress to the following grade with probability:

$$P(g_{it+1} = 1|X_i, \eta_i, X_k, S_{it}) = \frac{exp(\phi_g)}{1 + exp(\phi_g)} \tag{5}$$

The probability of approval depends on one's endowment, school characteristics, and current approved grade level $S_{it}$. If one does not go to school, he will not progress to the next grade, i.e., $g_{it+1} = 0$. At the end of the school stage, one will have reached a human capital level $G_{iT}$, which depends on the maximum grade reached and whether or not he was arrested during the school years.:

$$G_{iT} = \begin{cases} (1-\delta)S_{iT-1} & \text{if } J_{iT-1} \geq 1 \\ S_{iT-1} & \text{if } J_{iT-1} = 0 \end{cases} \tag{6}$$

where $S_{iT-1}$ represents cumulative schooling at the end of high school and $\delta$ captures the human capital depreciation due to arrest.

If one decides to participate in crime, he faces a probability of being arrested, $\rho_{l_i}$, which change by neighborhoods. For identification reason we need to assumed that everyone in the neighborhood face the same probability of being arrested. We calculate it using neighborhood-level crime and arrest data, as the ratio of the aggregate arrests over crimes in that neighborhood. We assume that the sentencing length $\tau$ is drawn from an order probit distribution that depends on the age and criminal record of the teenager. During the time in jail, one can not make choices.

## 5.2 Teenager's Problem

The teenager's problem at school stage $t < T$, unless he is in jail which unable them to make choices, is:

$$V_t(\Omega_{it}) = max_{(d^{(s,c)})}\{V_t^{(s,c)}(\Omega_{it})\}$$

Where $V_t^{(s,c)}$ are the specific-choice value functions. We define the school stage value functions first, and then the adulthood transition value functions, which are the terminal values at time $T$.

### 5.2.1 School Stage Value Functions

◇ $(s_{it}, c_{it}) = (0, 0)$**:**

$$V_t^{(0,0)}(\Omega_{it}) = \epsilon_{it}^{(0,0)} + \beta E_\epsilon V_{t+1}(\Omega_{it+1}) \tag{7}$$

where the mean utility of being inactive is normalized to zero, $\epsilon_{it}^{(0,0)}$ is the choice specific shock, and $\beta$ is the discount factor. The expectation is taken over the distribution of $\epsilon_{it+1}$.

◇ $(s_{it}, c_{it}) = (1, 0)$**:**

$$\begin{aligned} V_t^{(1,0)}(\Omega_{it}) =& U^s(X_i, \eta_i, X_k, Subsidy_{it}, d_{it}^{(1,1)}, g_{it}, J_{it-1}) - \phi(1 - s_{it-1}) + \epsilon_{it}^{(1,0)} \\ &+ \beta \sum_{q=0}^{1} Pr(g_{it=1} = q | X_i, X_k, \eta) E_\epsilon V_{t+1}(\Omega_{it+1}) \end{aligned} \tag{8}$$

Where $U^s$ is the flow utility of attending school, which depends on one's endowment $X_i$, type $\eta_i$, and school characteristics $X_k$. We include the subsidy to capture the additional benefits of school attendance for the teens with the subsidy. Criminal participation affects the utility through the cost of engaging on both activities. To capture some possible stigma effects, we allow the utility of depend on whether or not the teen is repeating a grade $(1 - g_{it})$, and on his criminal records $J_{it-1}$. $\phi$ captures the cost of re-enrolling in school if not enrolled in the previous period.

◇ $(s_{it}, c_{it}) = (0, 1)$**:**

$$\begin{aligned} V_t^{(0,1)}(\Omega_{i1}) =& \gamma_{\eta_i} + \alpha_{c,1} Gangs_{l_i} + \alpha_{c,2}(Gangs_{l_i} \times DBE_t) + \alpha_{c,3}\, DBE_t + \epsilon_{it}^{(0,1)} \\ &+ (1 - \rho_{l_i})[U^{free}(X_i, X_{l_i}) + \beta E_\epsilon V_{t+1}(\Omega_{it+1})] \\ &+ \rho_{l_i} E_\tau [U^{jail}(J_{it-1}) + \beta^{\tau+1} E_\epsilon V_{t+\tau+1}(\Omega_{it+\tau+1})] \end{aligned} \tag{9}$$

Each teenager receives a type-specific utility for criminal participation ($\gamma_{\eta_i}$). To capture the change in the utility of participating in crime after the Don Berna extradition, we include the interaction term

between gang presence and the time after the extradition ($DBE_t$), in the reduced-form way. If one is not arrested, with neighborhood-specific probability ($1 - \rho_{l_i}$), he will get additional reward $U^{free}(X_i, X_{l_i})$, and proceeds to the next period without criminal records. With probability $\rho_{l_i}$, he is arrested and serves a jail time ($\tau \geq 0$) draw from a distribution that depends on his age and criminal record. The utility of being arrested is $U^{jail}(J_{it-1})$, which depends on his criminal history. while in jail, one cannot make choices. After serving his time, he will return at time $t + \tau + 1$ when he is out of jail and proceeds with an updated criminal record.

We model the utility of not being arrested as a function of neighborhoods crime rate ($CrimeRate_{l_i}$), individual age, neighborhood average income (middle income, $MidInc_{l_i}$; and high income $HighInc_{l_i}$) and their own family income (low income $FamilyLow_i$), as follows:

$$\begin{aligned} U^{free}(X_i, X_{l_i}) = \; & \alpha_{c,4} CrimeRate_{l_i} + \alpha_{c,5} age_i \\ & + MidInc_{l_i}(\alpha_{c,6} + \alpha_{c,7} FamilyLow_i) \\ & + HighInc_{l_i}(\alpha_{c,8} + \alpha_{c,9} FamilyLow_i) \end{aligned} \tag{10}$$

If one is arrested, the utility of being in jail depends on his criminal history, as follows:

$$U^{jail}(J_{it-1}) = \mu_1 + \mu_2 \mathbb{1}(J_{it-1} = 0) \tag{11}$$

where $\mu_1$ is the mean disutility of being arrested, and $\mu_2$ captures the additional cost of being in arrested for the first time.

◇ $(s_{it}, c_{it}) = (1,1)$**:**

$$
\begin{aligned}
V_t^{(1,1)}(\Omega_{it}) = \; & U^s(X_i, \eta_i, X_k, Subsidy_{it}, d_{it}^{(1,1)}, g_{it}, J_{it-1}) - \phi(1 - s_{it-1}) \\
& + \gamma_{\eta_i} + \alpha_{c,1} Gangs_{l_i} + \alpha_{c,2}(Gangs_{l_i} \times DBE_t) + \alpha_{c,3} DBE_t + \epsilon_{it}^{ec} \\
& + (1 - \rho_l)[U^{free}(X_i, X_{l_i}) + \sum_{q=0}^{1} Pr(g_{it=1} = q | X_i, X_k, \eta_i) \beta E_\epsilon V_{t+1}(\Omega_{it+1})] \\
& + \rho_l E_\tau [U^{jail}(J_{it-1}) + \beta^{\tau+1} E_\epsilon V_{t+\tau+1}(\Omega_{it+\tau+1})]
\end{aligned} \tag{12}
$$

When engaging in both activities, ones enjoys the flow utility from both (lines 1 and 2 of (15)). If not arrested, one will get the additional reward from crime and proceed to the next period with the possibility of grade progression (line 3 of (15)). The last line describe the utility if arrested.

### 5.2.2 Adulthood Transition Value Functions

At time $T$, the choice set in the adulthood transition depends on the completion of high school. If one graduated from high school, he can pursue higher education or enter the labor market. While for those who did not graduate, higher education is not an option. The terminal value of each choice is:

$$
V_{T+1}(\Omega_{iT}) = U_{T+1}^{(he,c,wf,wi)}(\Omega_{iT}) \tag{13}
$$

Where $U^{(he,c,wf,wi)}$ is the choice-specific utility of each option. We define each of them below.

**Higher education (**$(he_{iT}, c_{iT}, wf_{iT}, wi_{iT}) = (1,0,0,0)$**):**

$$
U_{iT}^{(1,0,0,0)} = f^{he}(X_i, \eta_i, X_{ki}, J_{iT-1}) + \epsilon_{iT}^{(1,0,0,0)} \tag{14}
$$

The utility of attending to college is a function of the individual background and type $\eta_i$, the high school characteristics and his criminal record.

**Work formal (**$(he_{iT}, c_{iT}, wf_{iT}, wi_{iT}) = (0,0,1,0)$**):**

$$U_{iT}^{(0,0,1,0)} = ln(w_{iT}^{wf}) = f^{wf}(X_i, \eta_i, X_{ki}, G_{iT}, J_{iT-1}, S_{iT-1}) + \epsilon_{iT}^{(0,0,1,0)} \tag{15}$$

The utility of working in the formal sector is the wage of the job, which is a function of the individual background characteristics $X_i$, type $\eta_i$, high school characteristics $X_{k_i}$,human capital $G_{it}$, and criminal record. We also include a premium for graduation of high-school ($S_{iT-1} = 11$).

**Work informal ($(he_{iT}, c_{iT}, wf_{iT}, wi_{iT}) = (0, 0, 0, 1)$):**

$$U_{iT}^{(0,0,0,1)} = ln(w_{iT}^{wi}) = f^{wi}(X_i, \eta_i, X_{ki}, G_{iT}, J_{iT-1}, S_{iT-1}) + \epsilon_{iT}^{(0,0,0,1)} \tag{16}$$

Similar than the formal sector, the utility of working in the informal sector is the wage of the job, which is a function of the individual background characteristics $X_i$, type $\eta_i$, school characteristics $X_{k_i}$, human capital $G_{iT}$, and the criminal record $J_{iT-1}$.

## 5.3 Estimation and Identification

We pre-set the annual discount factor $\beta = 0.9$[7]. We assume all teenagers in the same neighborhood face the same arrest probability, we calculate it using neighborhood-level crime and arrest data, as the ratio of the aggregate arrests over crimes in that neighborhood. We assume that the sentencing length $\tau$ is drawn from an order probit distribution that depends on the age and criminal record of the teenager.

We estimate all other model parameters using indirect inference, which allows us to match the model's predictions to the observed data patterns.

$$\Theta = \{\boldsymbol{\alpha}_{school}, \boldsymbol{\alpha}_{crime}, \boldsymbol{\gamma}, \boldsymbol{a}_{Pg}, \boldsymbol{\pi}_{P\eta}, \delta, \boldsymbol{\lambda}_{college}, \boldsymbol{\lambda}_{crime}, \boldsymbol{\lambda}_{formal}, \boldsymbol{\lambda}_{informal}, \boldsymbol{\lambda}_{wi}\} \tag{17}$$

The vector $\Theta$ contains all the parameters to be estimated, which include the parameters governing preferences (utility of school ($\boldsymbol{\alpha}_{school}$), utility of crime ($\boldsymbol{\alpha}_{crime}$)), the type-specific criminal tastes ($\boldsymbol{\gamma}$), the distribution of the unobserved types ($\boldsymbol{\pi}_{P\eta}$), and grade progression ($\boldsymbol{a}_{Pg}$), the human capital depreciation

[7] We follow Fu et al. (2022) for these decision, Imai and Krishna (2004) estimated an monthly discount factor of 0.99, which is equvalent to 0.89 annually.

due to arrest ($\delta$), and the parameters of the choice-specific payoffs in the adulthood transition: college ($\boldsymbol{\lambda}_{college}$), crime ($\boldsymbol{\lambda}_{crime}$), formal work ($\boldsymbol{\lambda}_{formal}$) and informal work ($\boldsymbol{\lambda}_{informal}$).

The estimation is done in two steps. In the first step, we use the actual data to calculate auxiliary models that will be used to estimate the parameters of the model ($\Theta$). In the second step, to solve the model for each neighborhood separately, in that way we can reduce the state space and solve the problem using Rust (1987) approach. Then we simulate all neighborhoods together, creating $N * P(\eta_i = 1)$ copies with type 1 and $N * (1 - P(\eta_i = 1))$ copies with type 2 for each individual. Finally, we calculate the moments and auxiliary models, and simulate until converges. The estimation is done by minimizing the distance between the simulated data and the actual data. The parameter estimator is the solution of:

$$\hat{\Theta} = argmin_{\Theta} \left[ (\hat{B}(\Theta) - \bar{B})' W (\hat{B}(\Theta) - \bar{B}) \right] \tag{18}$$

Where $\hat{B}(\Theta)$ denote the corresponding auxiliary model parameters obtained from the model, $\bar{B}$ denote our chosen set of auxiliary model parameters computed from actual data, and $W$ is a weighting matrix.

## Identification

The model is identified through a set of auxiliary models, each informative about key structural parameters. Below, I outline the main parameters we aim to identify and the auxiliary models used in the estimation.

To identify the unobserved types, we leverage the dynamic structure of the model. Specifically, we exploit the fact that children with similar observable characteristics often make different choices over time. To capture this, we estimate conditional probabilities of persistent choices across periods, dropout and graduation rate distributions, arrest rates, and the mean of log wages in the labor market.

The change in the criminal payoff is identified through the change in dropout rates following the Don Berna extradition. We apply a difference-in-differences estimator to isolate the impact of the criminal shock on dropout behavior. This change provides key variation for identifying the model, and we use the auxiliary model to back out the parameters driving the observed shifts in choices.

The dropout decision depends on the subsidy, criminal payoff, and the characteristics of the teenager

and their school. To identify parameters associated with the utility of being in school, we estimate a dropout regression using the subsidy and background characteristics. We also estimate neighborhood-level transition rates to capture persistence in school and crime choices over time. Furthermore, we use the proportions of kids enrolled in school and arrested at each period to help identify dynamic choice probabilities.

To identify the number of youth choosing crime, we rely on the model-implied conditional choice probabilities and observed neighborhood-level arrest rates. Under the assumption that all kids in the same neighborhood face the same arrest probability, we can recover the probability of choosing crime as the ratio of observed arrests to the probability of arrest conditional on choosing crime.

To capture the depreciation of human capital due to arrest, we examine variation in log wages among individuals with similar education levels but different arrest records. We also estimate a Mincer-type earnings equation to quantify the return to education and the penalty associated with a arrest record. These results are used in an auxiliary model to inform the reward structure for work choices in the model.

## 5.4 Results

### 5.4.1 Parameter Estimates

Table 5 presents the estimated parameters for both school and crime utility functions, and the human capital depreciation parameter. Panel A shows the parameters for the utility of schooling. Low-income are students in the lower income bracket, while high educated parents are those with any higher education. Age is the age of the kids at the beginning of the model. High-quality schools are those in the top 25% of the quality distribution, while private(voucher) represents kids in private school payed by the voucher system. Grade repetition represents the cost that student has by repeating a grade, and re-enrollment captures the cost of come back to school for students who were not enrolled in the previous period. Arrest history indicates whether the student has been previously arrested. Grade level is the current grade of the student, and subsidy indicates whether the student receives a CCT subsidy. The interaction term $e = 1, c = 1$ captures the additional cost of engaging in both activities simultaneously.

For the utility of crime, Panel B shows the parameters. The first four parameter represents the reduced-form of the criminal shock affter Don Berna extradition. The intercept captures the baseline utility of

Table 5: Estimated Parameters: Utility of School and Crime

| **A. Utility of School** | | | **B. Utility of Crime** | | |
|---|---|---|---|---|---|
| Parameter | Coefficient | SE | Parameter | Coefficient | SE |
| $\alpha_{s1}$ : intercept | 4.7733 | 0.0008 | $\alpha_{c1}$: intercept | 0.04533 | 0.0008 |
| $\alpha_{s2}$ : low income | -1.2831 | 0.0004 | $\alpha_{c2}$: gangs | 1.0150 | 0.0005 |
| $\alpha_{s3}$ : high edu parents | 0.0937 | 0.0005 | $\alpha_{c3}$: DBE | 1.7766 | 0.0005 |
| $\alpha_{s4}$ : age at $t = 0$ | 1.8183 | 0.0005 | $\alpha_{c4}$: gangs×DBE | 9.4665 | 0.0007 |
| $\alpha_{s5}$ : high quality school | 0.5327 | 0.0005 | $\alpha_{c5}$:crime rate | 1.1145 | 0.0000 |
| $\alpha_{s6}$ : private(voucher) | -2.8765 | 0.0005 | $\alpha_{c6}$: MidInc | 1.9689 | 0.0006 |
| $\alpha_{s7}$ : Type=2 | 4.2200 | 0.0001 | $\alpha_{c7}$: HighInc | -1.5668 | 0.0004 |
| $\alpha_{s8}$ : grade repetition | -2.1691 | 0.0003 | $\alpha_{c8}$: age at $t = 0$ | -1.1109 | 0.0003 |
| $\alpha_{s9}$ : re-enroll | -3.2991 | 0.0003 | $\alpha_{c9}$ : MidInc × low income | 0.8167 | 0.0004 |
| $\alpha_{s10}$ : Arrest history | -1.9926 | 0.0004 | $\alpha_{c10}$ : HighInc × low income | 1.51748 | 0.0010 |
| $\alpha_{s11}$ : Grade level | 1.6485 | 0.0010 | $\gamma_1$ | 6.7214 | 0.0005 |
| $\alpha_{s12}$ : Subsidy | 4.3549 | 0.0010 | $\gamma_2$ | 1.3594 | 0.0000 |
| $\alpha_{s13}$ : $e = 1, c = 1$ | -19.9804 | 0.0000 | | | |
| | **Human Capital:** | | $\delta$ | 0.21 | 0.0234 |

*Notes.* Table presents the estimated parameters for the utility of school (Panel A) and utility of crime (Panel B), and the human capital depreciation parameter. SE are in the second column.

engaging in crime. Gangs represent the presence of gangs in the neighborhood, DBE is a dummy for the period after the Don Berna extradition, and the interaction term between gangs and DBE captures the change in the utility of crime after the extradition in neighborhoods with gang presence. Crime rate is the overall crime rate in the neighborhood. MidInc and HighInc are dummies for middle- and high-income neighborhoods, respectively. Age at $t = 0$ is the age of the teenager at the beginning of the model. The interaction terms between neighborhood income and family low income capture how family income affects the utility of crime depending on neighborhood income. Finally, $\gamma_1$ and $\gamma_2$ are type-specific parameters capturing unobserved heterogeneity in criminal tastes. Overall, the estimates show that type 1 individuals have a much higher intrinsic utility for crime than type 2 individuals, and type 2 enjoys school better.

The human capital depreciation parameter ($\delta = 0.21$) indicates that arrest and incarceration lead to a substantial 21% reduction in accumulated human capital, highlighting the long-term costs of criminal involvement during the school years.

Table 6 present the estimated parameters, for type probabilities, grade progression probabilities, the terminal value functions are in the appendix. We include additional individual characteristics to explain the probability types, such as being an only child, number of siblings, single parent, or living with adults who are not their parents. We also complemented the school characteristics, with morning shift, school in Colombia can be either morning or afternoon shift,and only male school. Neighborhood characteristics

include crime rate and gang presence. For the grade progression we use a smaller set of individual and school characteristics and the individual type.

Table 6: Estimated Parameters: Type Probability and Grade Progression Probability

| **A. Type Probability** | | | **B. Grade Progression Probability** | | |
|---|---|---|---|---|---|
| Param | Est. | SE | Param | Est. | SE |
| $\pi_1$: intercept | 11.3305 | 0.0006 | $a_1$: intercept | 0.0203 | 0.0005 |
| $\pi_2$: low income | 1.9772 | 0.0006 | $a_2$: low income | 0.7156 | 0.0003 |
| $\pi_3$: high edu parents | -0.0141 | 0.0001 | $a_3$: high edu parents | -0.9481 | 0.0002 |
| $\pi_4$: age at $t = 0$ | -0.6399 | 0.0009 | $a_4$: age at $t = 0$ | 0.3543 | 0.0005 |
| $\pi_5$: only child | -0.1420 | 0.0006 | $a_5$: high quality | 0.4390 | 0.0005 |
| $\pi_6$: one sibling | -0.3906 | 0.0004 | $a_6$: private(voucher) | 0.4674 | 0.0002 |
| $\pi_7$: more than one sibling | -0.6484 | 0.0004 | $a_7$: type 2 | 0.1958 | 0.0000 |
| $\pi_8$: single parent | 2.4701 | 0.0010 | $a_8$: Grade level | -0.0431 | 0.0015 |
| $\pi_9$: non parents | 4.3025 | 0.0006 | $\sigma_g$ | 1.1611 | 0.0005 |
| $\pi_{10}$: high quality | 0.5736 | 0.0009 | | | |
| $\pi_{11}$: private(voucher) | 0.0643 | 0.0007 | | | |
| $\pi_{12}$: morning school | -0.1379 | 0.0008 | | | |
| $\pi_{13}$: only male school | -0.3846 | 0.0009 | | | |
| $\pi_{14}$: neighborhood crime | 0.0450 | 0.0004 | | | |
| $\pi_{15}$: gangs | -0.8832 | 0.0001 | | | |

*Notes.* Table presents the estimated parameters for the type probability (Panel A) and grade progression probability (Panel B).

### 5.4.2 Model Fit

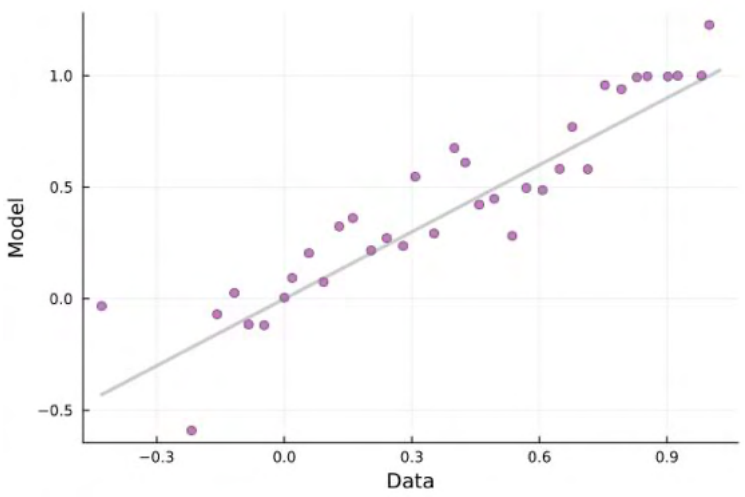
Figure 8 plots the simulated and observed moments we use to estimate the model. Moments include average choice per period, dropout rate, arrest rate, and graduation rate. As well as distribution of choice and grade attainment at the end of high school by individual characteristics. We also include terminal choice probabilities, and the design based estimates, among others.

The model makes a fair job fitting the data, capturing the main patterns in the data. However, there is still room for improvement.

# 6 Counterfactual Analysis

We use the model to assess the role of subsidies and endowment characteristics in shaping high school outcomes across neighborhoods. We then conduct three policy simulations targeting the most disadvantaged students in different types of neighborhoods.

Figure 8: Model Fit




*Notes.* Figure presents the model fit. The x-axis presents the actual data moments, while the y-axis presents the simulated moments from the estimated model. The 45-degree line is included for reference.

## 6.1 Value of Subsidy and Endowment Characteristics

To evaluate the importance of subsidies and endowment characteristics, we classify students into three socioeconomic groups: disadvantaged, middle, and advantaged. The classification is based on family background. Disadvantaged students are those with low income and low parental education; middle students have either low income and high parental education or high income and low parental education; and advantaged students have both high income and high parental education.

We begin by simulating a counterfactual scenario in which subsidies do not exist and compare high school outcomes across the three groups. To assess the role of endowment characteristics, we simulate a scenario in which all students are assigned the same endowment characteristics as the advantaged group, again comparing outcomes across the three groups.

Table 7 presents results for both counterfactuals. The top panel reports baseline outcomes, while the bottom panel shows percentage changes relative to the baseline. Initial endowment characteristics play an important role in improving high school graduation rates and reducing arrests during school years, particularly among disadvantaged students. If all students had the endowment characteristics of

the advantaged group, the graduation rate would increase by 20.1% for disadvantaged students and by 16.4% for middle students, while the arrest rate would decrease by 26.7% and 18.2%, respectively.

Subsidies also have a meaningful effect on improving high school outcomes, especially for disadvantaged students. In the absence of subsidies, the graduation rate would fall by 3.5% for disadvantaged students and by 0.6% for middle students, while the arrest rate would rise by 6.7% for disadvantaged students and remain unchanged for middle students.

Focusing on gang-dominated neighborhoods, the effects of both subsidies and endowment characteristics are even more pronounced, particularly for students in the middle group. Eliminating the subsidy in all gang neighborhoods would reduce graduation rates by 7.6% for disadvantaged students and 1.8% for middle students. Although these changes are larger for the disadvantaged group, the decline for middle-group students in gang neighborhoods is almost three times greater than the overall decline for the same group (-0.6%).

If all students in gang neighborhoods had the endowment characteristics of the advantaged group, the graduation rate would rise by 34% for disadvantaged students and 31% for middle students. These effects are also relatively larger for the middle group compared to the overall change in the same group (20.1% and 16.4%, respectively). The subsidy plays a particularly important role in reducing arrests among disadvantaged students: without the subsidy, the arrest rate would increase by 8.7% for disadvantaged students and remain unchanged for middle students. If all students in gang neighborhoods had advantaged endowment characteristics, the arrest rate would decrease by 21% for disadvantaged students and 18% for middle students.

## 6.2 Policy Interventions

In this section, we conduct three counterfactual policy interventions to evaluate their effects on arrest rates and crime participation during school years, as well as on long-term adulthood outcomes. The three policy scenarios are defined as follows:

1. **Expanded CCT (CF1):** Every student in the disadvantaged group receives conditional cash transfer payments.

Table 7: High School Outcomes by Subsidy and Endowment Group

| Baseline | Grad, no arrest (%) | | Ever Arrest (%) | |
|---|---|---|---|---|
| **All Neighborhood** | | | | |
| Disadvantaged | 53.6 | | 1.5 | |
| Middle | 59.5 | | 1.1 | |
| Advantaged | 61.6 | | 0.8 | |
| **Gangs Neighborhood** | | | | |
| Disadvantaged | 32.9 | | 2.3 | |
| Middle | 32.5 | | 2.2 | |
| Advantaged | 33.9 | | 1.9 | |

| | No Subsidy | | | | Advantaged Endowment | | | |
|---|---|---|---|---|---|---|---|---|
| | Grad, no arrest (%) | | Ever Arrest (%) | | Grad, no arrest (%) | | Ever Arrest (%) | |
| | New | Change | New | Change | New | Change | New | Change |
| **All Neighborhood** | | | | | | | | |
| Disadvantaged | 51.7 | -3.5 | 1.6 | 6.7 | 64.4 | 20.1 | 1.1 | -26.7 |
| Middle | 59.2 | -0.6 | 1.1 | 0.0 | 69.4 | 16.4 | 0.9 | -18.2 |
| **Gangs Neighborhood** | | | | | | | | |
| Disadvantaged | 30.4 | -7.6 | 2.5 | 8.7 | 44.1 | 34.0 | 1.8 | -21.7 |
| Middle | 31.9 | -1.8 | 2.2 | 0.0 | 42.5 | 30.8 | 1.8 | -18.2 |

*Notes.* The top panel presents baseline outcomes: percent of students who graduated from high school and were never arrested, and percent who were ever arrested, for three endowment categories. The bottom panel reports simulated outcomes under two scenarios: (1) no subsidy, and (2) all students have advantaged endowment. "New" columns report the simulated rate under each scenario; "Change" columns report the percentage change relative to the baseline scenario.

2. **Enhanced Law Enforcement (CF2):** The probability of arrest ($\rho_l$) increases following the criminal shock.

3. **Combined Policy (CF3):** Implementation of both the expanded CCT and enhanced law enforcement policies.

Since our focus is on disadvantaged students, we present results only for this group. Expanding the subsidy to all disadvantaged students increases graduation rates by 33% relative to the baseline and reduces the share of teenagers ever arrested during school years by 41%. In contrast, enhanced law enforcement produces the opposite pattern: graduation rates fall by 9.6%, while arrests rise by 61.2% relative to the baseline. The combined policy increases graduation rates by 27.9% and reduces arrests by 9.8%, though

its effect is smaller than that of the expanded CCT policy alone. Overall, the expanded CCT intervention yields the most favorable impacts on high school outcomes, while enhanced law enforcement generates adverse educational effects. The combined policy delivers intermediate results.

Table 8 reports the distribution of choices during the adulthood transition for each policy scenario and the baseline, separately for neighborhoods with and without gang presence. This comparison allows us to assess whether different policy interventions affect students differently depending on their environment. Figure 9 presents the percentage change relative to the baseline for each outcome and counterfactual scenario.

The results show that the expanded CCT policy (CF1) substantially increases college attendance among disadvantaged students—from 19.7% in the baseline to 28.5% in gang neighborhoods, and from 42.4% to 44.1% in non-gang neighborhoods. This policy also reduces crime participation by 5%. The increase in college attendance is more modest in non-gang neighborhoods, but the reduction in criminal involvement is larger (7.3%).

Enhanced law enforcement (CF2) decreases college attendance in gang neighborhoods by 19.4%. However, it produces large reductions in crime participation—48.4% in neighborhoods with gangs and 23.3% in those without. The combined policy (CF3) generates effects similar to the expanded CCT policy, with increased college attendance, though the magnitude is slightly smaller than under CF1 alone. CF3 is the most effective intervention at reducing crime participation, with declines of 52.2% and 30% in gang and non-gang neighborhoods, respectively.

Formal employment decreases under the CCT expansion (CF1) in both types of neighborhoods but increases under enhanced law enforcement (CF2). Informal employment declines under all interventions in gang neighborhoods but rises in non-gang neighborhoods under CF1 and CF3.

Expanding the CCT program to all disadvantaged students appears to be the most effective policy for improving long-term educational outcomes and reducing criminal participation, particularly in neighborhoods with gang presence. Enhanced law enforcement, while successful in lowering crime rates, has detrimental effects on educational attainment—especially in gang-affected areas. The combined policy offers a more balanced approach, improving both education and crime outcomes, though its effects are less pronounced than those of the CCT expansion alone.

The total cost of expanding the CCT program to all disadvantaged students is approximately USD 8.8 million (COP 30 billion) for their entire high school period (six years). However, the expected gain in lifetime earnings for these students is about USD 90 million over forty years, more than offsetting the fiscal cost of the subsidy.

Table 8: Adulthood Transitions Outcomes by Gangs Presence

| | **Gang** | | | | **No Gangs** | | | |
|---|---|---|---|---|---|---|---|---|
| | BL | CF1 | CF2 | CF3 | BL | CF1 | CF2 | CF3 |
| College | 19.7 | 28.5 | 15.9 | 26.0 | 42.4 | 44.1 | 41.3 | 43.1 |
| Crime | 4.7 | 4.4 | 2.4 | 2.2 | 6.0 | 5.6 | 4.6 | 4.2 |
| Formal | 39.7 | 35.1 | 41.1 | 35.0 | 27.9 | 26.1 | 29.2 | 27.4 |
| Informal | 5.5 | 4.8 | 4.2 | 3.0 | 6.2 | 7.2 | 6.6 | 7.1 |

*Notes.* Each column shows the percentage of individuals in each outcome category (College, Crime, Formal, Informal) we omitted being inactive in all other activities, but it can be calculated as a 100 minus the sum of the other categories. Baseline=BL, CF1= Expanded CCT, CF2= Law Enforcement, and CF3= CF1+CF2. These results are for disadvantaged students only.

## 6.3 Cost-Benefit Analysis

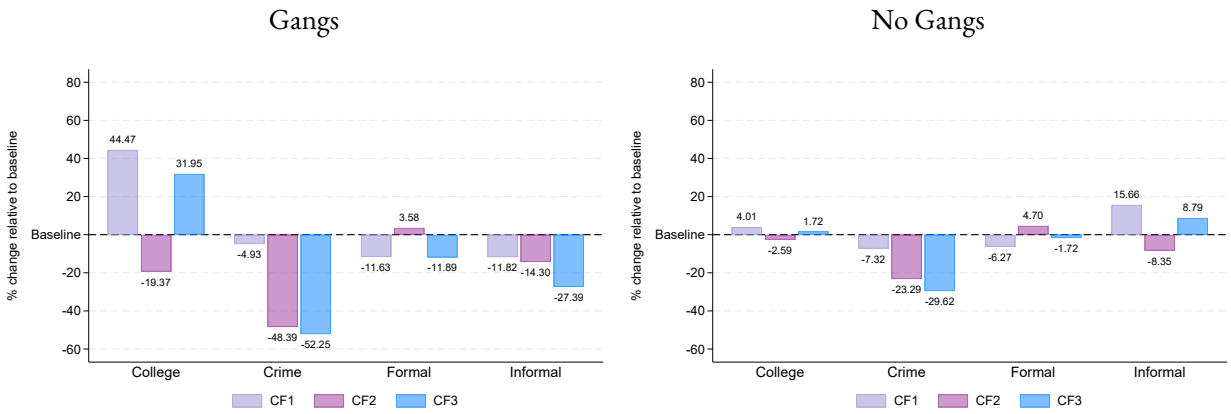
We conduct a back-of-the-envelope calculation for a cost-benefit analysis comparing the baseline scenario with each of the three policy interventions. The analysis incorporates multiple cost and benefit categories over a 40-year time horizon, including:

**Benefits:**

- Increased lifetime earnings, we calculate the present value of earnings over a 40-year horizon, using the discount rate of 3.6% and a growth rate of 3%, from World Bank indicators.
- Increased government revenue through VAT collection. We use a 13.3% rate, which was the VAT rate in Colombia during the period of analysis, and assume that all earnings are consumed in goods and services subject to VAT.[8]

[8] We do not include income tax revenue because most individuals in our sample earn below the taxable income threshold in Colombia.

Figure 9: CCT Effects on Dropout Rate by Gang Presence




*Notes.* Figure presents the percentage change in adulthood outcomes relative to the baseline for each counterfactual scenario, separately for neighborhoods with and without gang presence. CF1= Expanded CCT, CF2= Law Enforcement, and CF3= CF1+CF2. These results are for disadvantaged students only.

**Costs:**

- Direct program costs for conditional cash transfers, we calculate it as the cost of the subsidy for the 6 years of high school multiplied by the number of students in the disadvantaged group.
- Cost of crime to the public sector, we use estimates from the Inter-American Development Bank report on crime costs in Latin America and the Caribbean, which estimates that crime costs the public sector 3.5% of GDP in Colombia, given the crime rate in the country and 1.3% of the GDP associated with arrest costs and policing which we use as estimate of additional costs of increasing law enforcement.[9] We use these estimates to calculate the cost of crime under each scenario, adjusting for changes in arrest rates and crime participation predicted by the model.
- Criminal earnings (externality effects), we estimate the present value of earnings for individuals engaged in crime, using the same discount and growth rates as for legal earnings. This captures the potential earning from criminal activity, which we can considered a cost to society. [10]

Table 9 presents the complete cost-benefit analysis results.

[9] This includes direct cost of crime to the private and public sectors and justice system costs (Perez-Vincent et al., 2024).

[10] We estimate the criminal earning using the average criminal earnings from the survey of prisoners in Colombia (Blattman et al., 2019, 2025), which they report to be around the median wage of the city.

Table 9: Cost-Benefit Analysis Results (Millions USD)

| | Baseline | CF1 | CF2 | CF3 |
|---|---|---|---|---|
| Total Present Value of Earnings (40 yrs) | 1227.1 | 1281.1 | 1175.7 | 1235.7 |
| VAT Revenue (assuming 100% consumption) | 163.1 | 170.6 | 156.1 | 164.2 |
| Subsidy Cost | 0.9 | 8.8 | 0.9 | 8.8 |
| Cost of Crime | 375.8 | 359.2 | 240.4 | 226.5 |
| Cost of Additional Policing | - | - | 83.9 | 79.0 |
| Criminal Earnings (externalities) | 12.7 | 12.1 | 8.1 | 7.6 |
| Net Earnings After Taxes | 1065.2 | 1112.5 | 1018.6 | 1070.5 |
| Government Net Benefit | -213.6 | -197.3 | -169.0 | -150.1 |
| Net Social Benefit | 837.7 | 903.0 | 841.4 | 913.7 |

*Notes.* Table presents the cost-benefit analysis results for the baseline and three counterfactual scenarios: CF1= Expanded CCT, CF2= Law Enforcement, and CF3= CF1+CF2. All values are in millions of USD. The analysis includes total present value of earnings over a 40-year horizon, VAT revenue, subsidy costs, cost of crime, cost of additional policing, and criminal earnings (externalities). The net earnings after taxes, government net benefit, and net social benefit are total benefits minus total costs.

The results demonstrate that all three policy interventions generate positive net social benefits compared to the baseline scenario. The combined policy (CF3) achieves the highest net social benefit of $913.7 million, but it is relatively similar to the expanded CCT program (CF1) $903 million. The reduction in crime in the long-run plus the increase in college enrollment because of the subsidy makes CF3 most effective than CF2, which reduces the crime but since there are not effect in human capital accumulation these benefits are not realized.

# 7 Conclusion

This paper examines how neighborhood-level criminal shocks influence teenagers' educational decisions and long-term outcomes. Using rich administrative data from Medellín, Colombia, we analyze the impact of the 2008 extradition of Don Berna, the city's top gang leader, which triggered a gang war and generated a sharp increase in criminal labor demand. Our findings show that this shock had substantial effects on teenagers' schooling decisions, particularly among boys aged 12 to 15, who were most vulnerable to gang recruitment.

Dropout rates among boys in the most affected cohorts increased significantly in neighborhoods with gang presence, while no comparable effects were observed for girls. This pattern suggests that the primary mechanism was gang recruitment rather than general violence. Moreover, the effects persisted beyond high school, as affected boys were less likely to enroll in higher education, underscoring the long-term impact of criminal shocks on human capital accumulation.

We also evaluate the role of Colombia's Conditional Cash Transfer (CCT) program, Familias en Acción, in mitigating these effects. The program effectively reduced dropout rates overall and remained robustly effective in neighborhoods with gang presence, even as recruitment intensity increased.

To deepen our understanding of these mechanisms, we develop and estimate a dynamic structural model of teenagers' schooling, crime, and labor market choices from middle school through early adulthood. The model incorporates neighborhood-specific criminal payoffs, heterogeneity in endowments, and preferences for criminal activities, allowing us to simulate counterfactual policy scenarios. We consider three interventions: expanding the CCT program to all disadvantaged students, enhancing law enforcement to increase arrest probabilities, and a combined policy implementing both measures.

Expanding the CCT program to all disadvantaged students emerges as the most effective policy for improving long-term educational outcomes and reducing youth crime, particularly in gang-affected neighborhoods. Strengthening law enforcement also reduces criminal participation but has adverse effects on educational attainment, especially during adolescence. A combined policy achieves a balanced outcome—reducing crime while preserving educational gains, though not as strongly as the CCT expansion alone. Expanding CCT coverage for all disadvantaged students would cost approximately 8.8 million USD (COP 30 billion) over six years of high school but would yield lifetime earnings gains of around 90 million USD, far exceeding the program's costs.

Overall, this study contributes to the literature on the intersection of human capital formation and crime by providing causal evidence on how shocks to the criminal sector influence educational decisions. It also underscores the value of integrating design-based and structural approaches to uncover the mechanisms behind these effects and to evaluate the effectiveness of policy interventions aimed at breaking the cycle between poverty, crime, and limited educational opportunity.

# References


Angrist, J., Bettinger, E., Bloom, E., King, E., and Kremer, M. (2002). Vouchers for private schooling in colombia: Evidence from a randomized natural experiment. *American economic review*, 92(5):1535–1558.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., and Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review*, 111(12):4088–4118.

Attanasio, O., Fitzsimons, E., Gomez, A., Gutierrez, M. I., Meghir, C., and Mesnard, A. (2010). Children's schooling and work in the presence of a conditional cash transfer program in rural colombia. *Economic development and cultural change*, 58(2):181–210.

Attanasio, O., Sosa, L. C., Medina, C., Meghir, C., and Posso-Suárez, C. M. (2025). Long term effects of cash transfer programs in colombia. *Working paper*.

Attanasio, O. P., Oppedisano, V., and Vera-Hernández, M. (2015). Should cash transfers be conditional? conditionality, preventive care, and health outcomes. *American Economic Journal: Applied Economics*, 7(2):35–52.

Bayer, P., Hjalmarsson, R., and Pozen, D. (2009). Building criminal capital behind bars: Peer effects in juvenile corrections. *The Quarterly Journal of Economics*, 124(1):105–147.

Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of political economy*, 76(2):169–217.

Billings, S. B., Deming, D. J., and Rockoff, J. (2014). School segregation, educational attainment, and crime: Evidence from the end of busing in charlotte-mecklenburg. *The Quarterly Journal of Economics*, 129(1):435–476.

Blattman, C., Duncan, G., Lessing, B., and Tobon, S. (2019). Gangs of medellín: How organized crime is organized. *Working in paper*.

Blattman, C., Duncan, G., Lessing, B., and Tobón, S. (2025). Gang rule: Understanding and countering criminal governance. *Review of Economic Studies*, 92(3):1497–1531.

Borusyak, K., Hull, P., and Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of economic studies*, 89(1):181–213.

Chetty, R. and Hendren, N. (2018). The impacts of neighborhoods on intergenerational mobility i: Childhood exposure effects. *The quarterly journal of economics*, 133(3):1107–1162.

Chetty, R., Hendren, N., and Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment. *American Economic Review*, 106(4):855–902.

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

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

Dell, M. and Querubin, P. (2018). Nation building through foreign intervention: Evidence from discontinuities in military strategies. *The Quarterly Journal of Economics*, 133(2):701–764.

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

Djebbari, H. and Smith, J. (2008). Heterogeneous impacts in progresa. *Journal of Econometrics*, 145(1-2):64–80.

Duncan, G. (2014). Drug trafficking and political power: oligopolies of coercion in colombia and mexico. *Latin American Perspectives*, 41(2):18–42.

Fella, G. and Gallipoli, G. (2014). Education and crime over the life cycle. *The Review of Economic Studies*, 81(4):1484–1517.

Fiszbein, A. and Schady, N. R. (2009). *Conditional cash transfers: reducing present and future poverty*. World Bank Publications.

Foureaux Koppensteiner, M. and Menezes, L. (2021). Violence and human capital investments. *Journal of Labor Economics*, 39(3):787–823.

Freeman, R. B. (1996). Why do so many young american men commit crimes and what might we do about it? *Journal of Economic perspectives*, 10(1):25–42.

Fu, C., Grau, N., and Rivera, J. (2022). Wandering astray: Teenagers' choices of schooling and crime. *Quantitative Economics*, 13(2):387–424.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.

Heckman, J., Pinto, R., and Savelyev, P. (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American economic review*, 103(6):2052–2086.

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

Imai, S. and Krishna, K. (2004). Employment, deterrence, and crime in a dynamic model. *International Economic Review*, 45(3):845–872.

Kling, J. R., Ludwig, J., and Katz, L. F. (2005). Neighborhood effects on crime for female and male youth: Evidence from a randomized housing voucher experiment. *The Quarterly Journal of Economics*, 120(1):87–130.

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.

Lochner, L. (2004). Education, work, and crime: A human capital approach. *International Economic Review*, 45(3):811–843.

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.

Mancino, M. A. (2022). A search model of early employment careers and youth crime. *International Economic Review*, 63(1):329–390.

Mancino, M. A., Navarro, S., and Rivers, D. A. (2016). Separating state dependence, experience, and heterogeneity in a model of youth crime and education. *Economics of Education Review*, 54:274–305.

Martin, G. (2012). *Medellín tragedia y resurrección: mafia, ciudad y estado, 1975-2012*. planeta.

Merlo, A. and Wolpin, K. I. (2015). The transition from school to jail: Youth crime and high school completion among black males. *European economic review*, 79:234–251.

Perez-Vincent, S. M., Puebla, D., Alvarado, N., Mejía, L. F., Cadena, X., Higuera, S., and Niño, J. D. (2024). The costs of crime and and violence: Expansion and update of estimates for latin america and the caribbean.

Rose, E. K., Schellenberg, J. T., and Shem-Tov, Y. (2022). The effects of teacher quality on adult criminal justice contact. Technical report, National Bureau of Economic Research.

Rust, J. (1987). Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica: Journal of the Econometric Society*, pages 999–1033.

Salazar, D. F. (2023). Criminal capital, education, and employment: Evidence from juvenile offenders. *Education, and Employment: Evidence from Juvenile Offenders (October 23, 2023)*.

Sickles, R. C. and Williams, J. (2008). Turning from crime: A dynamic perspective. *Journal of Econometrics*, 145(1-2):158–173.

Sviatschi, M. M. (2022). Making a narco: Childhood exposure to illegal labor markets and criminal life paths. *Econometrica*, 90(4):1835–1878.

Todd, P. E. and Wolpin, K. I. (2006). Assessing the impact of a school subsidy program in mexico: Using a social experiment to validate a dynamic behavioral model of child schooling and fertility. *American economic review*, 96(5):1384–1417.

Todd, P. E. and Wolpin, K. I. (2023). The best of both worlds: combining randomized controlled trials with structural modeling. *Journal of Economic Literature*, 61(1):41–85.

# Appendices

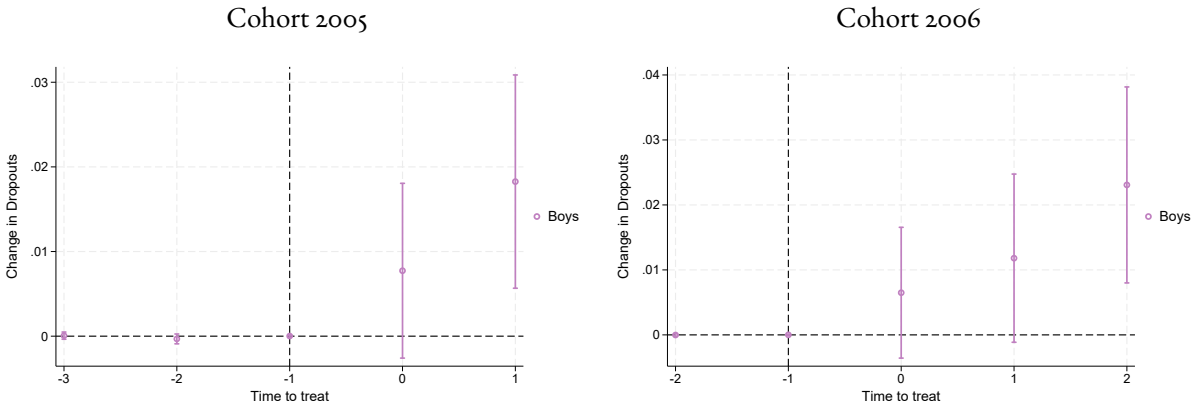
## .1 Additional Figures and Tables Robustness Checks

Table 10: Placebo Tests

| | Cohort 2005 | Cohort 2004 |
|---|---|---|
| $ATT_{boy}$ (Placebo) | 0.004 | 0.010 |
| | (0.008) | (0.009) |
| Observations | 132,625 | 135,440 |

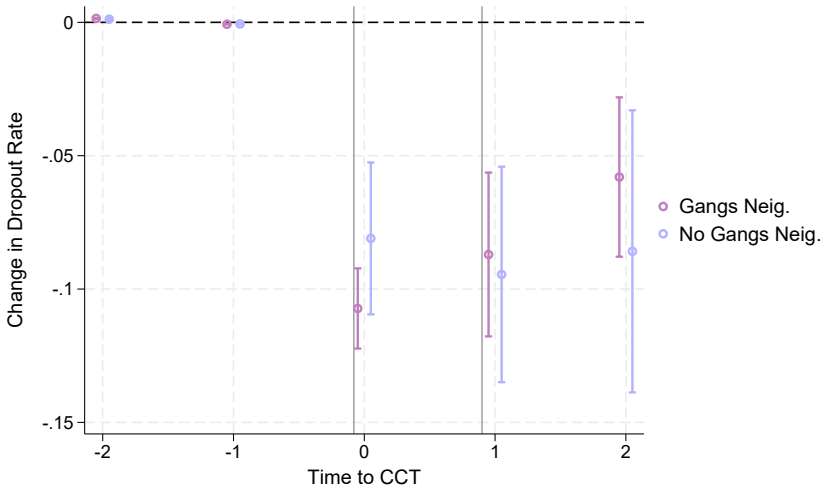
*Notes.* Placebo test is conducted by assigning the shock one year earlier than the actual event, in 2007 instead of 2008. Regressions include neighborhood and year fixed effects. Control variables inlcude: family income, parents education, age, school quality and public school indicator. We estimate the same specification as in Table **??**, but for cohorts 2005 and 2004. We do not use cohort 2004 in our main estimitation, but it serves as a placebo to examine additional to the sample cohort a different cohort which did not get the shock during most sensitives year of recruitment. Standard errors are clustered at the neighborhood level.

Figure 10: Synthetic Difference-in-Differences: Dropout Rates and Criminal Shock




*Notes.* Figure presents the synthetic difference-in-differences estimates for dropout rates for cohorts 2005 and 2006. The estimates are obtained by comparing the treated group (gang-affiliated youth) with a synthetic control group constructed from non-treated youth. The vertical line indicates the timing of the criminal shock.

Figure 11: Synthetic Difference-in-Differences: Dropout Rates and CCT program




*Notes.* Figure presents the synthetic difference-in-differences estimates for dropout rates by CCT program participation for cohort 2005. The estimates are obtained by comparing the treated group (CCT participants) with a synthetic control group constructed from non-participants. The vertical line at zero indicates the timing of CCT, and the subsequent lines represent the Don Berna extradition.

## .2 Estimated Parameters - Terminal Value Functions

Table 11: Estimated Parameters: Terminal Value Functions College

| Param | Est. | SE |
|---|---|---|
| $\lambda_{he1}$ | 4.7182 | 0.0008 |
| $\lambda_{he2}$ | -2.2322 | 0.0008 |
| $\lambda_{he3}$ | 1.4895 | 0.0007 |
| $\lambda_{he4}$ | 1.7808 | 0.0007 |
| $\lambda_{he5}$ | 1.5082 | 0.0008 |
| $\lambda_{he6}$ | 0.6619 | 0.0008 |
| $\lambda_{he7}$ | 2.1475 | 0.0001 |
| $\lambda_{he8}$ | 0.2985 | 0.0006 |
| $\lambda_{he9}$ | -0.0478 | 0.0005 |

Table 12: Estimated Parameters: Terminal Value Functions Crime

| Param | Est. | SE |
|---|---|---|
| $\lambda_{c1}$ | -1.6472 | 0.0007 |
| $\lambda_{c2}$ | -1.1218 | 0.0007 |
| $\lambda_{c3}$ | 1.4513 | 0.0008 |
| $\lambda_{c4}$ | -1.6398 | 0.0007 |
| $\lambda_{c5}$ | 1.9321 | 0.0002 |
| $\lambda_{c6}$ | 4.9567 | 0.0009 |
| $\lambda_{c7}$ | 7.4549 | 0.0000 |
| $\lambda_{c8}$ | 11.9185 | 0.0005 |
| $\lambda_{c9}$ | 2.8726 | 0.0004 |

Table 13: Estimated Parameters: Terminal Value Functions Formal Work

| Param | Est. | SE |
|---|---|---|
| $\lambda_{wf1}$ | 0.7032 | 0.0008 |
| $\lambda_{wf2}$ | -0.6274 | 0.0008 |
| $\lambda_{wf3}$ | -0.5096 | 0.0007 |
| $\lambda_{wf4}$ | 0.3207 | 0.0007 |
| $\lambda_{wf5}$ | -0.0781 | 0.0008 |
| $\lambda_{wf6}$ | -0.8271 | 0.0008 |
| $\lambda_{wf7}$ | 1.3833 | 0.0001 |
| $\lambda_{wf8}$ | -0.1349 | 0.0006 |
| $\lambda_{wf9}$ | 0.0365 | 0.0005 |
| $\lambda_{wf10}$ | 0.6150 | 0.0005 |
| $\lambda_{wf11}$ | -0.4788 | 0.0005 |

Table 14: Estimated Parameters: Terminal Value Functions Informal Work

| Param | Est. | SE |
|---|---|---|
| $\lambda_{wi1}$ | -0.7816 | 0.0008 |
| $\lambda_{wi2}$ | 0.0006 | 0.0008 |
| $\lambda_{wi3}$ | 0.7295 | 0.0007 |
| $\lambda_{wi4}$ | -0.3393 | 0.0007 |
| $\lambda_{wi5}$ | 0.1811 | 0.0008 |
| $\lambda_{wi6}$ | 0.1439 | 0.0008 |
| $\lambda_{wi7}$ | 1.2988 | 0.0001 |
| $\lambda_{wi8}$ | -0.1121 | 0.0006 |
| $\lambda_{wi9}$ | 0.1887 | 0.0005 |
| $\lambda_{wi10}$ | -0.5099 | 0.0005 |
| $\lambda_{wi11}$ | -0.0645 | 0.0005 |