The Aftermath of My Friend's Murder: Analyzing the Impact of Classmate Homicide on Juvenile Detention

Gil do Vigor *

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Abstract

This paper examines the impact of peer homicide exposure on juvenile criminal behavior, focusing on students in Pernambuco, Brazil. Leveraging a novel panel dataset that links detailed homicide records with administrative data on school enrollment and juvenile detention from 2008 to 2022, I exploit the random timing of student homicides to estimate the causal effect of a classmate's murder on juvenile detention. Using a staggered difference-in-differences framework, I find that exposure to a classmate homicide significantly reduces the likelihood of juvenile detention—by approximately 1.5 percentage points, or 39 percent relative to the baseline mean. The effects are more pronounced for full-time detention, typically associated with more serious offenses. Heterogeneity by crime type reveals stronger deterrent effects for drug-related and violent crimes than for property crimes. Additional analyses show that older, more disadvantaged students enrolled in adult education programs (EJA) exhibit the largest declines in detention risk, consistent with greater baseline exposure to risk factors and heightened responsiveness to peer violence. These findings highlight the role of traumatic peer events in shaping youth behavior and underscore the importance of peer environments in juvenile crime prevention.
Keywords: Crime Engagement, Juvenile Detention, Homicides, Brazil

JEL Codes: D91, I25, K42, O12

*PhD Candidate at University of California - Davis

1 Introduction

Youth violence in Brazil is a pressing and critical issue, with homicide emerging as the leading cause of death for individuals aged 12 to 19 years in numerous states in the country. The youth homicide rate in Brazil was 54.9 per 100,000 for people aged 15 to 19 in 2017, being a strong indicator of the gravity of this problem and ranking Brazil among the countries with the highest homicide rates in the world (Waiselfisz (2017)). In doing so, while several studies highlight the socioeconomic impacts of exposure to violence on human capital accumulation and academic performance (Koppensteiner and Menezes (2021), Padilla-Romo and Peluffo (2023), Burdick-Will (2013)), there is also a growing body of literature that explores how significant life events influence individuals' behavioral and decision-making processes, particularly regarding criminal activity. Studies such as Massenko and Rose (2022), Eichmeyer and Kent (2022) and Britto et al. (2024) highlight parenthood as a pivotal life event that can shape criminal behavior, often leading to decreased engagement in crime in developed countries, and increasing in developing countries context, as in Brasil. Building on this idea, our paper introduces a novel approach by examining the impact of a friend's murder as a potential turning point capable of reshaping criminal behavior.

To address this gap in the literature, this paper examines whether the murder of a classmate serves as a pivotal event that reshapes short-term criminal behavior among adolescents. Focusing on the state of Pernambuco, a state in northeastern Brazil marked by persistently high rates of youth violence, I estimate the causal impact of peer homicide exposure on the likelihood of juvenile detention. The empirical strategy leverages variation in the timing of peer deaths across classrooms, restricting the analysis to students who shared the same class as the murdered peer. By narrowing the sample in this way, the identification strategy captures more immediate and personal peer effects, under the assumption that classmates have stronger social ties and are more directly impacted by the loss. The model is implemented using a staggered difference-in-differences framework following callaway2021difference, which allows for credible identification of the short-run effects of peer homicide exposure while accounting for treatment timing heterogeneity across cohorts.

I use data from FUNASE[1] as a proxy for youth criminal behavior. The data provide detailed records on admissions into the juvenile justice system, capturing cases involving more severe offenses. To construct a comprehensive individual-level panel, I merge three administrative datasets: juvenile offense records from FUNASE, homicide records from the mortality registry, and student-level information from the national educational census. The resulting panel contains 766,367 observations of students enrolled in grades 1 through 12 in Pernambuco from 2009 to 2018. Within this sample, 3,966 homicides involving students are recorded, alongside 19,000 documented instances of juvenile detention. This rich dataset allows for tracking individuals over time, enabling the identification of the causal effects of peer homicide exposure on subsequent criminal behavior.

In particular, our analysis leverages the randomness in the timing of exposure by comparing comparable students from classrooms that experienced a classmate's murder during different time periods. Specifically, an individual is considered treated in year t if they were in the same classroom as a homicide victim in the year of the shock $t - i$ ($i = 0, 1, 2, 3, \ldots, 7$). In doing so, I adopt a not-yet-treated design, whereby the control

[1]FUNASE stands for *Fundação de Atendimento Socioeducativo*, the institution responsible for the socio-educational rehabilitation of juvenile offenders in Pernambuco, Brazil

group consists of students who have not yet been exposed to a classmate's homicide but will be treated in a future period. This identification strategy ensures that comparisons are made between individuals who are, in expectation, similar in their likelihood of eventual exposure to peer violence. By focusing on variation in the timing of treatment among future-treated units, we strengthen the internal validity of our estimates and mitigate concerns about time-invariant differences across cohorts or classrooms. The difference-in-differences design thus captures the causal effect of exposure to a classmate's murder on subsequent criminal behavior, isolating how this traumatic peer event reshapes short-run trajectories within the juvenile justice system.

This paper contributes to the literature on peer effects, violence exposure, and the determinants of youth crime by providing novel causal evidence on how traumatic peer events shape adolescent delinquency. While prior research has largely focused on the impact of violence on academic outcomes, this study is, to the best of our knowledge, the first to causally examine whether the murder of a peer influences criminal behavior among remaining students. In doing so, it broadens our understanding of how peer-based trauma functions not only as an educational disruption but also as a potential deterrent for engagement in criminal activity. Using administrative data from Pernambuco, Brazil, and a staggered difference-in-differences design, I estimate that exposure to a classmate's homicide leads to a substantial reduction in juvenile detention. The baseline effect represents a 1.48 percentage point decline—equivalent to a 39 percent decrease relative to the pre-treatment mean. The deterrent effect is especially pronounced for drug-related offenses (81.7 percent), violent crimes (45.5 percent), and full-time detention episodes (43.3 percent), underscoring the severity of behavioral change in response to peer violence.

In contrast, we find no statistically significant effects among female students, aligning with prior evidence that young women are less involved in the types of criminal behavior captured by detention records.

These findings are robust to a range of identification concerns. The estimates hold in the presence of school and time fixed effects, show no evidence of differential pre-trends, and are not driven by spillover exposure from neighboring schools. A battery of placebo tests using alternative causes of peer death, combined with heterogeneity analyses by age, grade level, and crime type, supports the reliability of the results.

Moreover, the theoretical framework I adopt suggests that traumatic events act as informational shocks, potentially altering perceptions of crime-related risks, consistent with rational choice theories outlined by Becker (1968). In Pernambuco, data from FUNASE show that a considerable proportion of youth victims, 15%, had criminal records in the juvenile system. This highlights the potential correlation between youth homicide and criminal activities. Given that young people often misperceive the true cost of their actions, as discussed by Lochner and Moretti (2004) and Jacob and Lefgren (2003), they are more likely to engage in crime.

The remainder of the paper is organized as follows. In section 2, I provide the background. In the section 3, I present the literature review. In section 4, I describe the theoretical framework. In section 5, I describe the data, and in section 6, I address the identification strategy. Finally, in section 6, I show the results, and in section 7, I display the robustness checks. Section 8 exhibits the conclusion.

2 Background

2.1 Homicides as a Mechanism to Crime

How does the homicide of a peer impact the probability that the youth will be in juvenile detention? The literature already discusses that young people are very likely to misperceive the causal impact of their actions, underestimating the real cost of their illegal activities, but they used to adjust their perception based on their peers' realizations (Knoll et al., 2015). Based on this intuition, adolescent mortality judgments are correlated with their perception about the direct risk of being killed, as their perception adjusts based on information about the threats that occurred with their peers. In addition, this belief update implies an increase in the perceived probability of a more severe punishment such as death, which increases the marginal cost of engaging in illegal activities, because when adolescents become more well informed about those risks through peers' death information, it operates as a cost in their decision-making process. As a result, if the perceived benefit of crime ceteris paribus, the classmate's homicide may lead to higher perceived cost of crime, deterring juvenile detention.

2.2 Brazil versus Other Countries Juvenile Courts Measures

Here's a revised version incorporating the 7 measures and the suggested changes:

The Brazilian juvenile system is governed by the *Estatuto da Criança e do Adolescente* (ECA) [2]. For minor crimes, juveniles are not allowed to be judged, and small infractions are handled by the police. In the case of repeated minor infractions or infractions that put people's lives at risk, the more severe offenses can lead the youth to be judged in the juvenile courts.

The ECA establishes seven socioeducational measures that can be applied to adolescent offenders: warning, obligation to repair damage, community service, supervised freedom, semi-liberty regime, internment in educational establishment, and cumulative application of any previous measure with protective measures. Among these seven measures, only internment in educational establishment results in total deprivation of liberty for the offender, equivalent to juvenile detention in the US system. The other measures are executed in open environments or with partial freedom restrictions.

It is important to point out the main difference between the United States and Brazil regarding the juvenile justice system. In most countries including the USA, when youth are sentenced, they often receive punitive measures based on the belief that through punishment, individuals will change their behavior when they balance the cost and benefit of their actions. However, in Brazil, the focus is on the fact that youth are not properly integrated into society, which is the reason why they engage in such infractions. Therefore, the measures should focus on rehabilitating and reeducating these adolescents through education and social support rather than punishment.

2.3 Historical Background of Pernambuco and Violence

Pernambuco, a state in Brazil's Northeast Region (Figure 1), has a population of approximately 9 million people and 185 municipalities IBGE (2022) and faces structural

[2](Child and Adolescent Statute) - which was established on July 13, 1990, to protect juveniles in all aspects

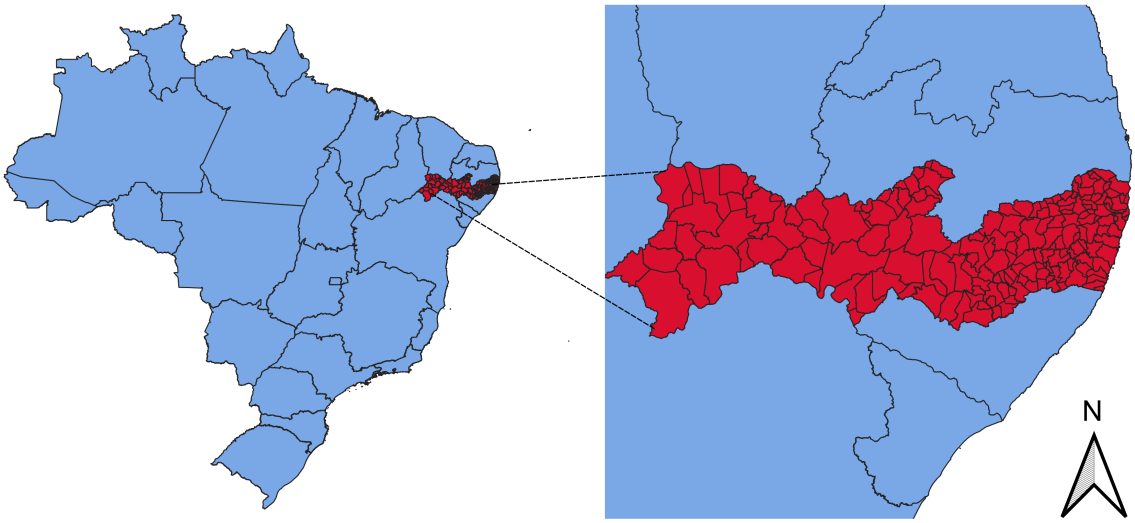


Figure 1: Map of Pernambuco, Brazil

conditions that foster youth involvement in crime. The state's per capita GDP is around $5,000 USD, significantly lower than the national average of $9,800 USD IBGE (2015). The lack of economic and social opportunities for youth, combined with extreme poverty and inequality, reduces the marginal cost of engaging in crime Becker (1968), creating an environment that facilitates the recruitment of vulnerable individuals by criminal organizations. Additionally, a crucial factor is that young people in Pernambuco are frequently exposed to crime from an early age, whether through the pervasive presence of criminal organizations or the routine violence that characterizes their daily lives.

In 2006, Recife, the capital of Pernambuco, with a population of approximately 1.5 million, recorded the highest homicide rate in Brazil, reaching 69 murders per 100,000 inhabitants—more than double the national average. Among young individuals aged 20–29, the homicide rate exceeded 137 murders per 100,000 (Ratton et al. (2011)). To address this crisis, the state implemented the Pacto pela Vida (Pact for Life) program,[3] which initially achieved a 39% reduction in homicide rates between 2006 and 2013 Neto et al. (2022).

Despite this decline, homicide rates in Pernambuco remained high compared to the national average. Figure 2 illustrates the evolution of annual homicide and non-homicide deaths between 2010 and 2017. While non-homicide deaths remained relatively stable over time, the proportion of homicides increased sharply after 2014. By 2015, homicides not only equaled non-homicide deaths but also surpassed them, creating a significant gap by 2017. Notably, in 2017, Pernambuco was among the most violent states in Brazil, recording one of the highest homicide rates per 100,000 inhabitants—almost twice the national average Waiselfisz (2016). The persistent exposure to violence and crime lowers the perceived cost of engaging in illicit activities, particularly in an environment where the sense of impunity is prevalent.

[3]The Pacto pela Vida (Pact for Life) is a public security initiative launched in Pernambuco, Brazil, aimed at reducing violence and homicide rates through integrated efforts involving law enforcement, social policies, and community engagement.

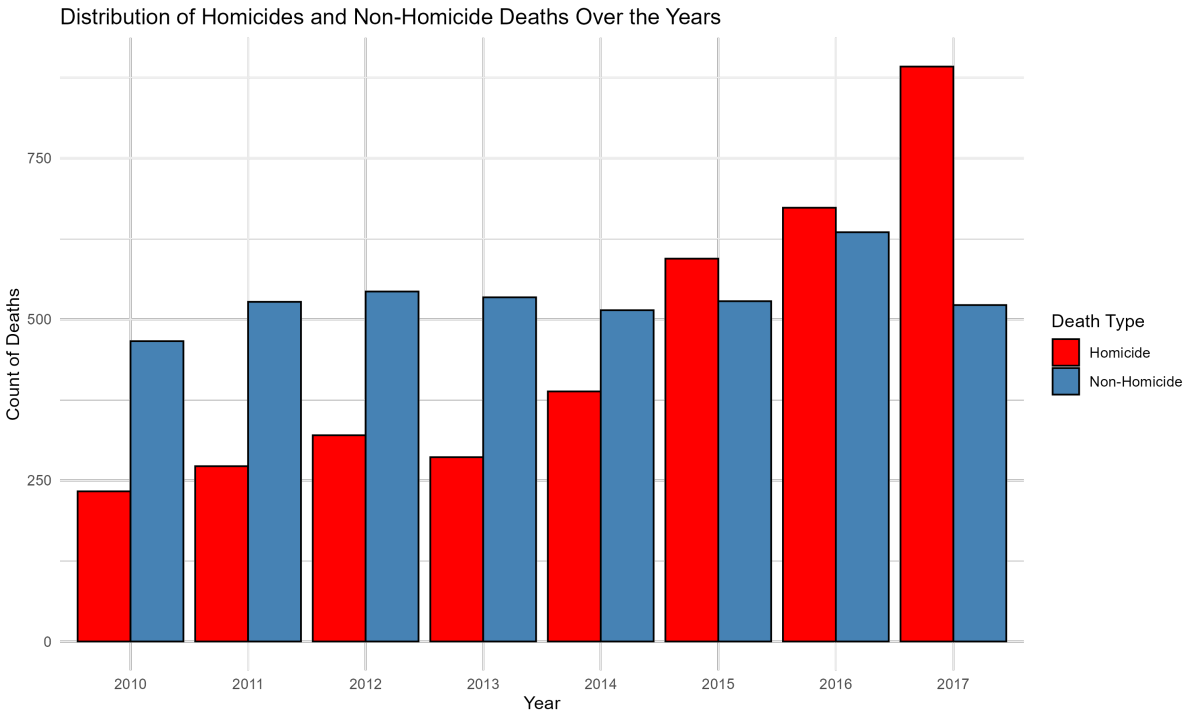


Figure 2: Annual Distribution of Homicides and Non-Homicide Deaths (2010 - 2017)

Understanding youth crime in Pernambuco requires recognizing that it is not merely a matter of individual choice, but a consequence of the socioeconomic conditions that shape the opportunities available to young people. In this context, examining how youth respond to the murder of a schoolmate is essential to understanding the psychological dynamics that emerge in situations of extreme violence. In vulnerable communities, relationships between schoolmates often extend beyond the school environment, serving as crucial emotional and social support in the face of adversity. When a peer is murdered, young people experience intense psychological effects, including trauma, fear, and increased feeling of exposure and the position of greater change of mortality, generating psychological responses that can influence criminal involvement.

The figure 3 highlights the historical victimization rate of young people by gender in Pernambuco between 1990 and 2020 and shows not only the gender gap in victimization of young people, but also the vulnerability of the age to death. As youth age, especially between the ages of 15 and 24, they become more exposed to homicide, which seems to be related to their increased involvement in crime. This same age pattern appears again later in the paper, when I show that the highest rates of juvenile detention also concentrate in these age ranges. Specifically, for those aged 15 to 19, the increase in homicide rate suggests a period in which many youth drop out of school, becoming more exposed to violence, and increasing their likelihood of being killed. Although this issue affects both genders, it affects predominantly male adolescents, as seen by the sharp increase in homicide rates among boys, which is not reflected in the female graph. This does not mean that the problem is irrelevant for girls, but it indicates that male adolescents are at particularly high risk.

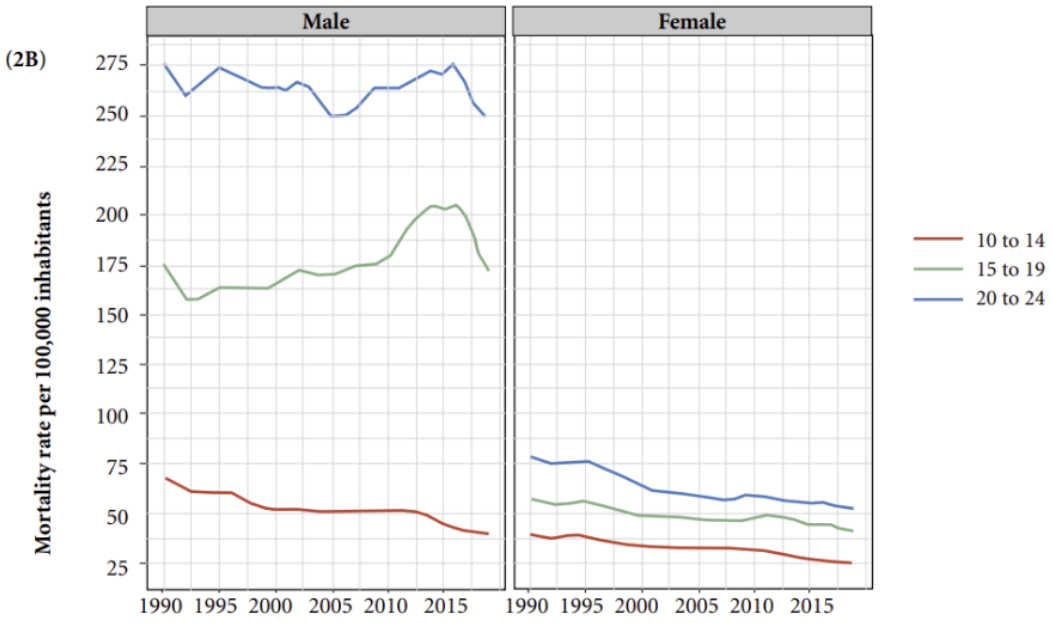


Figure 3: Youth Homicide Rate by Gender in Pernambuco

3 Literature Review

This paper builds upon a growing body of research examining the effects of violence exposure, crime, and peer effects on youth outcomes, particularly in education and criminal behavior. The literature has documented how exposure to violence can shape individual decision-making, academic performance, and criminal engagement, with varying effects depending on socioeconomic status, geographic proximity to violent events, and the nature of the exposure.

3.1 Violence on Human Capital and Criminal Behavior

Several studies have explored how exposure to violence affects human capital accumulation and criminal behavior. Koppensteiner and Menezes (2021) analyze the impact of localized homicides on primary school students in São Paulo, Brazil. They find that an additional homicide within a 25-meter radius of a school leads to a 4.6% and 5.5% standard deviation reduction in math and language test scores, respectively. Additionally, student absences increase by 1% per additional homicide. These findings highlight how localized violence disrupts learning, potentially through stress and trauma, rather than through direct personal grief.

In Mexico, Padilla-Romo and Peluffo (2023) examines the long-term spillover effects of violence on educational outcomes. Their study shows that exposure to violence has detrimental effects on middle school GPA, grade progression, and performance on high school admission exams. Students migrating from violent areas disrupt classrooms, reduce teacher effectiveness, and shift peer dynamics, leading to lower academic achievement. Interestingly, their findings indicate that female students experience a more pronounced negative impact on GPA and educational aspirations.

At an even more extreme level, Bharadwaj et al. (2021) analyzes the effects of surviving a mass shooting in Norway. They find that exposed students exhibit lower GPAs, reduced high school completion rates, increased psychological diagnoses, and lower employment rates years after the event. While direct victims suffer the most severe consequences, their peers do not experience significant long-term effects, except for slight declines in test scores among female students. These findings suggest that while school-based violence disrupts educational and labor market trajectories, the intensity and proximity of exposure may shape the extent of these effects.

3.2 Peer Effects and Crime Engagement

The role of peer effects in shaping youth behavior has been widely studied in economics. Research consistently shows that peer networks influence educational performance, aspirations, and even criminal activity. For instance, Moreira (2016) investigates the impact of academic achievement recognition on peer outcomes in Brazil. The study finds that students in close proximity to an award-winning classmate are 10% more likely to enroll in a selective college and improve their test scores. However, this influence is primarily driven by physical classroom proximity rather than broader social connections, underscoring the importance of direct peer interactions in shaping educational aspirations.

Similarly, Vogel et al. (2024) examine the acute effects of community violence exposure on adolescents in St. Louis, USA. Their study finds that adolescents exposed to spatially proximate homicides exhibit increased adherence to a "Code of the Streets", stronger attitudes endorsing violent conduct, heightened fear of victimization, and greater odds of gang membership (+52%). These results indicate that proximity to violence not only affects perceptions of safety but can also reinforce cultural norms of violence, increasing the likelihood of criminal engagement.

3.3 Criminal Behavior and Economic Pressures

Beyond peer influences and exposure to violence, economic pressures also play a critical role in shaping criminal behavior. While studies such as Massenko and Rose (2022) and Eichmeyer and Kent (2022) analyze the impact of childbirth on criminal behavior in developed countries, Britto et al. (2022) extend this analysis to Brazil, focusing on the effects of childbirth on criminal behavior among low-income parents. Their findings indicate that fathers experience an 18% increase in criminal prosecution, particularly for economically motivated crimes, in the two years following childbirth. In contrast, mothers experience a 60% reduction in criminal activity around childbirth, but this effect fades within a year. Their findings suggest that financial strain following childbirth may push individuals toward crime as a coping mechanism, particularly when they lack stable employment.

Additionally, their study reveals that the increase in crime among fathers is driven by those with no prior formal income, reinforcing the idea that economic vulnerability is a key determinant of criminal behavior. Notably, households where the mother is not formally employed before childbirth exhibit even stronger increases in male criminal activity. These findings highlight how economic instability and lack of formal employment contribute to crime involvement, particularly for young fathers.

3.4 Social Interaction and Crime

The social interaction mechanism plays a crucial role in shaping juvenile criminal behavior, particularly within school environments where students' daily interactions can either deter or facilitate engagement in crime. Jacob and Lefgren (2003) examine the impact of school closures on crime in the United States, leveraging unexpected teacher-in-service days and strikes as exogenous variations in school attendance. Their findings suggest that keeping students in school reduces property crimes due to incapacitation effects but simultaneously increases violent crimes, possibly due to the heightened concentration of students in a confined environment, which may lead to conflicts.

Similarly, Brilli and Tonello (2018) investigates the relationship between education and crime in Italy, exploiting a staggered school-leaving age reform. Their difference-in-differences estimates display that extending compulsory schooling reduces overall crime rates — driven primarily by incapacitation — but increases crime within school facilities, likely due to a higher concentration of students in shared spaces. While displacement effects could theoretically explain this pattern, their analysis finds no evidence that criminal activity shifts to after-school hours or non-school periods. These studies underscore the dual role of schools as both protective and risk-enhancing environments, where peer interactions can either deter or reinforce criminal behavior depending on the social dynamics at play.

4 Theoretical Framework: Information Shock and Crime Decision Making

4.1 The Basic Model

This section introduces a theoretical framework examining how exposure to social shocks, specifically the murder or detention of peers, such as schoolmates, affect youths' perceptions regarding the risks related to association with criminal groups to commit illegal activities, in turn shaping their decisions about criminal behavior.

This model draws on the pioneering work of Becker (1968), which introduces the rational choice framework for crime behavior. I further elaborate on this approach by including a belief-updating mechanism, highlighting that juveniles frequently lack clear information about the costs (or "risks") and benefits associated with criminal activities. Instead, their actions are shaped by perceptions derived from their peers' direct experiences with violence and interaction with law enforcement through their schoolmates getting caught by the police and sent to juvenile detention, being more clear when a peer is killed or placed in juvenile detention.

This model builds on the rational choice framework by assuming juveniles strategically decide the optimal number of offenses to maximize their expected utility. Their choices rely on perceived cost-benefit analyses, in which they balance the risks of penalties, the severity of sanctions, and the likelihood of death versus the potential gains from engaging in criminal behavior.

Youth involved in criminal activities typically commit illegal actions in groups, creating stronger ties to criminal networks. Consequently, if one member of the group is murdered, their criminal peers might feel increasingly vulnerable, perceiving themselves as potential next targets. This heightened sense of danger could prompt greater migration among these individuals. We can verify this hypothesis empirically by examining our dataset

and isolating the migration patterns of classmates following the homicide event. Indeed, preliminary observations indicate noticeable changes in the movements of students with criminal records in FUNASE after their schoolmate's murder, adding robustness to our argument.

With this framework established, let us clearly define the key parameters involved. First, we introduce p_f, representing how juveniles perceive the chance of their peers being apprehended, p_j, representing the perceived chance that they will be sent to juvenile detention. Next, we have p_d, the perceived chance of being killed. Importantly, each of these perceptions can change based on the experiences of their peers. For example, young people typically understand that engaging in crime carries serious risks, including death. However, research highlights that youths often underestimate the real dangers associated with their actions. If a peer is murdered, the juveniles immediately revise their perception of fatal risk p_d, leading to the following:

$$\Delta p_d > 0,$$

This upward adjustment increases the perceived cost of committing crimes, deterring further criminal involvement among peers.

On the other hand, if a peer is incarcerated, the perception of risk of apprehension by juveniles p_j also increases given $p_j(p_f)$; the perceived probability by youth is a function of their peers' experiences. Interestingly, empirical evidence shows that this increase might paradoxically lead to greater criminal activity. This occurs through a replacement effect, where the removal of one individual from the criminal network creates an opportunity for others to step in and fill the gap, maintaining the stability of these networks (Dell, 2015).

4.2 Utility Function and Objective

The paper by Becker (1968) mentions that the theories about the determinants to an individual engage in crime and decide the optimal number of infractions he is going to commit are going to differ from individual to individual, and those differences depends a lot of variables, like, socio-economic conditions, the probability of conviction or the severity of punishment. He argues that, usually, the person decides to commit an illegal action based on their cost and benefits analysis. In other words, they are going to engage in crime if the expected utility of the crime exceeds the utility the person could achieve if he spent the same amount of time in a legal activity. Then, following the same approach, I will assume that an individual is going to engage in criminal activity and chooses the optimal number of infractions, I^*, by maximizing their expected utility, which balances the perceived benefits and costs of crime:

$$U(I) = B_c(I) - C(I, p_f(p_j), S, p_d, p_j). \tag{1}$$

where:

- $B_c(I)$ represents the benefits of engaging in crime, such as financial gain, social status, and protection.
- $C(I, p_f(p_j), S, p_d, p_j)$ represents the total cost of engaging in crime.
- The costs include three components:

- **Legal Punishment Cost:** $C_f(I) = p_f(p_j)SI$, where p_f is the probability of being caught and detained, which depends on p_j, the probability of the schoolmate being detained. This reflects the idea that law enforcement actions targeting one individual may increase the likelihood of their peers also being apprehended. S denotes the severity of punishment, and I is the number of infractions committed by the individual.
- **Fatal Risk Cost:** $C_d(I) = p_d DI$, where p_d is the probability of being killed due to criminal engagement, and D is the perceived disutility of death.
- **Market Replacement Effect:** $C_j(I) = -p_j RI$, where p_j is the probability of a schoolmate being arrested and sent to juvenile detention, and R is the redistribution of criminal opportunities among remaining individuals.

Thus, the total cost function becomes:

$$C(I, p_f(p_j), S, p_d, p_j) = (p_f(p_j)S + p_d D - p_j R)I. \tag{2}$$

This approach implies that there is a function relating the number of offenses by any person to his probability of conviction, to his punishment if convicted, the fatal risk cost and other variables, such as the income available to him in legal and other illegal activities.

4.3 Functional Form of Crime Benefits

We assume the benefits of crime increase with the number of infractions but at a decreasing rate due to diminishing returns:

$$B_c(I) = \beta I - \frac{\gamma}{2} I^2, \tag{3}$$

where:

- β is the base marginal benefit per infraction.
- To remain that benefits remain positive, β also be strictly positive ($\beta \quad 0$)
- If $\beta = 0$, crime has no initial benefits. In addition, if $\beta < 0$, crime has immediate negative returns, making it irrational to commit infractions. Thus, we assume $\beta > 0$.
- γ represents diminishing returns to crime participation.
- To guarantee that benefits never become negative, we impose an upper bound on γ:

$$0 < \gamma \leq \frac{2\beta}{I_{\max}} \tag{4}$$

- This ensures that, for any feasible number of infractions I, benefits remain non-negative.

4.4 Optimization Problem

The individual maximizes:

$$U(I) = \beta I - \frac{\gamma}{2} I^2 - (p_f(p_j)S + p_d D - p_j R)I. \tag{5}$$

Taking the first-order condition (FOC):

$$\frac{dU}{dI} = \beta - \gamma I - (p_f(p_j)S + p_d D - p_j R) = 0. \tag{6}$$

Solving for the optimal number of infractions:

$$I^* = \frac{\beta - (p_f(p_j)S + p_d D - p_j R)}{\gamma}. \tag{7}$$

4.5 Effect of Increased Perceived Mortality Risk

A schoolmate's murder leads to an increase in the perceived probability of death:

$$p_d' = p_d + \Delta p_d, \quad \text{where } \Delta p_d > 0. \tag{8}$$

Differentiating I^* with respect to p_d:

$$\frac{dI^*}{dp_d} = \frac{-D}{\gamma} < 0. \tag{9}$$

As expected, when a youth perceives a higher chance of death, they engage in *fewer* infractions, confirming the deterrent effect of violence exposure.

4.6 Effect of Increased Juvenile Detention Among Peers

When a schoolmate is detained, the probability of juvenile detention increases:

$$p_j' = p_j + \Delta p_j, \quad \text{where } \Delta p_j > 0. \tag{10}$$

In addition, since p_j positively influences p_f, the probability of being caught also rises:

$$p_f' = p_f + \frac{dp_f}{dp_j}\Delta p_j, \quad \text{where } \frac{dp_f}{dp_j} > 0. \tag{11}$$

Differentiating I^* with respect to p_j:

$$\frac{dI^*}{dp_j} = \frac{R - \frac{dp_f}{dp_j}S}{\gamma}. \tag{12}$$

This result supports the idea that when police enforcement removes youth from the crime market, remaining members increase their criminal activity to compensate for the lost member's share of profits. However, this effect is mitigated by the fact that an increase in p_j also raises p_f, the probability of being caught. Since p_j positively affects p_f, a stronger law enforcement presence increases the overall perceived risk of apprehension, which may deter criminal activity. Thus, the effect on infractions depends on the balance between the replacement effect and the deterrent effect, driven by the interaction between p_j and p_f.

4.7 Effect of Increased Police Enforcement

Differentiating I^* with respect to p_f:

$$\frac{dI^*}{dp_f} = \frac{-S}{\gamma} < 0. \tag{13}$$

Then, this confirms that as p_f (perceived probability of being detained) increases, the optimal number of infractions I^* decreases, reinforcing the deterrence effect or law enforcement.

4.8 Policy Implications and Conclusion

- **Why More Arrests Can Increase Crime:** - If enforcement actions are removing peers but not dismantling networks, vacancies open up for new individuals to replace arrested offenders. - As a result, remaining individuals have greater incentives to commit infractions.
- **Why Perceived Mortality is a Stronger Deterrent than Arrest Risk:** - Since death is irreversible and more severe than arrest, its deterrent effect is stronger. - Policies focusing on increasing the *perceived risk of death* (e.g., through education on violence consequences) may be more effective.
- **How to Prevent the Crime Substitution Effect:** - Instead of simply arresting individuals, policies should target entire criminal networks to prevent market restructuring. - Economic programs offering alternative legal income sources can reduce the replacement effect.

This model explains the paradox where higher police enforcement can increase crime when arrests create vacancies in illicit networks. The findings suggest that strategic enforcement is necessary to disrupt criminal networks rather than just removing individual offenders.

5 Data

5.1 Juvenile Detention

The *Fundação de Atendimento Socioeducativo* (FUNASE) is a public institution in Pernambuco, Brazil, responsible for providing socio-educational services to adolescents aged 12 to 20 who are in conflict with the law. FUNASE aims to reintegrate these young individuals into society, rather than merely punishing them, through structured programs that emphasize education, vocational training, and psychological support. Currently, there are 20 facilities in Pernambuco, with distinct types of socio-educational measures.

Once adolescents are apprehended, they are first taken to a provisional unit, where they may be held for up to 45 days while awaiting a judicial decision. Depending on the outcome, they may be released or assigned to one of the following measures:

- **Semi-liberty**: The adolescent may leave the facility during the day for work or school but must return in the evening.

- **Internment**: The adolescent loses their right to freedom and must remain within the facility full-time.

Some insights from the complete FUNASE dataset (2008–2024) are presented in Figure 4, which illustrates the distribution of the number of admissions in juvenile detention. The data show that most individuals experience only one admission, with the frequency declining sharply as the number of admissions increases. While a small proportion of individuals undergo multiple admissions, cases beyond four admissions become significantly rarer. This pattern suggests a highly skewed distribution, where repeated detentions are uncommon, yet a subset of individuals appears to cycle through the system multiple times.

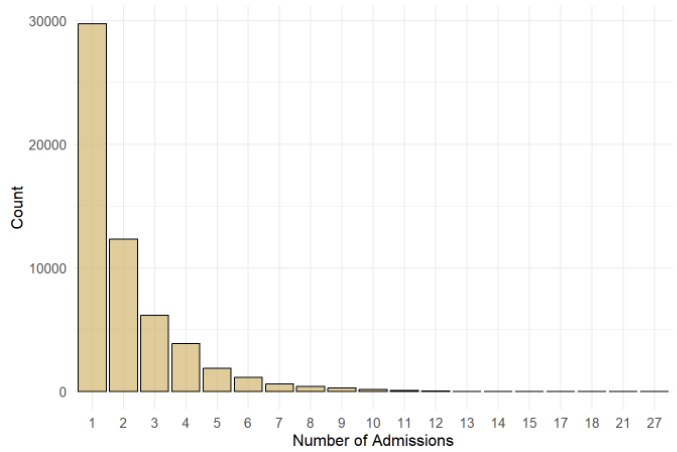


Figure 4: Number of Admissions per Individual in FUNASE (2008 - 2024

Likewise, Figure 5 shows the age distribution of individuals admitted to FUNASE. The data indicate that most admissions occur between ages 15 and 18, peaking at age 17, making this age group the most prevalent in juvenile detention. Admissions decline sharply for younger individuals (under 14) and those older than 19, suggesting that mid-to-late adolescence is the critical period for youth detention. This pattern aligns with broader trends in juvenile crime, where late teenage years are often linked to higher rates of criminal involvement.

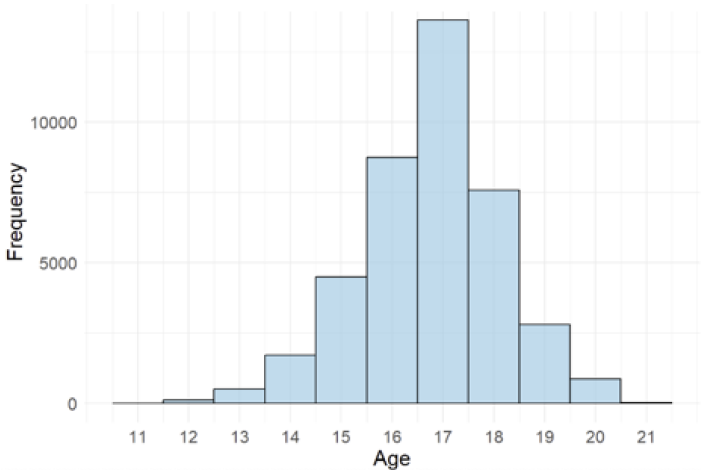


Figure 5: Age Distribution of Individuals in FUNASE (2008 - 2024)

FUNASE dataset includes sensitive information such as the names of the offenders, birthdates, names of their mothers, gender, types of crimes committed, the facility assigned,

and their educational status. It is worth noting that our sample utilizes FUNASE data from 2010 to 2016 as it aligns with other datasets, enabling a more comprehensive longitudinal analysis to track individuals and assess the effect over time. At last, this sample provides a rich source for understanding the pathways of youth who become involved in the juvenile justice system.

5.2 Mortality Data

I also use mortality data from the *Sistema de Informações sobre Mortalidade* (SIM) under the Ministry of Health. This data contains detailed records including names, mothers' names, birthdates, socio-economic characteristics, and causes of death, which are essential for identifying homicide cases. The data available for our analysis covers the years 2008 to 2016, allowing us to cross-reference with educational and socio-educational data to investigate the impact of violence on youth outcomes.

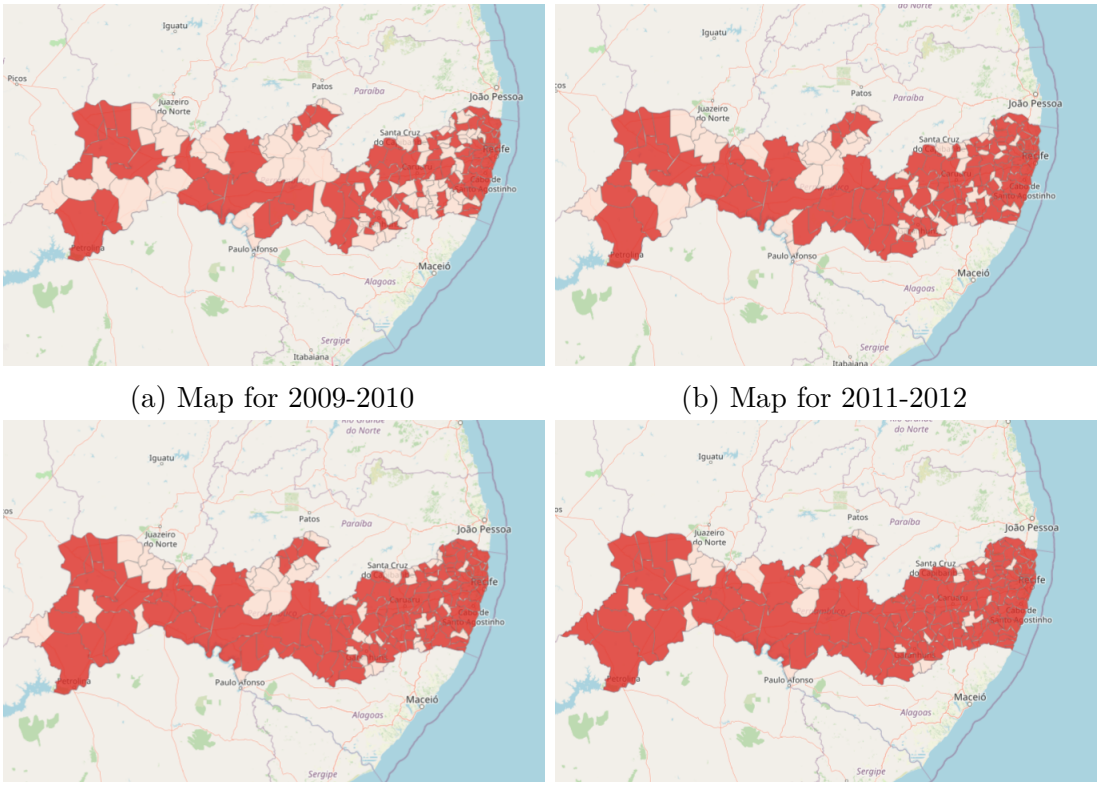
Table 1 presents a summary of death types recorded in the complete database, highlighting different causes of mortality. The data show that homicides account for the vast majority of cases, with 4,389 recorded incidents, underscoring the prevalence of violent crime. In contrast, deaths caused by police intervention are extremely rare. Traffic accidents represent another significant category, with 137 deaths, while suicides account for 102 cases, reflecting broader social and psychological factors. Additionally, the dataset includes 238 intentional homicides classified as undetermined, suggesting challenges in accurately identifying the circumstances of these deaths.

Table 1: Summary of Death Types in the Complete Database

Type (Complete Database)	Count
Number of Homicides	4,389
Deaths Caused by Police Interventions	1
Deaths Caused by Traffic Accidents	137
Number of Suicides	102
Intentional Homicides Not Determined	238

Since homicide accounts for approximately 90% of all recorded deaths in the dataset during the analyzed period, this underscores the severity of violence as a critical public safety issue. Given its predominance, I focus on this crime outcome by merging the schoolmate's homicide data with the FUNASE and educational databases to analyze its impact on youth criminal behavior.

By the way, Figure 6 illustrates the geographic distribution of homicides in Pernambuco, Brazil. By highlighting the prevalence of violence across the Pernambuco municipalities, this map provides essential context for understanding the widespread and localized impacts of violent shocks.



(a) Map for 2009-2010

(b) Map for 2011-2012

(c) Map for 2013-2014

(d) Map for 2015-2016-2017

Figure 6: Homicide Data Across Different Year Intervals in Pernambuco Municipalities, Brazil

Figure 7 illustrates the distribution of homicide victims by age at the time of death. The data indicate that homicide rates remain relatively low for individuals under 14 years old, but increase sharply from age 15 onward. The highest concentration of homicides occurs between ages 17 and 19, making these age groups the most affected. After age 19, the number of homicides declines significantly.

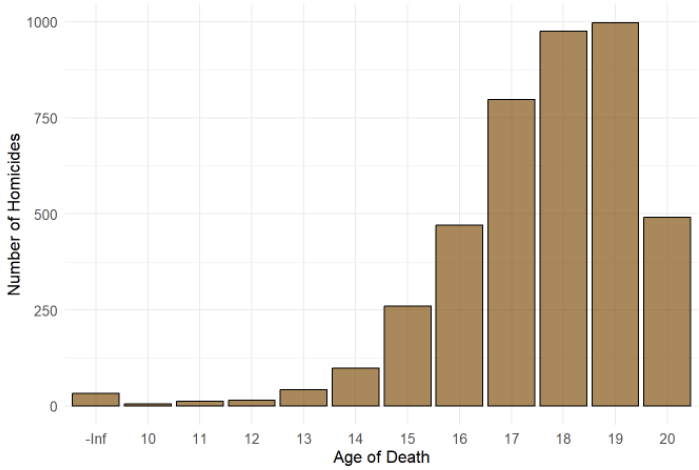


Figure 7: Number of Homicides by Age at Death

This pattern closely mirrors the age distribution of individuals in FUNASE (5), suggesting that late adolescence represents the period of highest vulnerability to lethal

violence. These findings underscore the urgent need for targeted interventions aimed at reducing youth violence and implementing effective crime prevention strategies.

5.3 Educational Enrollment Data

Finally, our educational data is sourced from the *Secretaria de Educação de Pernambuco*, encompassing all school enrollments (both public and private) from 2008 to 2016. This dataset includes identified records with student names, mothers' names, birthdates, socio-economic status, and academic details such as grades, classes, and school information. The comprehensive nature of this data allows us to track students longitudinally and assess their exposure to violence and subsequent engagement with the juvenile justice system. Additionally, the data is crucial for implementing our differences-in-differences identification strategy, as it provides the necessary structure to compare treated and non-treated students before and after exposure to homicides.

5.4 Descriptive Statistics

To define treatment, I consider homicides among male students enrolled in school, including K-12 grades and Youth and Adult Education, between 2009 and 2017, which serve as exogenous shock in the analysis. The sample consists of 26,855 male students born from 1997 to 2003, who are tracked from 2009 to 2021. The choice of this birth cohort is motivated by two critical considerations. First, students born between 1997 and 2003 are all within the eligible age range (12 to 18 years old) to enter the juvenile system (FUNASE) throughout the entire observation window. This ensures consistent eligibility for detention across cohorts, which is critical to identifying treatment effects over comparable exposure periods. Second, limiting the sample to these cohorts allows for a balanced panel structure: all individuals can be followed over the same span of years, avoiding uneven right- or left-censoring that would otherwise result from including younger or older students. As a result, the analytical design maximizes the comparability between treated and control units while aligning with the institutional age requirements for entry into the juvenile justice system.

Table 2 presents summary statistics for the treated and never treated groups at baseline (2009), highlighting key characteristics of the school and the student. In general, most variables appear balanced between the groups. However, notable differences emerge in school characteristics, particularly regarding socioeconomic status (SES) distribution. The treated group has a significantly lower proportion of high SES schools and a higher share of medium SES schools, suggesting that students exposed to the shock tend to come from more socioeconomically disadvantaged backgrounds. In contrast, student characteristics, such as age, race, and urban residency, are generally similar between the two groups.

6 Identification Strategy and Results

6.1 Empirical Framework and Specification

Our identification strategy builds on the staggered Difference-in-Differences (DiD) approach proposed by Callaway and Sant'Anna (2021). This method implies that our estimates are not significantly influenced by the biases inherent in difference-in-differences strategies when time-varying effects. It addresses the potential bias arising from treatment

Table 2: Summary Statistics by Treatment Group (At Baseline - 2009)

			Treated	
Variable	Never-treated	Treated	Not FUNASE	FUNASE
Municipality Characteristics				
GDP per Capita (thousands)	14.8	15.3	15.2	16.5
Population (thousands)	340.1	438.8	428.7	756.0
School Characteristics				
SAEB Score (2009)	4.2	4.2	4.2	4.2
Urban (%)	79.7	86.2	86.0	93.5
High SES	3.5	0.6	0.7	0.0
Low SES	23.7	23.6	27.7	18.7
Medium SES	30.4	48.4	55.6	74.2
Missing SES	41.7	27.3	16.0	7.1
Federal	0.1	0.0	0.0	0.0
Municipal	40.8	55.3	64.3	60.0
Private	11.1	3.9	4.6	3.2
Student Characteristics				
State	23.0	27.0	31.1	36.8
Average Age	12.1	12.1	12.1	12.0
Number of Students	739,512	26,855	25,837	1,018
Brown	18.1	24.5	28.2	34.2
Black	1.4	2.2	2.6	3.9
Indigenous	0.2	0.2	0.2	0.0
White	7.9	7.9	9.0	14.2
Other	72.4	65.3	60.1	47.7

effects that vary over time and appropriately handle comparisons between early and late treatment groups (De Chaisemartin and d'Haultfoeuille (2020); Goodman-Bacon (2021)).

I specifically adopt the "not yet treated" group specification, which includes individuals who have not received the treatment at a given point in time but will eventually be exposed. This approach allows for a more flexible and temporally consistent comparison across periods, improving the reliability of causal inference.

In our case, the control group consists of students in classrooms that have not yet experienced a classmate's homicide during a given period, even though they will eventually be exposed to such an event. By comparing these students to those who have already been affected by the homicide shock, this method enables us to estimate the causal impact of exposure to a classmate's murder on youth engagement in crime while accounting for the staggered timing of treatment across cohorts.

In other words, the treatment in question is the occurrence of a classmate's homicide, with each cohort experiencing this shock at different points in time. Initially, all students are part of the control group. Once exposed to the shock, they transition to the treated group and remain treated for the rest of the analysis period. For instance, consider two students, João and Matheus, who both experienced the loss of a schoolmate but in different years: João in 2014 and Matheus in 2016.

Mathematically, our approach estimates the Average Treatment Effect on the Treated

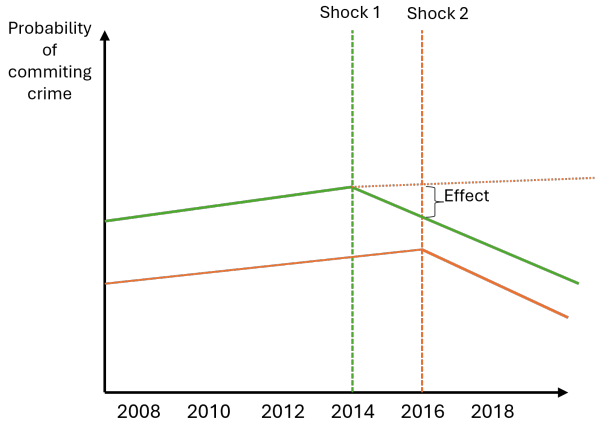


Figure 8: Illustration: Research Design

(ATT) using the following formulation:

$$\begin{aligned} ATT(g,t) = &\mathbb{E}[Y_t - Y_{g-1} \mid G = g] \\ &- \mathbb{E}[Y_t - Y_{g-1} \mid D_t = 0, G = g], \end{aligned}$$

where g represents the cohort exposed to the treatment, t is the time period, Y_t denotes the outcome variable, and D_t indicates treatment status. To summarize the treatment effects over time, we aggregate all group-time average treatment parameters by years after the treatment shock. Then, we calculate:

$$\theta_D(e) = \sum_{g=2}^{T} \mathbf{1}_{\{g+e \leq T\}} ATT(g, g+e) P(G = g \mid G + e \leq T),$$

where $\theta_D(e)$ represents the weighted average of the ATT over cohorts and time.

Therefore, I use a dynamic difference-in-difference specification to assess pretreatment and posttreatment effects. In particular, I estimate the following model:

$$FUNASE_{it} = \sum_{\tau=-K}^{K} \beta_\tau \times (PeriodsAfterMurder = \tau) + \phi_i + \rho_t + \lambda \boldsymbol{X}_{it} + \epsilon_{it}, \qquad (14)$$

where $FUNASE_{it}$ is a dummy variable indicating juvenile detention in FUNASE for student i in period t; The indicator variable $PeriodsAfterMurder = \tau$ takes a value of 1 τ periods away from the classmate's murder timing for the student i and period t and 0 otherwise; ϕ_i is the student fixed effects; ρ_t is the time fixed effects; $\boldsymbol{X}_{it}$ is a vector for characteristics at the student-period level, and ϵ_{it} is the error term. Finally, the parameter β_t represents the dynamic treatment effect for each cohort of students affected in year t. Since the detention in FUNASE is represented by dummy variable, each coefficient β_t should be interpreted as a change in percentage points in the probability of youth detention relative to the base period.

In our model, I also control for the age difference between the murdered classmate and the affected students at the time of the incident, which is included as a covariate to capture the degree of proximity between them. A smaller age gap likely indicates that the students belonged to the same cohort, increasing the likelihood of social interaction. This proximity may significantly shape the effect of a schoolmate's murder on criminal behavior

and the probability of detention among peers. This approach is consistent with the peer effects literature, which emphasizes the strong influence of peers on both academic and behavioral outcomes, including involvement in criminal activity Jacob and Lefgren (2003); Duflo et al. (2011); Lavy et al. (2012).

In addition, I examine whether the impact of a classmate's murder on juvenile detention varies according to the spatial proximity between the incident and the school. Following Koppensteiner and Menezes (2021), who emphasize the importance of geographic closeness in shaping the effects of exposure to violence, I incorporate the Euclidean distance between the location of the homicide and the school as a measure to capture this dimension of proximity. Table 3 presents the quartile distributions for age difference, as well as for the distances from the murder location to both the school and the student's residence.

Table 3: Quartile Distribution of Age and Geographic Proximity to a Schoolmate's Homicide Shock

	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
Distance to Age Shock	[0-0)	[0-1)	[1-3)	[3-11)
Distance to Shock (km)	[0-0.6)	[0.6-1.3)	[1.3-5.9)	[5.9-207.8)

For age difference, half of the students experienced the shock within a 0 to 1-year gap from the victim, suggesting close peer relationships. The third quartile extends only up to 3 years, indicating that most students belonged to the same or adjacent academic cohorts. The upper quartile ranges from 3 to 11 years, capturing less proximate age groups. This overall proximity likely amplifies the social and psychological impact of the event. For geographic distance, 25% of students were within 0 to 0.6 kilometers of the homicide location, representing immediate exposure to the event. The second quartile shows that half of the students were located within 1.3 kilometers, while the third quartile extends this range further. The final quartile indicates that the remaining 25% were more than 5.9 kilometers away, suggesting significantly lower direct exposure.

7 Results

In this section, I present the results on the effect of exposure to classmate homicides on juvenile detention, using a novel panel dataset that links student records to the timing and location of peer homicides. I start by estimating the impact of exposure on overall juvenile detention. I also investigate heterogeneous effects by detention regime and crime type, and recidivism. Finally, I explore variation by student profile, including education track and age group, to assess which adolescents are most affected by peer violence.

7.1 Main Effects on Juvenile Detention

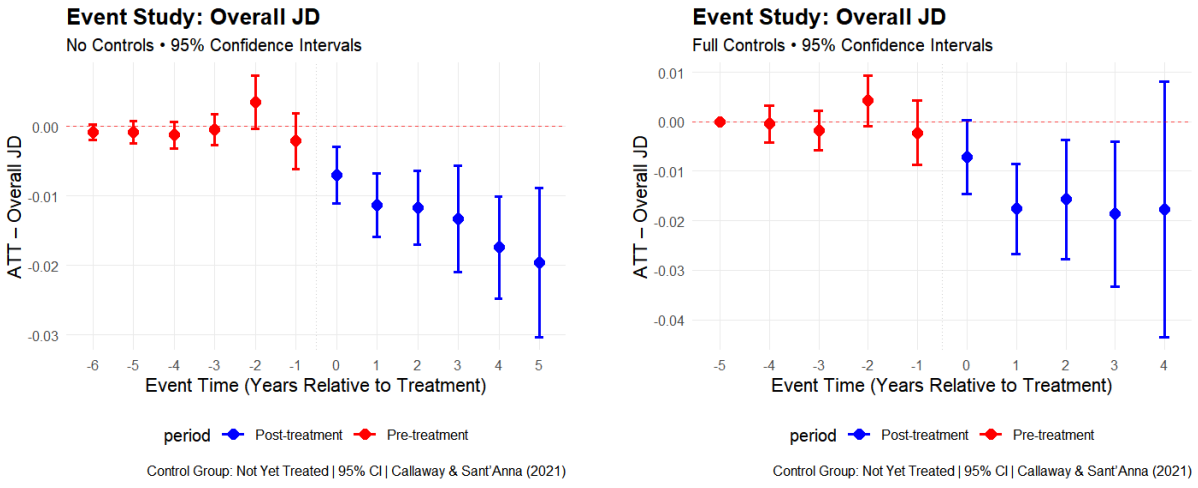
I begin by estimating the impact of exposure to a classmate's homicide on the likelihood of juvenile detention, which serves as a proxy for criminal behavior under Brazil's Child and Adolescent Statute, where youth are not formally charged with crimes. The treatment is defined at the classroom level: students are considered treated if they shared a class with the victim. The analysis includes all student homicides from 2009 to 2016, regardless of whether the homicide occurred during school enrollment or up to four years after the

student dropped out. Importantly, we treat the timing of homicide as exogenous. While some observable characteristics may influence the risk of victimization, the exact timing of a homicide is unpredictable from the perspective of classmates, allowing us to exploit this variation for identification.

Panel (a) of Table 4 reports the estimated effects of exposure to a classmate's homicide on the likelihood of appearing in juvenile detention records, using the full set of detention cases as the outcome. Column (1) presents the baseline model, which includes school and year fixed effects but no additional covariates. Columns (2) through (4) sequentially introduce controls for the age difference between the murdered student and their classmates, the distance between the homicide location and the school, and both controls combined.

Given that Brazilian classrooms are not strictly age-homogeneous, it is common for students of varying ages to share the same classroom. As peer networks are unobserved, we use age proximity as a proxy, under the assumption that students of similar ages are more likely to form closer social ties and thus be more affected by a classmate's death. Likewise, students are more likely to be aware of a peer's homicide if it occurs near the school, potentially influencing not only classmates but also other schoolmates.

The results are statistically significant across all specifications. In the most saturated model (column 4), having a classmate murdered reduces the likelihood of juvenile detention by 1.5 percentage points (a 39% reduction relative to the baseline mean). This likely represents a lower bound of the true effect, as students outside the affected classroom who are nonetheless influenced by the event are not included in the treatment group.



(a) No Controls (b) Age and Distance Controls

Figure 9: Effect of Classmate Homicide on Overall Juvenile Detention

Notes: This figure presents event study estimates for the effect of classmate homicide on overall juvenile detention using the Callaway and Sant'Anna (2021) difference-in-differences estimator. Panel (a) shows results without controls, while Panel (b) includes controls for age difference between student and victim (months) and distance between school and homicide location (km). Red dots represent pre-treatment periods, and blue dots represent post-treatment periods. Confidence bands are at the 95% level with standard errors clustered at the school level. The vertical dashed line indicates the treatment period. The dependent variable is a binary indicator for any juvenile detention record in the FUNASE system.

The Figure 9 illustrates the dynamic estimated effects by year of exposure of classmate homicide on overall juvenile detention. The event-study estimates exhibit pre-treatment

coefficients that are statistically indistinguishable from zero, supporting the validity of the parallel trends assumption. This indicates that, prior to the homicide, there were no systematic differences in juvenile detention trends between treated and not yet treated students. Post-treatment, the estimated effects become increasingly negative and statistically significant over time, suggesting a delayed but growing impact of the violent shock on student behavior. This temporal pattern reinforces the interpretation that the homicide event causally influences the reduction in juvenile detention likelihood.

7.2 Heterogeneity Analysis Results

7.2.1 Heterogeneity by Detention Regime, Crime Type and Recidivism

To further explore the mechanisms behind the observed effects, Table 4 also disaggregates the results by detention regime, type of crime, and recidivism behavior. Juvenile detention in Brazil includes two types of detention regimes: full-time and part-time. The sentence and the judge's decision depend on the severity of the infraction. More serious offenses, such as those that involve violence that endangers lives, such as homicide, drug trafficking, or armed robbery, typically result in full-time detention, in which the adolescent loses the right to leave the facility during the sentence period. Part-time detention is applied to less severe infractions. In this regime, youth are allowed to attend school, work, or other activities during the day, but must return to the detention unit at night. The decision between full and part-time detention also takes into account the severity of the act, the adolescent's history of recidivism, their age, and family circumstances. Panel (a) of Table 4 reveals that the reduction in juvenile detention is concentrated in full-time detention cases, with consistently negative and statistically significant coefficients across all specifications. The estimated average treatment effect ranges from -0.0096 to -0.0113 (without and with both controls, respectively), indicating a substantial decline in more severe forms of detention following exposure to a classmate's homicide. Part-time detention (Semi-detention), while also showing negative point estimates, exhibits less consistent significance, suggesting that students in more stringent custodial settings experience the largest reductions.

Figure 10 presents the event-study estimates for full-time juvenile detention. The results reveal a dynamic treatment effect: the probability of detention declines progressively following exposure to a classmate's homicide. While the initial effects are modest, the magnitude of the reduction increases steadily over time. This pattern suggests that the deterrent impact of the traumatic event is not immediate but becomes stronger as students gradually internalize the consequences of violence within their peer group. Crucially, the pre-treatment coefficients are statistically indistinguishable from zero, supporting the parallel trends assumption and validating the use of the event-study framework in this setting.

On the other hand, Figure 11 displays the event-study estimates for part-time juvenile detention, which typically refers to semi-liberty or non-custodial measures. Unlike the pattern observed for full-time detention, the estimated effects for part-time detention are smaller in magnitude and less consistently statistically significant. While there is some indication of a decline in the likelihood of part-time detention following a classmate's homicide, the estimates are more erratic and the confidence intervals are wider, suggesting greater uncertainty around these effects.

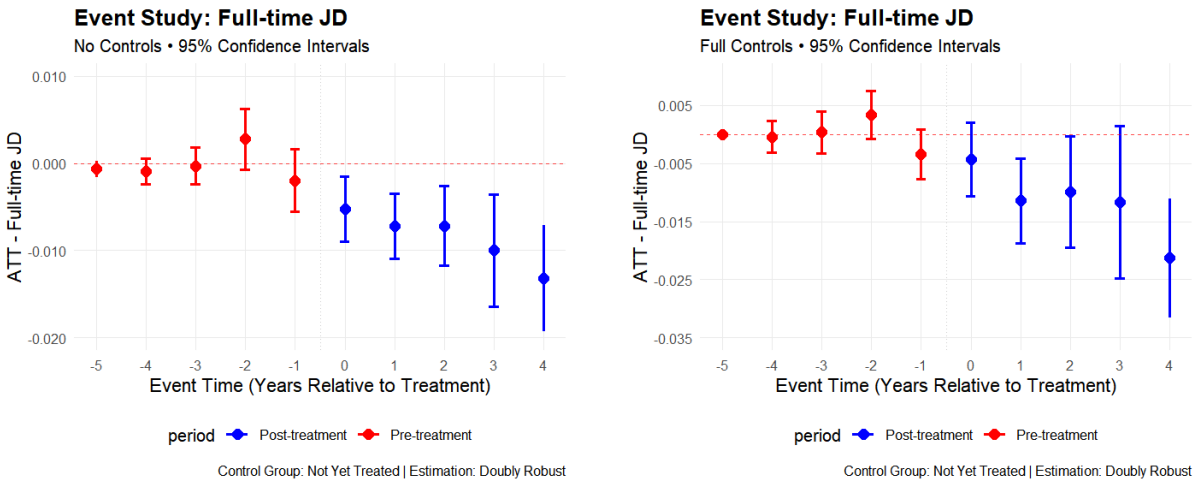
Moreover, Panel (b) of Table 4 examines heterogeneity in the estimated effects by type of offense, distinguishing between violent crimes, property crimes, and drug-related

Table 4: Dynamic ATT Estimates by Detention Regime, Crime Type and Recidivism

Dependent Variable: Juvenile Detention Records (FUNASE)				
	Specification			
	(1)	(2)	(3)	(4)
Panel (a): All Juvenile Detention				
Overall Detention	-0.0134***	-0.0223***	-0.0167***	-0.0148***
	(0.0017)	(0.0059)	(0.0020)	(0.0044)
Full-time Detention (Internação)	-0.0096***	-0.0164***	-0.0117***	-0.0113***
	(0.0012)	(0.0049)	(0.0015)	(0.0033)
Part-time Detention (Semiliberdade)	-0.0038***	-0.0060	-0.0050***	-0.0034
	(0.0011)	(0.0041)	(0.0014)	(0.0026)
Panel (b): Crime Type Analysis				
Violent Crimes				
ATT	-0.0020***	-0.0047**	-0.0023***	-0.0035**
	(0.0007)	(0.0018)	(0.0007)	(0.0015)
Property Crimes				
ATT	-0.0070***	-0.0093*	-0.0091***	-0.0019
	(0.0013)	(0.0050)	(0.0016)	(0.0030)
Drug Crimes				
ATT	-0.0035***	-0.0075***	-0.0044***	-0.0085***
	(0.0007)	(0.0025)	(0.0009)	(0.0029)
Panel (c): Recidivism Analysis				
Repeat Offenses				
ATT	-0.0028***	0.0002	-0.0040***	0.0007
	(0.0011)	(0.0020)	(0.0014)	(0.0021)
Controls and Specification				
Age controls (months)	No	Yes	No	Yes
Distance controls (km)	No	No	Yes	Yes
Observations	187,925	187,925	187,925	187,985
Number of Students	26,855	26,855	26,855	26,855
Number of Schools	4,096	4,096	4,096	4,096
Time Period	2009-2018	2009-2018	2009-2018	2009-2018

Notes: This table reports dynamic average treatment effects on the treated (ATT) from the Callaway and Sant'Anna (2021) difference-in-differences estimator. The treatment is exposure to a classmate's homicide. Panel (a) shows the effects on overall juvenile detention and by detention regime. Panel (b) shows effects by crime type. Panel (c) shows effects on recidivism, defined as having multiple detention episodes. Standard errors in parentheses, clustered at the school level. Age controls include the difference in age (months) between the student and the victim. Distance controls include distance (km) between the student's school and the homicide location. *** p<0.01, ** p<0.05, * p<0.1.

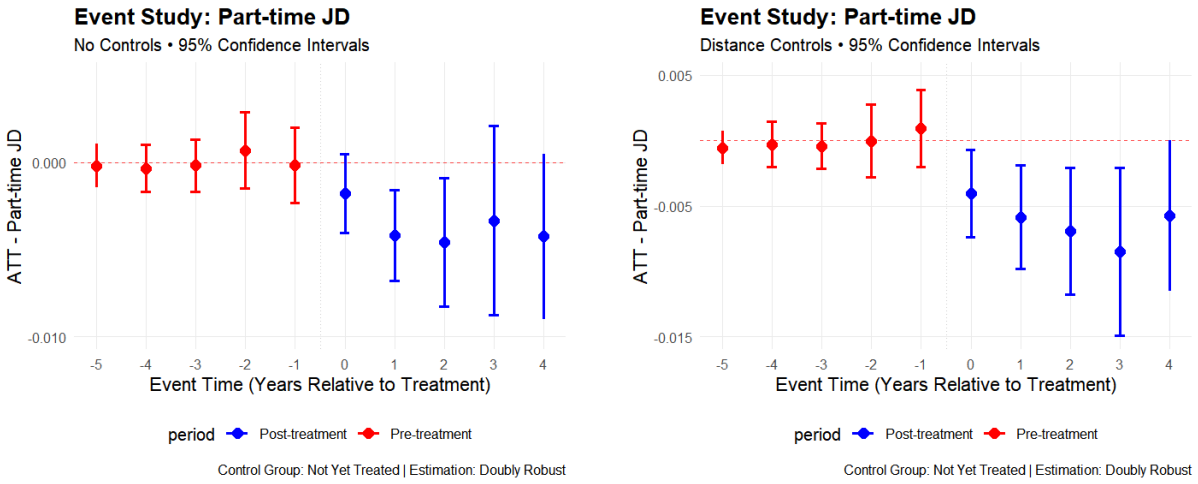
offenses. The results demonstrate that reductions are not uniform across offense categories. Drug-related crimes show the most robust and persistent declines, with ATT estimates



(a) No Controls (b) Age and Distance Controls

Figure 10: Effect of Classmate Homicide on Full-Time Juvenile Detention

Notes: This figure presents event study estimates for the effect of classmate homicide on full-time juvenile detention (*internação*) using the Callaway and Sant'Anna (2021) difference-in-differences estimator. Panel (a) shows results without controls, while Panel (b) includes controls for age difference between student and victim (months) and distance between school and homicide location (km). Red dots represent pre-treatment periods, blue dots represent post-treatment periods. Confidence bands are at the 95% level with standard errors clustered at the school level. The vertical dashed line indicates the treatment period.



(a) No Controls (b) Distance Controls

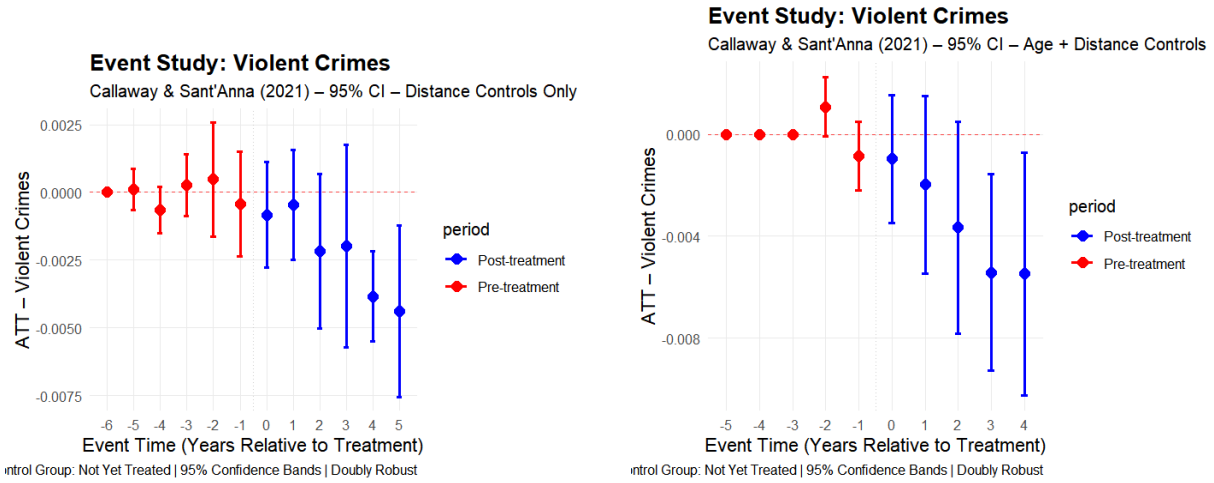
Figure 11: Effect of Classmate Homicide on Part-Time Juvenile Detention

Notes: This figure presents event study estimates for the effect of classmate homicide on part-time juvenile detention (*semiliberdade*) using the Callaway and Sant'Anna (2021) difference-in-differences estimator. Panel (a) shows results without controls, while Panel (b) includes controls for the distance between the school and the homicide location (km). Red dots represent pre-treatment periods, blue dots represent post-treatment periods. Confidence bands are at the 95% level with standard errors clustered at the school level. The vertical dashed line indicates the treatment period.

between -0.0035 and -0.0085, all statistically significant at the 1% level. This finding

is particularly noteworthy, as it suggests that peer violence may serve as a deterrent for behaviors associated with informal or high-risk markets. Violent crimes also decline significantly, with effects ranging from -0.0020 to -0.0047, while property crimes show initially strong reductions (-0.0070 to -0.0093), but effects become statistically weaker when full controls are included.

I also highlight Figure 12 and Figure 13, which display the event-study estimates for violent crimes and drug-related crimes, respectively. These figures serve to examine the temporal dynamics of the treatment effect and provide additional evidence on the consistency and robustness of the main results. The pattern for violent crimes displays a more gradual trajectory. The reduction in juvenile detention probability becomes statistically significant only in the later years following the exposure. This lagged effect may indicate that behavioral responses related to violent conduct, often rooted in deeper psychological or social dynamics, take longer to manifest. Over time, the sustained impact of the traumatic event may reshape students' attitudes, conflict resolution strategies, or engagement in confrontational behaviors, ultimately leading to a delayed but meaningful deterrent effect. By contrast, in the case of drug-related offenses, the estimates reveal a relatively immediate decline in the likelihood of juvenile detention following exposure to a classmate's homicide. The effect emerges soon after the event and remains statistically significant over time, suggesting that students may quickly internalize the shock and adjust their behavior accordingly, potentially by disengaging from risky peer networks or avoiding illicit activities that carry immediate consequences.



(a) No Controls (b) Age and Distance Controls

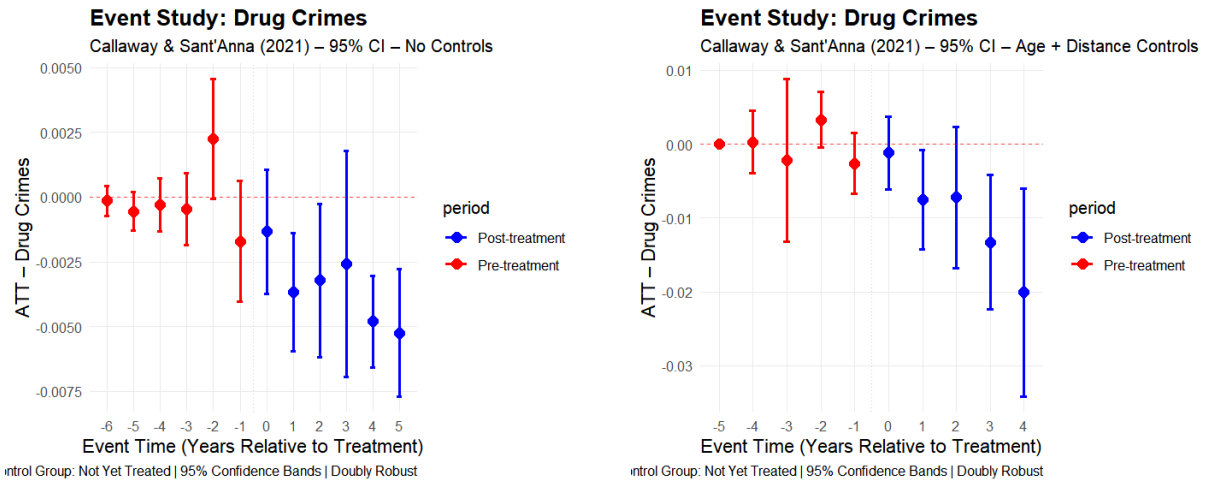
Figure 12: Effect of Classmate Homicide on Juvenile Detention for Violent Crimes

Notes: This figure presents event study estimates for the effect of classmate homicide on juvenile detention for violent crimes using the Callaway and Sant'Anna (2021) difference-in-differences estimator. Panel (a) shows results without controls, while Panel (b) includes controls for age difference between student and victim (months) and distance between school and homicide location (km). Red dots represent pre-treatment periods, and blue dots represent post-treatment periods. Confidence bands are at the 95% level with standard errors clustered at the school level. The vertical dashed line indicates the treatment period. The dependent variable is a binary indicator for any juvenile detention record in the FUNASE system.

Finally, Panel (c) of Table 4 examines the impact of exposure to a classmate's homicide on recidivism, defined as having multiple juvenile detention episodes. The results show a

statistically significant reduction in repeat offenses in two of the four specifications, with an estimated effect of -0.0028 in the baseline model. However, this effect loses statistical significance when both age and distance controls are included.

These findings suggest that the deterrent effect of the shock may be less pronounced for students with prior involvement in the juvenile justice system. This group may exhibit greater behavioral rigidity or be less responsive to peer-related traumatic events, indicating that prior institutionalization potentially dampens the impact of external shocks on future criminal behavior.



(a) No Controls (b) Age and Distance Controls

Figure 13: Effect of Classmate Homicide on Juvenile Detention for Drug Offenses

Notes: This figure presents event study estimates for the effect of classmate homicide on juvenile detention for drug offenses using the Callaway and Sant'Anna (2021) difference-in-differences estimator. Panel (a) shows results without controls, while Panel (b) includes controls for age difference between student and victim (months) and distance between school and homicide location (km). Red dots represent pre-treatment periods, and blue dots represent post-treatment periods. Confidence bands are at the 95% level with standard errors clustered at the school level. The vertical dashed line indicates the treatment period. The dependent variable is a binary indicator for any juvenile detention record in the FUNASE system.

In summary, the heterogeneity results reinforce the conclusion that the behavioral response to peer violence is not only statistically significant but also varies meaningfully by the nature of the outcome. The most consistent and sizable reductions are found among severe detention cases and drug-related offenses, implying a selective deterrent effect triggered by exposure to lethal peer violence.

7.2.2 Grade-Level and Age-Based Heterogeneity

I also explore whether the impact of exposure to a classmate's homicide varies by students' educational stage or age, Table 5 presents heterogeneity analyses based on three sample definitions: students in 6th–8th grade (Panel (a)), students enrolled in EJA (youth and adult education programs) (Panel (b)), and students aged 14–18 at the time of the incident (Panel (c)). These distinct groupings allow us to capture meaningful differences in students' developmental stage, institutional context, and degree of exposure to peer networks.

Table 5: Dynamic ATT Estimates by Grade Level – 6th-8th Grade vs EJA vs Age 14-18 Restriction

Dependent Variable: Juvenile Detention Records (FUNASE)				
	Specification			
	(1) Baseline	(2) Age Ctrl	(3) Dist Ctrl	(4) Full Ctrl
Panel (a): 6th-8th Grade Students				
Overall Detention	-0.0132***	-0.0050	-0.0224***	-0.0059
	(0.0020)	(0.0046)	(0.0030)	(0.0051)
Panel (b): EJA Students				
Overall Detention	-0.0150***	-0.0479***	-0.0213***	-0.0456***
	(0.0042)	(0.0097)	(0.0049)	(0.0088)
Panel (c): Age 14-18 Restriction				
Overall Detention	-0.0097***	-0.0081**	-0.0133***	-0.0086**
	(0.0016)	(0.0040)	(0.0023)	(0.0038)
Panel D: Sample Characteristics				
6th-8th Grade				
Total Observations	107,737	107,737	107,737	107,737
Mean Age at Treatment	14.4	14.4	14.4	14.4
EJA Students				
Total Observations	107,737	107,737	107,737	107,737
Mean Age at Treatment	16.3	16.3	16.3	16.3
Age 14-18 Restriction				
Total Observations	150,941	150,941	150,941	150,941
Mean Age at Treatment	16.3	16.3	16.3	16.3
Controls and Specification				
Age controls (months)	No	Yes	No	Yes
Distance controls (km)	No	No	Yes	Yes
Number of Schools	4,096	4,096	4,096	4,096
Time Period	2009-2018	2009-2018	2009-2018	2009-2018

Notes: This table reports dynamic average treatment effects on the treated (ATT) from the Callaway and Sant'Anna (2021) difference-in-differences estimator. The treatment is exposure to a classmate's homicide. Panel (a) shows effects for students in 6th-8th grade at the time of treatment. Panel (b) shows effects for students in EJA (Adult Education) programs at the time of treatment. Panel (c) restricts the sample to students aged 14-18 at the time of treatment, excluding 5,292 students aged 12-13. Panel D presents sample characteristics by restriction type. Age controls include the difference in age (months) between the student and the victim. Distance controls include distance (km) between the student's school and the homicide location. Standard errors in parentheses, clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1.

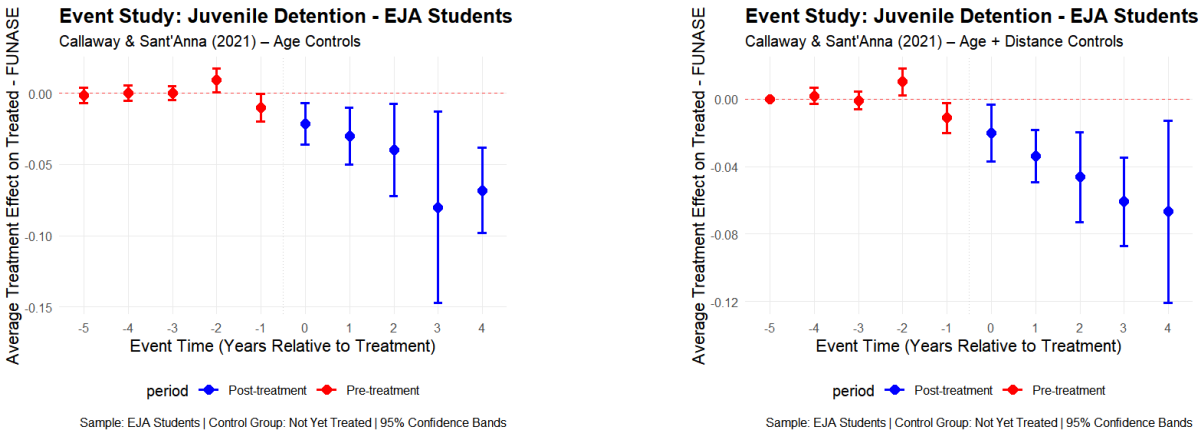
The results suggest heterogeneous treatment effects across groups. Among 6th–8th grade students, I find a significant reduction in juvenile detention only in the specification

that includes distance controls (column 3), with an estimated effect of –0.0224. In the other specifications, the estimates are smaller in magnitude and statistically insignificant, suggesting that younger students may be less sensitive to peer violence, or that institutional responses and peer dynamics differ in earlier school grades.

In contrast, EJA students consistently exhibit large and statistically significant reductions in juvenile detention across all specifications. The effects range from –0.0150 to –0.0479, indicating a stronger behavioral response in this group. This result could reflect the greater autonomy and maturity of older students enrolled in alternative education settings, who may experience peer homicides more viscerally or interpret them as salient warnings. Additionally, older students may already be at higher risk of contact with the justice system, making the deterrent effect of the shock more visible in the outcome.

Panel (c) restricts the sample to students aged 14–18, excluding those aged 12–13 to ensure comparability in peer age and risk profiles. The results are statistically significant in all but one specification, with treatment effects ranging from –0.0081 to –0.0133. These magnitudes fall between those of the 6th–8th grade and EJA groups, reinforcing the notion that treatment effects intensify with age and educational stage.

Figures 14 and 15 illustrate the dynamic patterns of these effects for two of the subsamples. In particular, the event-study plots confirm that the strongest and most immediate effects are observed among EJA students, while reductions among 14–18-year-olds appear more gradual. Both figures show that pre-treatment coefficients are flat and close to zero, supporting the parallel trends assumption.



(a) Age Control

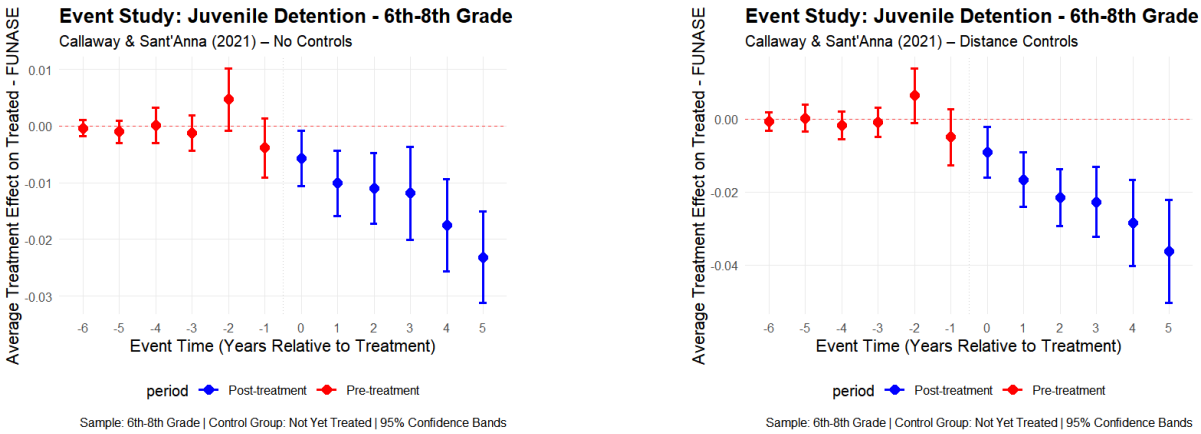
(b) Age and Distance Controls

Figure 14: Effect of Classmate Homicide on Juvenile Detention for 6th-8th Grade Students

Notes: This figure presents event study estimates for the effect of classmate homicide on juvenile detention for 6th-8th grade students using the Callaway and Sant'Anna (2021) difference-in-differences estimator. Panel (a) shows results controlled by age difference, while Panel (b) includes controls for age difference between student and victim (months) and distance between school and homicide location (km). Red dots represent pre-treatment periods, and blue dots represent post-treatment periods. Confidence bands are at the 95% level with standard errors clustered at the school level. The vertical dashed line indicates the treatment period. The dependent variable is a binary indicator for any juvenile detention record in the FUNASE system.

Together, these results highlight important differences in how students of different educational levels and age groups respond to the trauma of peer violence. They suggest that older or more autonomous students may be more responsive to the shock, possibly

due to a greater awareness of the consequences of violence or a more direct connection to at-risk environments.



(a) Without Controls

(b) Distance Control

Figure 15: Effect of Classmate Homicide on Juvenile Detention for Students Aged 14-18

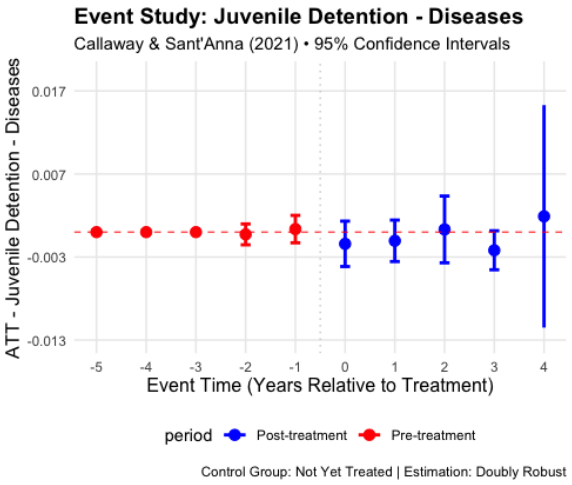
Notes: This figure presents event study estimates for the effect of classmate homicide on juvenile detention for students aged 14-18 at the time of the incident, using the Callaway and Sant'Anna (2021) difference-in-differences estimator. Panel (a) shows results controlled by age difference, while Panel (b) includes controls for age difference between student and victim (months) and distance between school and homicide location (km). Red dots represent pre-treatment periods, and blue dots represent post-treatment periods. Confidence bands are at the 95% level with standard errors clustered at the school level. The vertical dashed line indicates the treatment period. The dependent variable is a binary indicator for any juvenile detention record in the FUNASE system.

7.3 Robustness Checks

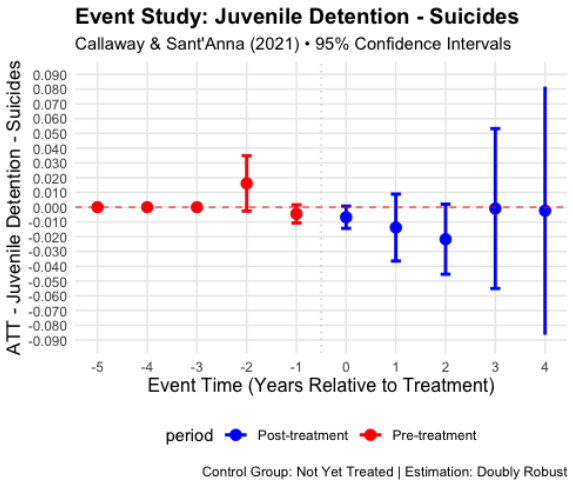
I extend the validity and specificity of the main findings, this section presents a series of robustness checks using alternative placebo treatments. Table 6 reports the overall ATT estimates when the treatment is redefined as exposure to a classmate's death from non-homicide causes—specifically, diseases, suicides, traffic accidents, and undetermined causes. I also estimate effects for female students separately, given that they are not typically the primary targets of juvenile justice involvement.

The results are consistent and reassuring. In all placebo scenarios—diseases, suicides, and traffic accidents—the estimated effects on the likelihood of juvenile detention are small and statistically insignificant. This suggests that the estimated reductions in detention observed in the main analysis are not merely driven by the general trauma of a classmate's death but are specific to homicides, which are likely more shocking and disruptive within peer groups.

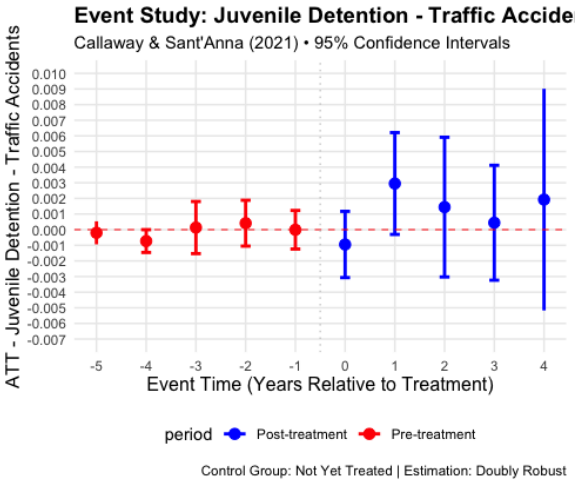
Figure 16 provides further evidence by plotting the dynamic event-study estimates for these alternative shocks. The pre-treatment coefficients are flat, and no meaningful post-treatment effects are detected in any of the placebo scenarios. These findings reinforce the interpretation that the main effects are driven by exposure to violent peer victimization rather than by general mortality.



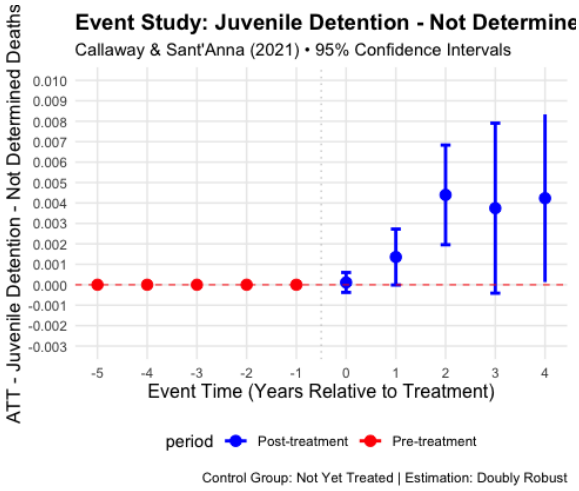
(a) Diseases



(b) Suicides



(c) Traffic accidents



(d) Not determined deaths

Figure 16: Robustness Check: Effect of Classmate Homicide on Juvenile Detention - Estimates by Alternative Deaths Shock

Notes: This figure presents event study estimates for the effect of classmate homicide on juvenile detention from alternative death shocks using the Callaway and Sant'Anna (2021) difference-in-differences estimator. Panel (a) shows results for diseases, Panel (b) for suicides, Panel(c) for traffic accidents, while Panel (D) for not determined deaths.

The only exception comes from the specification using undetermined causes of death, which yields a small but statistically significant positive effect. However, this category may include homicides that were misclassified or lacked sufficient detail for accurate classification, which could explain the deviation.

In addition, Figure 17 presents the event-study results for female students. As expected, I find no significant effects, aligning with the fact that girls are less frequently involved in juvenile detention and are less likely to be directly affected by peer violence in this context.

In summary, these robustness checks strengthen the credibility of our main findings. They confirm that the observed reduction in juvenile detention is not related to broader mortality-related disruptions, nor is it driven by shocks to populations unlikely to be directly involved in youth offending. The results are specific, consistent, and robust to

Table 6: Robustness Check: Overall ATT Estimates by Alternative Shocks – Aftermath of Classmate Homicide

	Diseases	**Suicides**	**Traffic Accidents**	**Women**	**Not Determined**
Overall ATT	0.0024	-0.0091	0.0023	0.0011	0.0028**
	(0.0045)	(0.0122)	(0.0019)	(0.0005)	(0.0006)
Observations	27,251	3,213	50,225	23,422	3766
Students	3,893	459	7175	3,346	538
Schools	444	48	679	371	332
Years	2010–2016	2010–2015	2010–2016	2010–2015	2010–2015
Time FE	Yes	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes	Yes

Notes: Each column presents the overall ATT estimate from robustness checks using alternative types of student deaths as placebo treatments: diseases, suicides, traffic accidents, women (as victims), and undetermined causes. Estimates are based on Callaway Sant'Anna (2021). Standard errors (SEs) are shown in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1.

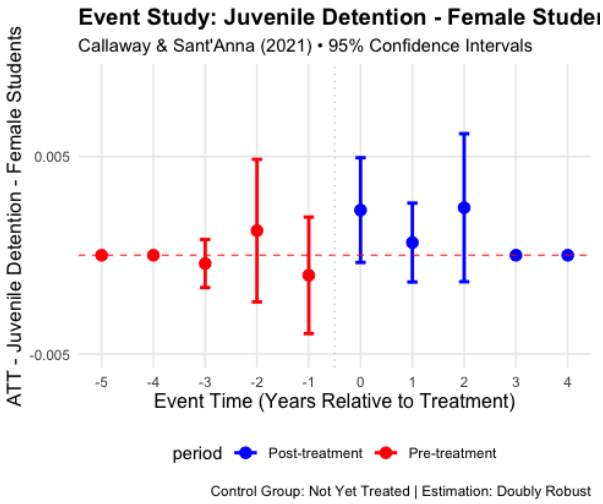


Figure 17: Effect of Classmate Homicide on Female Juvenile Detention

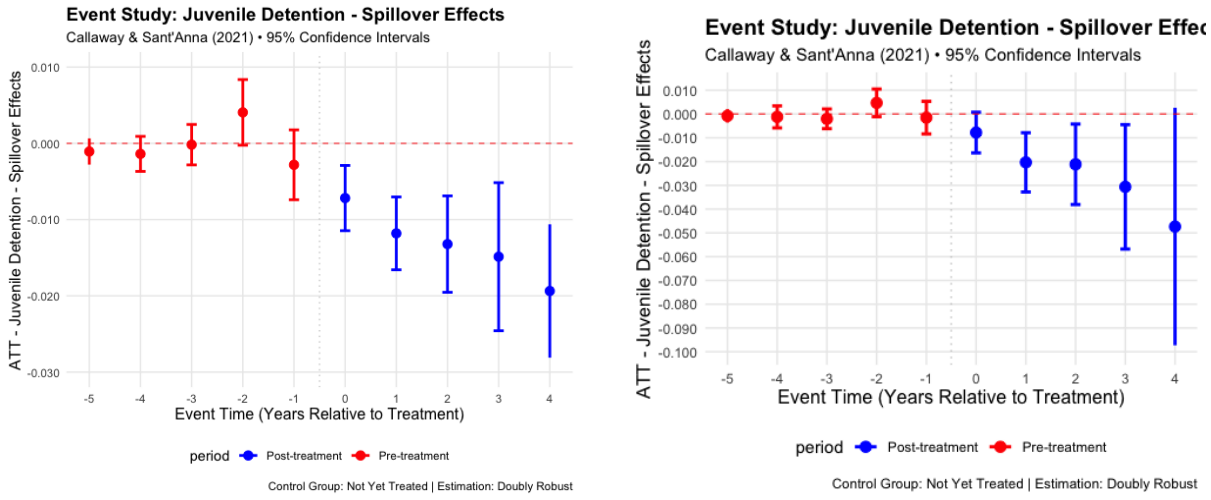
Notes: This figure presents event study estimates for the effect of classmate homicide on female juvenile detention using the Callaway and Sant'Anna (2021) difference-in-differences estimator, with 95% confidence intervals with standard errors clustered at the school level. The vertical dashed line indicates the treatment period.

alternative definitions of peer loss.

7.3.1 Accounting Spillover Effects

Furthermore, I examine the possibility of spatial spillover effects across nearby schools. When schools are located in close proximity, students may be indirectly exposed to similar traumatic events, such as the homicide of a peer in a neighboring institution. If such spillovers are not properly accounted for, they may bias the estimated treatment effects. To address this concern, this subsection presents two complementary exercises designed to assess the extent to which spatial proximity to violence may influence the main results.

Figure 18 presents event-study estimates for male students in schools potentially affected by spillovers from nearby schools. In this specification, I anticipate the murdered shock. I redefine treatment to incorporate earlier homicide events occurring in other schools located within a 500-meter radius. Specifically, if school A experiences a homicide in 2013 but is located within 500 meters of school B, which had a homicide in 2010, then School A is assigned the 2010 treatment year. This approach captures potential anticipatory effects whereby students might be indirectly exposed to trauma through spatial proximity, even if their own school has not yet been directly affected. When multiple nearby schools experience homicides, we assign the earliest year of exposure to account for the first relevant shock.



(a) No Controls (b) Age Control

Figure 18: Effect of Classmate Homicide on Juvenile Detention Considering Potential Spillover Effects

Notes: Event-study estimates for male students addressing potential spillover effects among treated schools, evaluating the impact of a classmate's homicide on juvenile detention. Panel (a) includes only age control; Panel (b) does not include any control. Estimates follow Callaway and Sant'Anna (2021), with 95% confidence intervals with standard errors clustered at the school level. The vertical dashed line indicates the treatment period.

Panel (a) presents estimates without additional controls, while Panel (b) includes controls for the age difference between the victim and the students. Across both specifications, the estimated treatment effects remain robust, suggesting that accounting for potential spillovers from nearby schools does not materially alter the main findings. If any spillover effects are present under these conditions, they appear to have no influence on the timing or magnitude of the estimated impacts. The estimated effects remains statistically significant over time.

To further test for spatial contamination, Figure 19 implements an alternative robustness check by redefining never-treated schools as treated if they are located within 500 meters of a treated school. In this setting, we assign the year of treatment based on the first homicide that occurred in the nearby treated school. This exercise evaluates whether untreated schools situated near treated ones might display similar post-treatment dynamics due to indirect exposure. I find consistent no significant effects on juvenile

detention under this approach, indicating that proximity alone, absent a direct classmate homicide, does not drive changes in juvenile detention outcomes.

Then, these exercises reinforce the credibility of our identification strategy. The results show that the observed treatment effects are not simply the result of geographic proximity to violence, but are instead specifically linked to direct exposure through a classmate's death. This further supports the internal validity of our main findings.

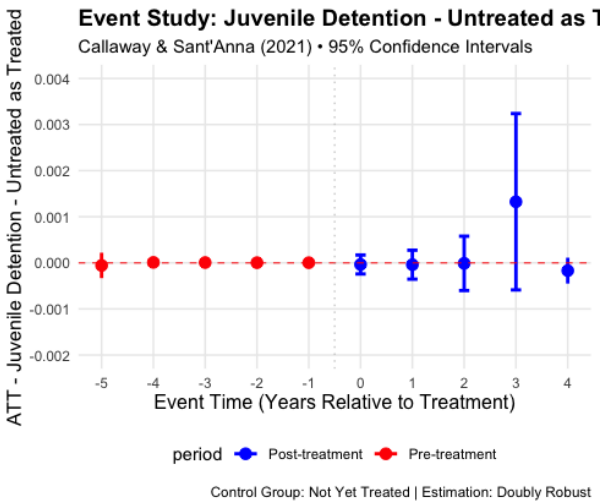


Figure 19: Effect of Schoolmate Homicide on Juvenile Detention Considering Never-Treated Schools as Treated

Notes: Event-study estimates for male students attending schools located within 500 meters of another school that had a student who was murdered. Panel (c) does not include any control. Estimates follow Callaway and Sant'Anna (2021), with 95% confidence intervals with standard errors clustered at the school level. The vertical dashed line indicates the treatment period.

8 Conclusion

This paper provides novel empirical evidence on the behavioral responses of adolescents to exposure to peer violence by estimating the causal effect of a classmate's homicide on subsequent juvenile detention. Leveraging rich administrative data from Pernambuco, Brazil, and applying the Callaway and Sant'Anna (2021) difference-in-differences framework, I document significant and robust reductions in juvenile detention following the murder of a classmate.

Our findings contribute to the literature on peer effects, the consequences of violence, and the determinants of youth crime by offering causal estimates of how traumatic peer events shape delinquent behavior. In particular, I find that exposure to a classmate's homicide leads to a substantial decline in juvenile detention, with a baseline reduction of 1.48 percentage points—equivalent to a 39% decrease relative to the pre-treatment mean. The effects are especially pronounced for drug-related crimes (81.7% reduction), violent crimes (45.5%), and full-time detention (43.3%), indicating that the shock has broad and enduring impacts on youth engagement in serious offenses. We also detect meaningful declines in recidivism, suggesting that the experience may alter long-run behavior for at-risk students.

Our results are robust to a range of potential threats to identification. I find no evidence of differential pre-trends or confounding shocks, and the estimates are not driven by spillover effects across proximate schools. A comprehensive battery of robustness checks, as well as heterogeneity analyses by age, grade level, and crime type, reinforces the consistency and credibility of our findings.

The findings carry important policy implications. First, they reveal that peer victimization, though homicide event, can act as a deterrent to criminal behavior, perhaps by making the risks of violence more salient to youth. Second, the asymmetric effects across types of offenses and detention regimes highlight the role of context in shaping behavioral responses. Third, the observed reductions suggest that timely psychosocial interventions in the aftermath of violence may reinforce these deterrent effects and help redirect at-risk youth away from criminal pathways.

More broadly, this study underscores the importance of understanding how local shocks propagate through peer networks and shape future outcomes. As policymakers and educators seek to mitigate the long-term consequences of violence on youth development, these findings emphasize the need for targeted strategies that both prevent violence and support students exposed to it.

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