Gil do Vigor
Ph.D. in Economics, University of California, Davis

Email: gjjunior@ucdavis.edu
Web: gildovigor.com

[September 15th, 2026]

Dear Professors Breza, Viviano, and Chandrasekhar,

I am writing to apply to the *Workshop on Development Economics and Networks for Early-Career Researchers*, to be held at the NBER in Cambridge on December 5, 2026. I recently completed my Ph.D. in Economics at the University of California, Davis, and my work lies at the intersection of development economics and the study of peer environments and social networks. The workshop's focus on the empirical frontier of network research speaks directly to the questions I am pursuing, and the chance to exchange ideas with both early-stage and established researchers would be extraordinarily valuable as I develop this agenda into a broader research program.

For the workshop I propose to present my paper, *The Aftermath of My Friend's Murder: Analyzing the Impact of Classmate Homicide on Juvenile Detention*. The paper asks how a violent shock experienced through one's peer environment—the homicide of a classmate—reshapes the choices of adolescents in Brazil. It finds that such exposure sharply reduces a young person's subsequent involvement in the juvenile justice system. Because the shock travels through the ties that connect students to one another, the paper bears directly on the workshop's central concern—how the networks linking people mediate development outcomes—and I would especially welcome feedback on the identification and inference challenges that peer exposure raises.

Enclosed with this letter are my curriculum vitae (including a complete list of current and completed Ph.D. courses), a one-page statement of motivation and research interests, and the paper I would present. Should my application be shortlisted, Professor Chris Blattman (University of Chicago; blattman@gmail.com) has kindly agreed to serve as a reference. Professor Blattman advised me during my time as a visiting scholar at the University of Chicago, and we currently collaborate on several projects on crime and development; he can therefore speak in detail to both my research and my potential.

Thank you very much for considering my application. It would be an honor to take part in the workshop.

Sincerely,

Gil do Vigor

Statement of Motivation and Research Interests

Gil do Vigor • Ph.D. in Economics, University of California, Davis

I became an economist to understand the forces that shaped the place I come from. I grew up in Pernambuco, in the northeast of Brazil, where the questions I now study were not abstractions but the texture of daily life: violence that reached into schools and homes, families for whom education was the only ladder out of poverty, and work that too often crossed into coercion. That experience left me convinced that the outcomes we care about in developing economies are seldom produced by individuals in isolation—they are transmitted through the people and institutions around us. My research puts that conviction to the test. I build large linked administrative datasets, mostly from Brazil, and use quasi-experimental methods to recover causal effects and the spillovers they set off across peers and communities. Two forms of disadvantage anchor my agenda: youth contact with the criminal justice system and coercive labor.

The first strand of my work studies crime and education, where peer environments are decisive. In one project, I show that exposure to the homicide of a classmate sharply reduces an adolescent's subsequent involvement in the juvenile justice system—evidence that a violent shock transmitted through the school peer network reshapes youth behavior. In ongoing work, I ask how the way schools and the justice system respond to a student's first recorded infraction—in particular, whether the police are called—alters the later trajectory of both the involved student and the classmates exposed to the incident, tracing effects on dropout, attendance, and eventual detention. Both projects link school-enrollment, school-incident, and juvenile-detention records for the state of Pernambuco, and both turn on measuring how a localized shock diffuses across peers.

A second strand turns to the institutional and technological determinants of modern slavery. In coauthored work, I exploit the staggered creation of indigenous lands and conservation units across hundreds of municipalities in the Legal Amazon to estimate how securing property rights affects the incidence of forced labor. A related project examines how technological change reshapes the returns to coercion, and thus the prevalence of modern slavery. Together, these projects ask when and where the institutions that govern land and labor manage to curb the most extreme forms of exploitation in a developing economy.

I am applying because the empirical heart of my agenda—identifying effects that travel through peer and community networks—raises exactly the challenges this workshop foregrounds: interference, spillovers, and inference when the relevant network is only partially observed. I would gain enormously from the lectures and from discussing my identification strategies with peers working on similar problems elsewhere, and I hope to bring a perspective grounded in large-scale Brazilian administrative data and in questions of first-order importance for the region I come from. My aim is to build a research program that pairs credible causal inference with an explicit account of the networks and institutions through which development outcomes are produced—and this workshop is an ideal place to sharpen it.

Gilberto Nogueira

Ph.D. in Economics

University of California, Davis

gildovigor@uchicago.edu | +1 (530) 309 8393

Education

2019–2026	**Ph.D. in Economics**, University of California, Davis.
2024–2026	**Visiting Ph.D. Student**, University of Chicago, Harris School of Public Policy.
2017–2019	**M.A. in Economics**, Universidade Federal de Pernambuco, Brazil. GPA: 4.0/4.0.

Research Interests

Primary	Economics of Crime, Development Economics, Education Economics.
Methods	Applied Microeconomics, Causal Inference, Experimental and Quasi-experimental Methods.
Regional Focus	Latin America, Brazil.

Job Market Paper

The Aftermath of My Friend's Murder: Analyzing the Impact of Classmate Homicide on Crime Engagement.

Working Papers

Property Rights and Modern Slavery: Evidence from Protected Areas in the Brazilian Amazon, with Daniel Araújo and Yuri Barreto.

From Violence to Value: How Security Reforms Shape Human Capital and Local Economies.

Technological Change and Labor Coercion, with Daniel Araújo and Yuri Barreto.

School Choice Dynamics: The Impact of Attributes and Information on Student Preferences, with Daniel Araújo and Leonardo Rosa.

Work in Progress

Drug Markets and Violence: The Effect of Repressive Policies on Traffickers' Behavior (Dissertation Chapter).

Conference Presentations and Seminars

2025	North East Universities Development Consortium (NEUDC), Tufts University, Boston.
2025	Econometric Society European Winter Meeting (EWMES), Nicosia, Cyprus.
2025	Latin American and Caribbean Economic Association / Latin American Meeting of the Econometric Society (LACEA/LAMES), Montevideo, Uruguay.
2025	Brazilian Meeting of Econometrics (SBE), Belo Horizonte, Brazil.
2025	XXI RIDGE Forum – Workshop on the Economics of Crime, Universidad del Pacífico, Lima. Co-organized with the LACEA Crime and Policy Network (AL CAPONE).

2024 Mini-Conference on Organized Crime in Latin America, University of Chicago.

2024 Development Tea Seminar, University of California, Davis.

Summer Schools and Workshops

2025 I.S.E.O. Summer School in Economics, Iseo, Italy. "Future Prospects for the Global Economy."

2017 RIDGE Summer School in Political Economy, Medellín, Colombia.

Teaching Experience

2024–2026 **Teaching Assistant**, University of California, Davis. Advanced Microeconomic Theory (Undergraduate).

2018–2019 **Teaching Assistant**, Universidade Federal de Pernambuco. Ph.D. Microeconomics.

2018–2019 **Instructor**, LCanpec. Statistics.

Research Experience

2017–2019 **Research Group Member**, Universidade Federal de Pernambuco. Politics, Industrial Organization, and Regulation Group.

Professional Service

Refereeing Ad-hoc Referee, *Journal of Development Economics* (JDE).

Honors and Awards

2021 Man of the Year, Brazil.

2005, 2007 Honorable Mention, Brazilian Mathematics Olympiad.

Skills

Programming Python (Advanced), Stata (Advanced), R (Intermediate), MATLAB (Intermediate), C#, C++ (Basic).

Software LaTeX, Git, ArcGIS, QGIS.

Methods Difference-in-Differences, Instrumental Variables, Regression Discontinuity, Machine Learning.

Languages Portuguese (Native), English (Fluent), Spanish (Intermediate).

Service and Leadership

2017–2019 **Academic Representative**, Universidade Federal de Pernambuco, Ph.D. Program.

Other Professional Experience

Insurance Sales Representative, Bertier Corretores.

References

Available upon request.

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

Gil do Vigor †

September 15, 2026

This paper investigates the effect of exposure to a classmate's homicide on juvenile engagement in infractions, focusing on students in Pernambuco, Brazil. Using a novel panel dataset that links detailed homicide records with administrative data on school enrollment and entries into the juvenile justice system for 766,367 students from 2008 to 2021, I exploit the random timing of student homicides to estimate the causal effect of peer homicide exposure on juvenile detention. Using a staggered difference-in-differences framework, I show that exposure to a classmate's homicide decreases the likelihood of juvenile detention by approximately 39 percent relative to the baseline mean. The effect is larger for full-time detention. The heterogeneity analyses reveal stronger deterrent effects for drug and violent offenses than for property violations. Finally, students enrolled in adult education programs present the largest decrease in detention risk, consistent with greater baseline exposure to risk factors. These results illustrate how traumatic peer events can shape youth decision-making and the role of peer environments in preventing juvenile infractions.

Keywords: Crime Engagement, Juvenile Detention, Homicides, Brazil

JEL Codes: D91, I25, K42, O12

*I thank Daniel Araujo, Chris Blattman, Leonardo Bursztyn, Anujit Chakraborty, Claudio Ferraz, Travis Liebert, Joana Monteiro, Diana Moreira, Santiago Pérez, Arman Rezaee, Breno Sampaio, Mônica Singhal, Maria Micaela Sviatschi, Paulo Vaz, and seminar participants at numerous conferences. I am solely responsible for this paper's contents. The author declares no relevant or material financial interests that relate to the research described in this paper.

†PhD in Economics at University of California - Davis, e-mail: gjjunior@ucdavis.edu

1 Introduction

Youth violence is a challenge to social stability, economic development, and the formation of human capital in both developed and developing countries (Krug et al., 2002; Sharkey, 2010; Organization et al., 2015). Each year, more than 200,000 young people lose their lives due to homicide worldwide, making it one of the leading causes of death among adolescents (Krug et al., 2002; Organization et al., 2015). Incidents of violence among youth represent not only a loss of life but also a moment of collective shock, reverberating through schools, families, and neighborhoods (Sharkey, 2010; Aizer and Doyle Jr, 2015; Koppensteiner and Menezes, 2021; Organization et al., 2015). The consequences of this violence can extend beyond the immediate victims, making it relevant for policymakers to know how these shocks affect the behavior of their peers. Around the world, major public health and educational challenges are linked to the aftermath of violence, and studying these effects can help design interventions that protect students in more vulnerable conditions. However, it is still unclear whether a peer's murder deters exposed students from crime or deepens their involvement. How violent shocks spread through peer networks matters for general theories of crime, education, and human development.

To understand how peer violence influences youth crime, in this paper, I develop a simple theoretical framework linking violent incidents within a student network to their future infractions. This framework operates through changes in perceived risks. When a student is informed about the murder of a classmate, their perceived probability of consequences from continued criminal involvement rises, resulting in an update to the expected costs and a reduction in infractions, in line with the logic of rational deterrence (Becker, 1968). In environments where illicit activity is group-based, such exposures also alter incentives through both changes in beliefs about violence and the opportunities available within the group. In the framework, I make a distinction between peer homicide, which increases perceived mortality risk, and peer detention, which combines standard deterrence with a possible replacement as criminal roles are vacated (Dell, 2015). These hypotheses give two main testable predictions. First, exposure to a classmate's homicide should result in a decline in infringement behavior among peer students. Second, exposure to peer detention has an ambiguous impact, due to the deterrence and the potential for substitution.

I study these questions in Brazil, which has among the world's highest rates of adolescent homicide (Waiselfisz, 2017), focusing on Pernambuco, a state with persistent youth homicide and deep socioeconomic inequality. To identify the causal impact of peer victimization on juvenile crime, I implement a staggered difference-in-differences design that exploits variation in the timing of homicides across schools (Callaway and Sant'Anna, 2021). To measure criminal involvement, I use administrative records from FUNASE[1][2], the state's socio-educational agency for juvenile offenders, and link them with homicide and educational census data. The linked data cover 766,367 students enrolled in grades 1 through 12. I compare students from classrooms where a classmate was murdered at different points in time, exploiting the randomness in when these events occur. 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 $(t - i)$ $(i = 0, 1, 2, 3, \ldots, 7)$. I adopt a not-yet-treated

[1]FUNASE stands for *Fundação de Atendimento Socioeducativo*.

[2]In Pernambuco, FUNASE data show that 15% of youth homicide victims had criminal records in the juvenile system.

design, where the control group consists of students not yet exposed to a classmate's homicide but who will be treated in a future period. I therefore compare individuals with similar chances of eventually losing a classmate to violence.

Exposure to a classmate's homicide leads to a large reduction in juvenile detention. The baseline effect is a 1.48 percentage point decline, or 39 percent relative to the pre-treatment mean. The effect is especially large for drug-related offenses and violent crimes. Full-time detention episodes also decline significantly. The effect is concentrated among male students, with no significant results for females. These results survive several robustness checks, including school and time fixed effects, pre-trend tests, spillover analysis from neighboring schools, and placebo tests using alternative causes of peer death. Heterogeneity analyses by age, grade level, and crime type confirm the results.

This paper contributes to two main branches of literature. The first branch examines how exposure to violence affects students' learning and may have later life consequences. Local homicides reduce test scores and increase absenteeism (Koppensteiner and Menezes, 2021), and these effects can spread through schools when students from violent areas join new classrooms, lowering teacher effectiveness and achievement (Padilla-Romo and Peluffo, 2023). Studying the effects of a mass shooting in Norway, Bharadwaj et al. (2021) finds lasting harm to education and mental health among exposed youths. Employment also suffers in the long run. However, little is known about whether fatal peer victimization within the same classroom deters or amplifies criminal involvement among surviving peers. I study this question, estimating how a classmate's murder affects subsequent juvenile crime. Unlike prior work that focuses on school performance, I follow students into the criminal justice system.

The second strand studies how peers shape aspirations and delinquency through close, local interactions. In Brazilian classrooms, Moreira (2019) shows that recognizing high achievers shifts classmates' test scores and college enrollment. Also in Brazil, Matavelli (2024) find that adolescents overestimate their peers' agreement with masculinity norms that endorse violence, and that lack of communication among classmates sustains these misperceptions. These studies suggest that peers transmit both positive and negative signals through close contact. But whether a classmate's death inside the classroom changes actual criminal behavior is still unclear, since most of this evidence concerns school choices, attitudes, or community violence. This paper shows that a classmate's murder reduces juvenile detention, suggesting that peer death can deter crime rather than amplify it. To my knowledge, this is the first evidence linking within-classroom fatal violence to criminal behavior rather than school performance.

The paper proceeds as follows. Section 2 describes the institutional and empirical background for youth violence and education in Pernambuco. Section 3 presents the theoretical framework that motivates the key predictions of my analysis. Section 4 details the data sources and construction of the main sample. Section 5 discusses the identification strategy for estimating the effects of peer homicide exposure, along with the empirical framework. Section 6 reports the main results. Section 7 concludes.

2 Background

2.1 Brazil versus Other Countries Juvenile Courts

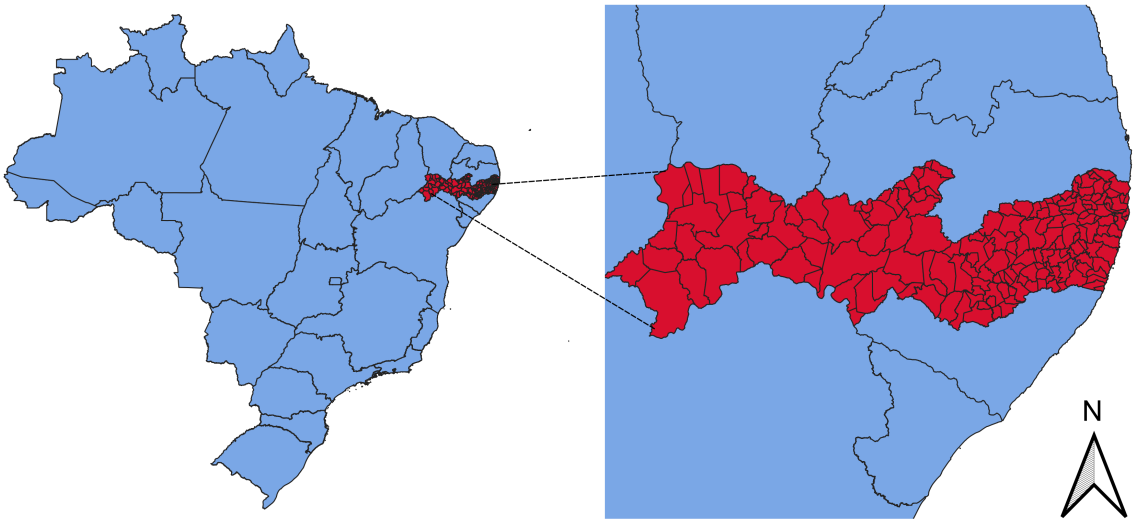
The Brazilian juvenile system is governed by the *Estatuto da Criança e do Adolescente* (ECA) [3]. For minor crimes, juveniles are not allowed to be judged, and small infractions are handled by the police. In the case of repeated minor infractions or infractions that put people's lives at risk, the more 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 an educational establishment, and cumulative application of any previous measure with protective measures. Among these seven measures, only internment in an 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.

2.2 Historical Background of Violence in the State of Pernambuco

Pernambuco, a state in Brazil's Northeast Region (Figure 1), has approximately 9 million people and 185 municipalities (IBGE, 2022). It is one of the poorest states in the country, with a per capita GDP of around $5,000 USD, about half the national average (IBGE, 2015). Poverty at this level makes adolescents vulnerable to recruitment by criminal organizations. Many of these adolescents grow up in neighborhoods where violence is part of daily life. In 2006, capital Recife had 69 murders per 100,000 inhabitants. Policy efforts reduced homicide rates by 39% between 2006 and 2013 (Neto et al., 2022), however, even after this intervention, the levels remained high. In Figure 2 we can see this pattern. While non-homicide deaths did not change much, homicides increased after 2014, and in 2017, more people were murdered than died of all the other causes combined Waiselfisz (2016). Figure 3 presents victimization rates by gender and age group in Pernambuco between 1990 and 2020. Males aged 15 to 24 have far higher homicide rates than females of any age or males aged 10 to 14. The gap is largest for boys aged 15 to 19, the same ages covered by most of my sample. Although both genders are affected, the violence is concentrated among boys.

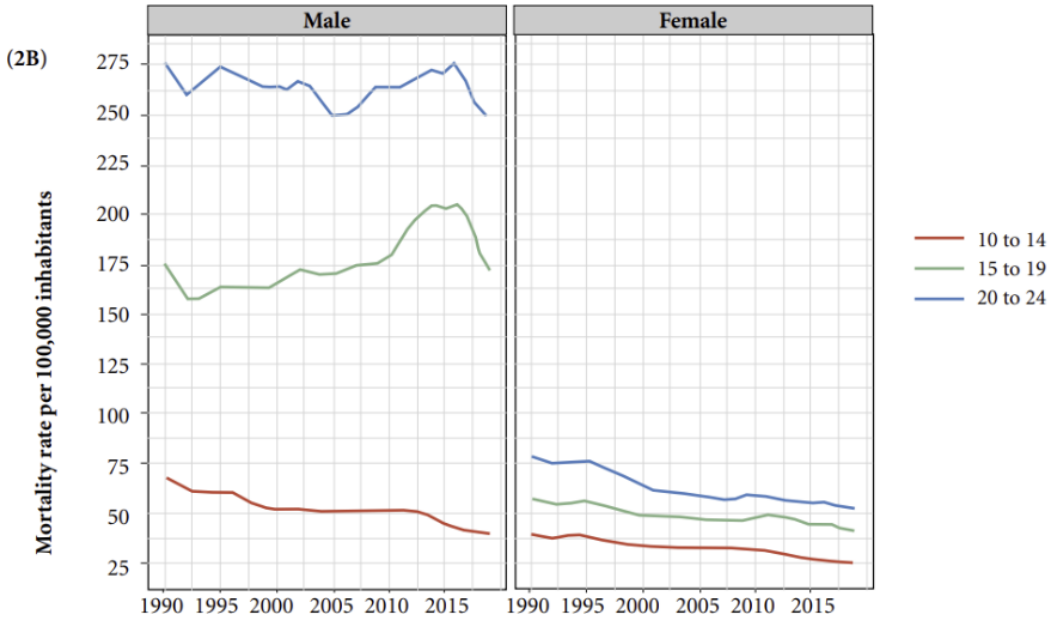
[3](Child and Adolescent Statute) - which was established on July 13, 1990, to protect juveniles in all aspects

Figure 1: Map of Pernambuco, Brazil



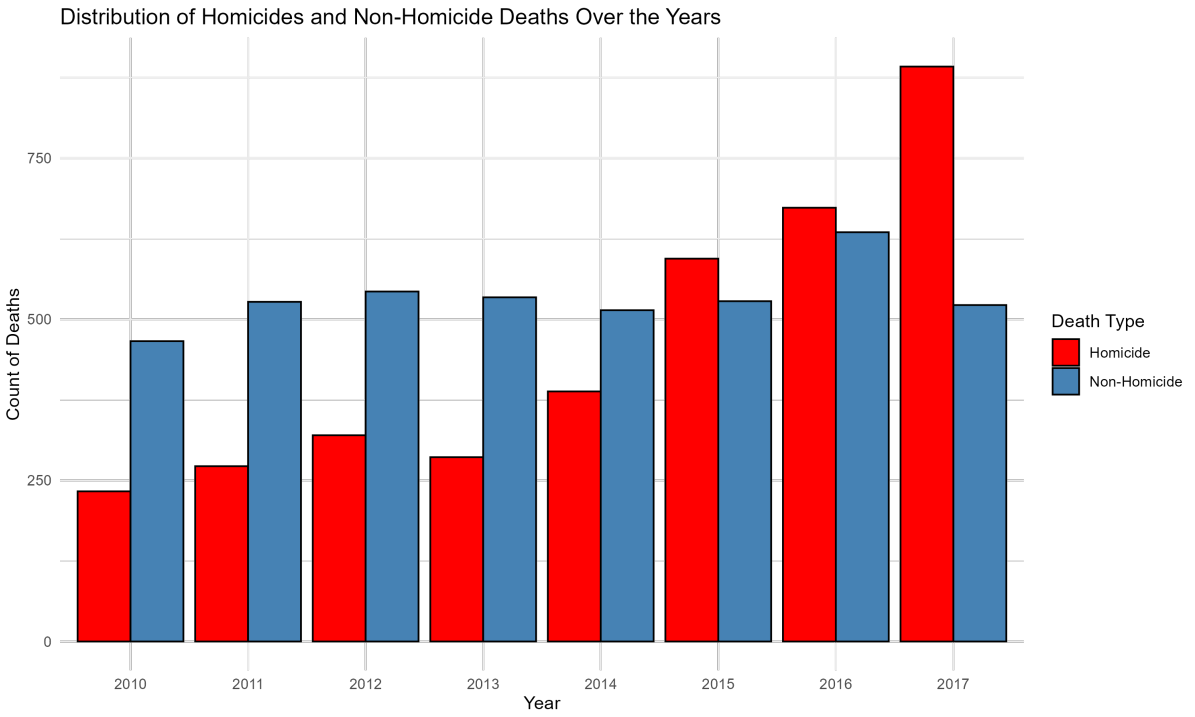
Notes: Location of the state of Pernambuco, in Brazil's Northeast Region, within the national territory. Pernambuco comprises 185 municipalities and roughly 9 million inhabitants. **Source:** Brazilian Institute of Geography and Statistics (IBGE).

Figure 3: Youth Homicide Rate by Gender in Pernambuco



Notes: Homicide victimization rates in Pernambuco by sex and age group, 1990–2020. Rates are far higher for males aged 15–24 than for females of any age or for males aged 10–14, with the largest gap among boys aged 15–19 (the ages covered by most of the sample). **Source:** *Sistema de Informações sobre Mortalidade* (SIM), Brazilian Ministry of Health.

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



Notes: Annual counts of homicide and non-homicide deaths in Pernambuco over 2010–2017. Non-homicide deaths remain relatively stable, whereas homicides rise sharply after 2014, matching non-homicide deaths in 2015 and exceeding them by 2017. **Source:** *Sistema de Informações sobre Mortalidade* (SIM), Brazilian Ministry of Health.

3 Theoretical Framework: Information Shock and Crime Decision Making

3.1 The Basic Model

Understanding how youth respond to violence in their immediate environment is central to the study of crime and deterrence. In this section, I will present a simple framework, connected to Becker (1968), to organize the predictions tested in the paper. Individuals weigh the perceived benefits of crime against the chance of getting caught or facing worse consequences. However, unlike a world with perfect information, adolescents rarely know the true risks associated with offending. Instead, their perception of risk depends on what happens within their networks. When a peer is caught and sent to juvenile detention, or killed, the remaining students see firsthand what crime can cost, allowing an update on the students' perception.

In this framework, students maximize their expected payoff by comparing the returns from crime against their costs, which have two parts: first, the formal punishment, and also the threat of violence. An important characteristic of this setting is that a significant part of the crimes is committed in groups, and therefore, group dynamics becomes a central aspect. If a classmate is murdered, peers who are also involved in crime realize they might be next and reassess how dangerous their activities are. Some may choose

to stop committing crimes, while others may leave the school or the area altogether. In fact, my data show that students with criminal records are more likely to migrate after a classmate is killed. I capture this with three probabilities reflecting each student's beliefs. The first is the probability of being caught for a crime, pf. The second is the probability of being sent to juvenile detention, pj. The third is the probability of being killed as a result of criminal involvement, pd. These beliefs change as students receive information about what happens to their peers. When a classmate is murdered, pd increases, which raises the expected cost of crime and pushes students away from offending.

The response to a peer's detention is more complex. When a classmate is detained, p_j increases for the remaining students, who now see that law enforcement is active. However, losing one member can also open opportunities for the rest. Dell (2015) call this the replacement effect. If one member is removed, some friends may think that they can take their place, and crime could even increase rather than fall. Since these mechanisms pull in opposite directions, which effect dominates is an empirical question.

3.2 Utility Function and Objective

This subsection changes the discussion focus to the students' utility function. In my environment, each adolescent chooses the number of infractions, I^*, to maximize the following expected utility.

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

where $B_c(I)$ is the total benefit from crime and $C(I, p_f, S, p_d, p_j)$ is the total perceived cost. The benefit function $B_c(I)$ includes direct returns like illegal earnings, social status among criminal peers, or the protection that comes from belonging to a group. These benefits grow with the number of offenses, though possibly at a decreasing rate.

The cost function above has three main parts. The first one is called the legal punishment cost, $C_f(I) = p_f SI$, where p_f is the perceived probability of being caught, and S is the severity of the punishment if caught. If a classmate is detained, students revise p_f upward because they see the police as more active. The second important aspect to highlight is that crime also has a risk of death. I model this as $C_d(I) = p_d DI$, where p_d is how likely the student thinks they are to be killed and D is the cost they perceive in dying. Finally, the model also includes a market replacement effect, $C_j(I) = -p_j RI$. Removing a peer creates new opportunities for the rest of the students. Here, p_j is the probability that a peer is removed, and R measures the size of the redistribution.

Integrating these elements, the total expected cost is given by:

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

Peer homicides and detentions shift the perceived costs of crime, but the net effect on offending depends on which channel dominates.

3.3 Functional Form of Crime Benefits

Now, let's turn to the functional form of the benefit function. One important aspect to notice about the crime benefits is that the gains from each additional infraction are unlikely to rise indefinitely. It makes sense that they would even fall as offenses accumulate. In the real world, there are several reasons why this could happen, for example, if profitable

opportunities become scarcer or the police pay closer attention to you. To capture this idea in a tractable way, I adopt a quadratic benefit function:

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

Where $\beta > 0$ is the benefit from the first infraction, reflecting aspects such as financial returns and social status gains. $\gamma > 0$ determines how fast these benefits fall as the youth commits more infractions. These parameters are important to ensure diminishing returns to crime participation. $\beta > 0$ means that there is always some initial gain from offending; otherwise, no one would choose to commit crimes, while $\gamma > 0$ determines how fast these benefits fall as the youth commits more infractions. Empirically, this should be larger for small criminal groups or tightly policed contexts. To ensure that benefits stay non-negative for all relevant I, I require the additional condition:

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

Where $I_{\max}$ is an upper bound on feasible infractions. This means that, even as infractions increase, youths are not "penalized" through the benefit channel alone for additional crimes. The quadratic form also gives closed-form solutions, which makes the comparative statics easy to interpret.

3.4 Optimization Problem

Given the benefit and cost structure, the student's decision rule is given by:

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

At the optimum, the marginal benefit of crime equals its marginal cost. This gives the first-order condition:

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

from which the optimal number of infractions, I^*, follows directly:

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

This problem solution finds that crime falls when perceived risks, such as arrests, punishments, or deaths, rise or when the returns from crime decrease. However, if removing a peer through detention opens up opportunities for the rest of the group, this can work against deterrence and keep crime high, or even increase it. These predictions will guide the analysis that follows.

3.5 Effect of Increased Perceived Mortality Risk

The main shock in this model is a classmate's murder, which raises the perceived risk of dying from crime. After such an event, the student revises p_d upward:

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

This decision changes the student's optimal choice. To find the consequences of this decision, it is possible to differentiate I^* with respect to p_d.

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

When students learn that crime led to a peer's death, they see dying as more likely and choose to commit fewer infractions. This effect should be strongest after events that are close and visible, like the killing of a classmate.

3.6 Effect of Increased Juvenile Detention Among Peers

The model also considers what happens when a classmate is detained. This raises the perceived probability of juvenile detention for the remaining group members:

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

Since group interactions and enforcement are often linked, an increase in p_j may also raise the perceived probability of being caught:

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

To see the overall effect, I differentiate I^* with respect to p_j:

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

As discussed in the previous section, the sign of this expression could go in any direction. Removing a peer creates new opportunities, which can make crime more attractive. But as pj rises, so does pf, which discourages crime. If the replacement effect is stronger, detentions can unintentionally sustain or even increase crime within the group.

3.7 Effect of Increased Police Enforcement

The model also allows considerations about the effect of direct shifts in police enforcement, separated from peer dynamics. Differentiating the optimal infractions with respect to the perceived probability of apprehension, p_f, gives

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

This is the standard deterrence result. When youths think they are more likely to be caught, whether because of more police or higher conviction rates, they commit fewer crimes.

4 Data

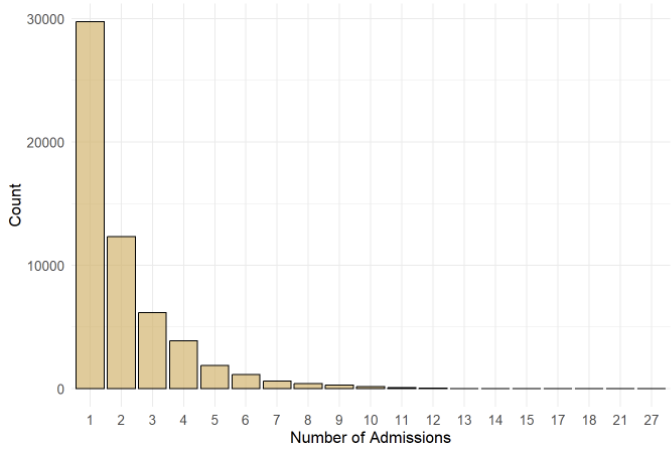
4.1 Juvenile Detention

The *Fundação de Atendimento Socioeducativo* (FUNASE) is a public institution in Pernambuco responsible for adolescents aged 12 to 20 who have committed serious

infractions. Instead of punishment, the institution focuses on reintegrating adolescents into society through schooling and job training. In Pernambuco, adolescents aged 12 to 20 who commit serious infractions are sent to the *Fundação de Atendimento Socioeducativo* (FUNASE). Instead of punishment, the institution focuses on reintegrating adolescents into society through schooling and job training. It operates 20 facilities across the state. Once apprehended, adolescents go to a provisional unit, where they can be held for up to 45 days while awaiting a judicial decision. After that, they may be released or assigned to one of two measures. Under semi-liberty, the adolescent can leave the facility during the day for work or school but must return in the evening. Under internment, the adolescent remains in the facility full-time.

In Figure 4, I present the distribution of the number of admissions in juvenile detention for the time span of our data (2008–2024). Most individuals experience only one admission, and the frequency drops sharply with each additional one. Cases beyond four admissions are rare, though a small group does return repeatedly. Likewise, Figure 5 shows the age distribution of the children at their admission to the institution. Most of them occur while they are between the ages of 15 and 18, with a peak at 17. Admissions fall sharply below age 14 and above 19, consistent with the criminology literature that finds offending concentrated in late adolescence.

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



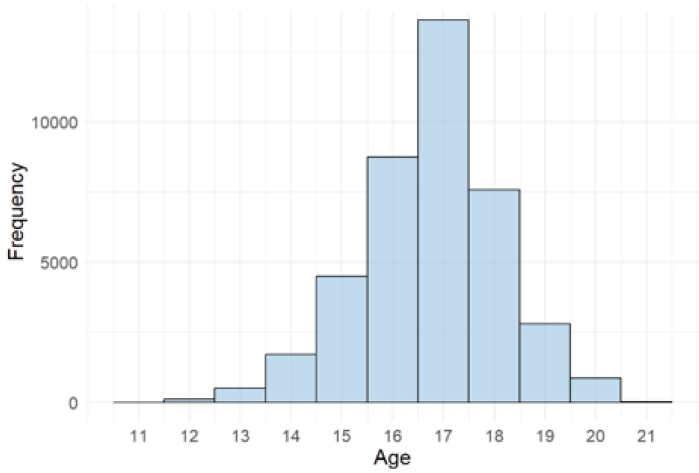
Notes: Distribution of the number of admissions to the juvenile socio-educational system per individual over 2008–2024. Each bar reports the count of individuals with the corresponding number of recorded admissions. Most individuals are admitted only once, and the frequency drops sharply with each additional admission. **Source:** FUNASE (*Fundação de Atendimento Socioeducativo*, Pernambuco) administrative records.

The dataset also 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. My final sample covers 2010 to 2016. I chose this time span as it overlaps with the other datasets I use and allows me to track individuals over time.

4.2 Mortality Data

I also use mortality data from the *Sistema de Informações sobre Mortalidade* (SIM) under the Ministry of Health. The data contains individual-level records including names, mothers' names, birthdates, socio-economic characteristics, and causes of death. I use

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



Notes: Distribution of individuals by age at admission to the juvenile socio-educational system over 2008–2024. Admissions concentrate between ages 15 and 18 and peak at age 17, falling sharply below age 14 and above age 19, consistent with offending concentrated in late adolescence. **Source:** FUNASE (*Fundação de Atendimento Socioeducativo*, Pernambuco) administrative records.

these records to identify homicide cases. The data covers 2008 to 2016, which I cross-reference with the educational and socio-educational datasets. Table 1 presents a summary of death types in the complete database. Of these, 4,389 are homicides, by far the most common cause. Deaths caused by police intervention are extremely rare. Traffic accidents account for 137 deaths, while suicides account for 102 cases. The dataset also includes 238 intentional homicides classified as undetermined, where the exact circumstances of death could not be established.

Table 1: Summary of Death Types in the Complete Database

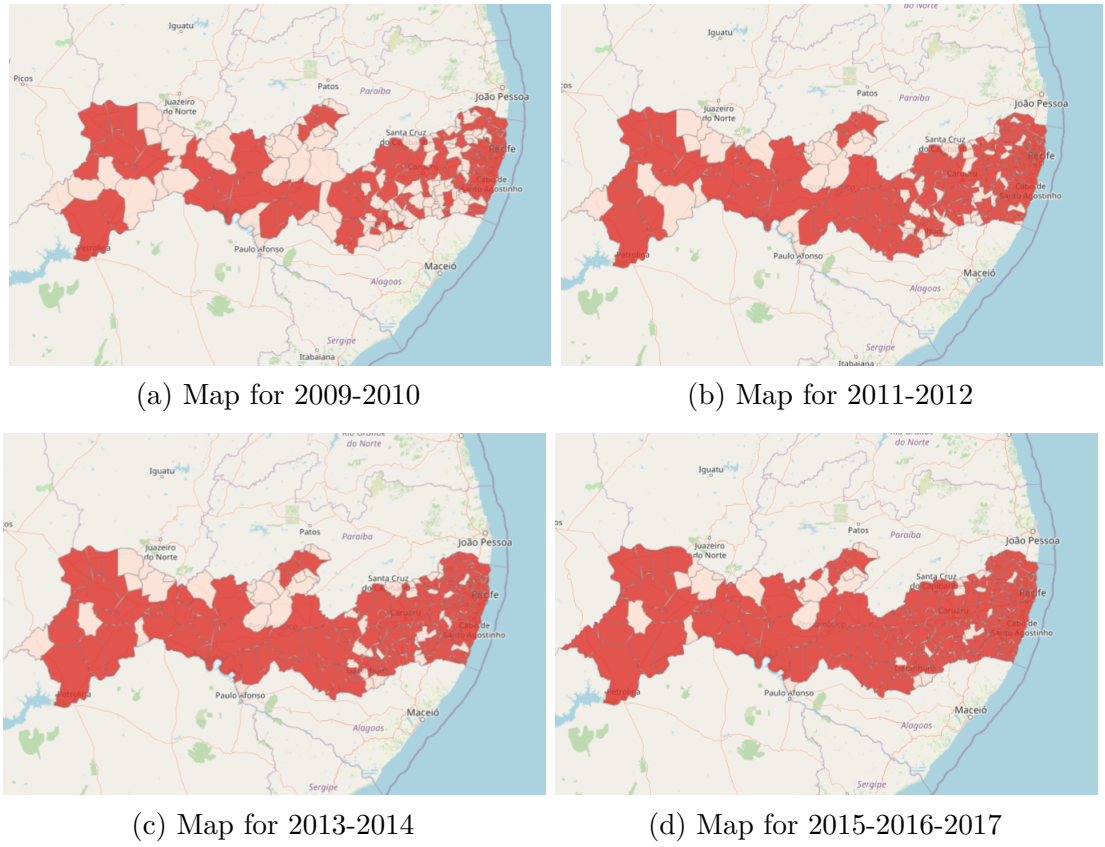
Type (Complete Database)	Count
Number of Homicides	4,389
Deaths Caused by Police Interventions	1
Deaths Caused by Traffic Accidents	137
Number of Suicides	102
Intentional Homicides Not Determined	238

Notes: Counts of recorded deaths by cause of death in the mortality database over 2008–2016. Homicides account for roughly 90% of recorded deaths in the analyzed period. "Intentional Homicides Not Determined" refers to violent deaths whose intent could not be established, a category that may include misclassified homicides. **Source:** *Sistema de Informações sobre Mortalidade* (SIM), Brazilian Ministry of Health.

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 main public safety issue. Given its predominance, I focus on this crime outcome by merging the classmate's homicide data with the FUNASE and educational databases to analyze its impact on

youth criminal behavior. Figure 6 presents the geographic distribution of homicides in Pernambuco. In Figure 7, I show the distribution of homicide victims by age at death. Homicide rates stay low for individuals under 14 but increase sharply from age 15 onward. The highest concentration falls between ages 17 and 19. After 19, the numbers drop. This age pattern closely mirrors the one observed in FUNASE admissions (see Figure 5).

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



(a) Map for 2009-2010

(b) Map for 2011-2012

(c) Map for 2013-2014

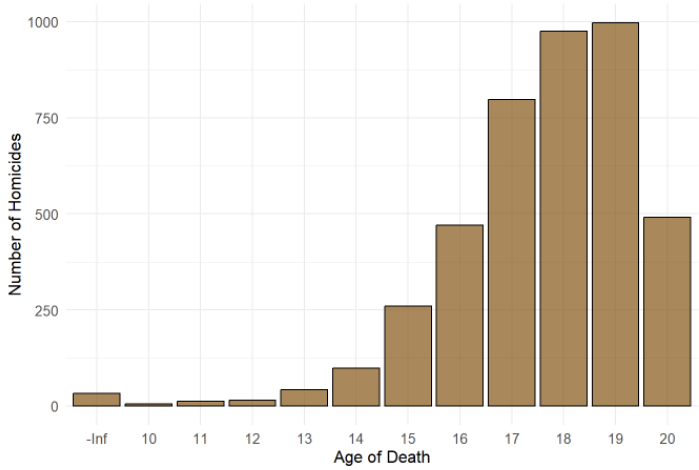
(d) Map for 2015-2016-2017

Notes: Spatial distribution of homicides across the municipalities of Pernambuco, shown separately for four periods: 2009–2010, 2011–2012, 2013–2014, and 2015–2017. In each panel, shading reflects the number of homicides recorded in the municipality during the corresponding period. **Source:** *Sistema de Informações sobre Mortalidade* (SIM), Brazilian Ministry of Health.

4.3 Educational Enrollment Data

Educational data comes from the *Secretaria de Educação de Pernambuco*, covering all school enrollments (public and private) from 2008 to 2016. Each record has several students' information, such as their name, mother's name, and birthdate, which I use for linking across datasets. It also reports the student's grade, class, school, and socio-economic background. With these records, I track students over time and link them to both mortality and FUNASE data. This linkage is also what makes the difference-in-differences strategy possible, since I can compare students in the same school and grade before and after a classmate's homicide.

Figure 7: Number of Homicides by Age at Death



Notes: Distribution of homicide victims by age at death over 2008–2016. Homicide counts remain low below age 14, rise sharply from age 15, concentrate between ages 17 and 19, and decline thereafter. This age pattern closely mirrors the age distribution of juvenile-detention admissions in Figure 5. **Source:** *Sistema de Informações sobre Mortalidade* (SIM), Brazilian Ministry of Health.

4.4 Descriptive Statistics

In this paper, I want to estimate the effects of student homicides on their peers. To define treatment, I identify homicides among male students enrolled in school, including K-12 grades and Youth and Adult Education, between 2009 and 2017. I consider that a student is treated when a classmate from the same school and grade is killed. Since most part of the students' homicides are tied to drug trafficking and gang disputes unrelated to the victim's classroom peers, the timing of these deaths is plausibly exogenous to the treated students' outcomes. The final sample has 26,855 male students, born between 1997 and 2003, followed from 2009 to 2021. Students in these cohorts turn 12 to 18 at some point in the sampled years, so they are eligible to enter FUNASE the entire time. All individuals are followed over the same years, without right- or left-censoring, including younger or older students. Table 2 shows baseline (2009) statistics for treated and never-treated groups. Most variables are balanced between groups. School socioeconomic status (SES) is the only one showing some difference. Treated students go to lower SES schools on average.

5 Identification Strategy and Results

5.1 Empirical Framework

The recent economic literature has extensively discussed how standard two-way fixed effects Difference-in-Differences can produce biased estimates when treatment effects are heterogeneous over time (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). To deal with these potential concerns, the identification strategy of this paper follows the staggered approach proposed by Callaway and Sant'Anna (2021). The Callaway and Sant'Anna (2021) estimator avoids this problem. I adopt the "not yet treated" group specification of the estimator, where the control group at any given period consists of

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

students whose classmates have not yet been killed but will eventually experience that shock. I compare these students to those already exposed to estimate how a classmate's homicide affects criminal behavior.

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 classmate but in different years: João in 2014 and Matheus in 2016.

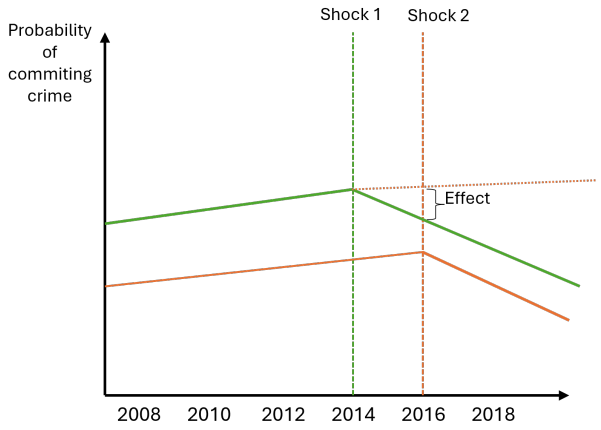
Formally, the approach estimates the Average Treatment Effect on the Treated as follows:

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

where g is 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, I aggregate all group-time average treatment parameters by years after the treatment shock. Then, calculate:

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

Figure 8: Illustration: Research Design



Notes: Illustration of the staggered difference-in-differences design of Callaway and Sant'Anna (2021). Students are assigned to cohorts according to the year in which a classmate is murdered (e.g., João in 2014 and Matheus in 2016), and not-yet-treated students serve as the comparison group for already-treated students. The figure is schematic and does not display data.

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 post-treatment 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 a 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 my main specification, I also control for the proximity between the affected students and the homicide event. The reason for this is that not all classmates are equally exposed. Students closer in age to the victim are more likely to have interacted with them, and a homicide near the school may affect students more than those far away. I capture the first dimension with the age difference between the murdered classmate and the affected students at the time of the incident (Jacob and Lefgren (2003); Duflo et al. (2011); Lavy et al. (2012)). For spatial proximity, I follow Koppensteiner and Menezes (2021) and use the Euclidean distance between the location of the homicide and the school. 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. For the age difference, half of the students experienced the shock within a 0 to 1-year gap from the victim, and the third quartile extends only to 3 years. Most students belonged to the same or adjacent academic cohorts. For geographic distance, half of the students were within 1.3 kilometers

of the homicide location, and 25% were within 0.6 kilometers. The upper quartile starts at 5.9 kilometers.

Table 3: Quartile Distribution of Age and Geographic Proximity to a classmate'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)

Notes: Quartile cutoffs of the two proximity measures between a treated student and the homicide event. "Distance to Age Shock" is the absolute difference in age (in years) between the student and the murdered classmate; "Distance to Shock (km)" is the Euclidean distance between the homicide location and the student's school. Each cell reports the range spanned by the corresponding quartile of the treated-student distribution. **Source:** linked FUNASE, mortality (SIM), and Pernambuco school-enrollment records.

Table 4: Summary Statistics by Treatment Group (At Baseline - 2009) - SAEPE Test Scores School Sample

Variable	Never-Treated	Treated
Test Scores (log SAEPE)		
Math, 9th grade	5.42	5.41
Math, 12th grade	5.52	5.49
Portuguese, 9th grade	5.37	5.37
Portuguese, 12th grade	5.49	5.47
Student Characteristics (Averages by School)		
Average age	14.3	16.1
Proportion of men	0.496	0.490
Proportion of women	0.504	0.510
Sex not declared (avg. count)	3.56	2.91
Race Composition (Proportions)		
White	0.291	0.244
Black	0.041	0.046
Brown	0.651	0.698
Other	0.017	0.011
Schooling Track (Proportions)		
Regular	0.901	0.848
EJA	0.096	0.151

Notes: School-level baseline (2009) means for the sample used in the school-performance analysis, reported separately for never-treated and treated schools. A school is classified as treated if at least one enrolled student was a homicide victim during the sample period. Test scores are log-standardized SAEPE proficiency; student characteristics, race composition, and schooling-track shares are computed as averages across students within each school. **Source:** SAEPE assessment and Pernambuco State Education Secretariat (*Secretaria de Educação de Pernambuco*) enrollment records.

6 Results

In this section, I examine the effects of exposure to classmate homicides on juvenile detention outcomes and educational persistence and performance, using a novel panel dataset that links individual student records to the timing and location of peer homicides. I first estimate the impact of exposure on overall juvenile detention, school dropout, and grade retention. I then explore heterogeneity across detention regimes, crime types, and recidivism. Next, I decompose the effects by interaction intensity and investigate variation across student characteristics, including educational track and age group, to identify which adolescents are most affected by peer violence. Finally, I present evidence on the effects of exposure to student homicides on school performance, using school-level standardized test scores.

6.1 Main Effects on Juvenile Detention

I first estimate how exposure to a classmate's homicide affects the likelihood of juvenile detention. 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. In table 5, I present the main results using the specification in equation 1 from the empirical section. The first column is the baseline model, which includes student and year fixed effects. The other columns (2-4) include 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. Panel (a) shows that overall detention falls by 1.3 to 2.2 percentage points, driven by full-time detention. Part-time detention is significant in some specifications but not all. The reduction is largest for drug-related crimes, significant at 1% in every specification, followed by violent crimes (Panel b). Property crime effects lose significance in the fully controlled model. Recidivism effects are significant in the baseline but disappear with controls (Panel c). An important assumption of the DID is that the treated and control groups should present common trends. To test this assumption, Figure 9 presents the estimates by time relative to the event. From the figure, it is possible to notice that while the coefficients are small and insignificant before the shock, they become significant and negative after it, supporting the identification strategy.

6.1.1 Heterogeneity by Detention Regime, Crime Type, and Recidivism

To better explore the mechanisms behind the observed effects, I focus on distinguishing different crime-related channels. Table 5 presents the results by detention regime, crime type, 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, like homicide, drug trafficking, or armed robbery, typically result in full-time detention, where the adolescent cannot leave the facility during the sentence. 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.

The first panel of Table 5 shows that the reduction in detention is concentrated in full-time detention cases, with consistently negative and statistically significant coefficients

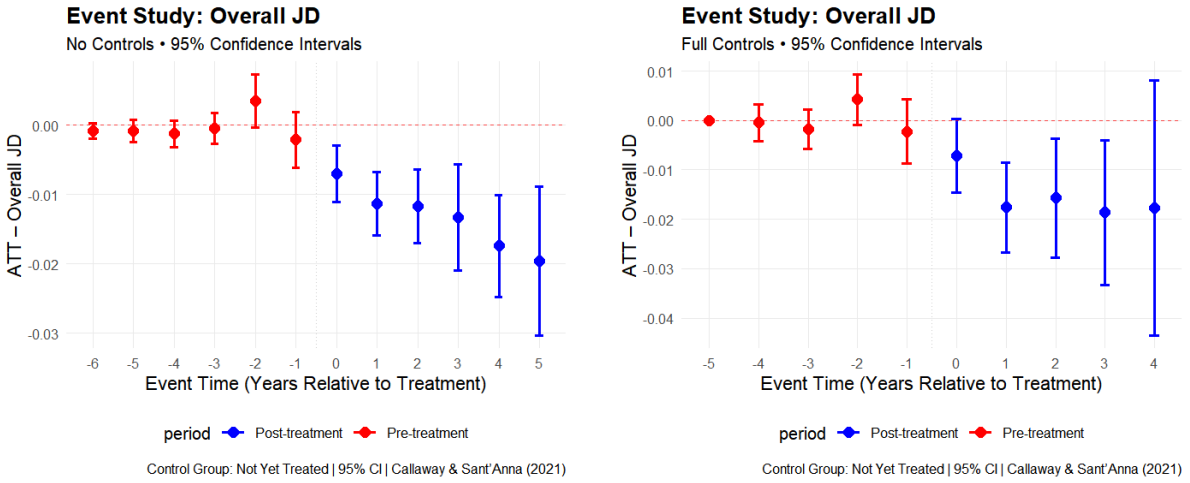
Table 5: Dynamic ATT Estimates by Detention Regime, Crime Type and Recidivism

Dependent Variable: Juvenile Detention Records (FUNASE)				
	(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 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 the distance (km) between the student's school and the homicide location. *** p<0.01, ** p<0.05, * p<0.1.

across all specifications. Part-time detention also shows negative point estimates, but the significance is less consistent. The stronger results for full-time detention point to an effect concentrated in more severe criminal behavior. Figure 10 presents the event-study estimates for full-time detention. The probability of detention falls after a classmate's

Figure 9: Effect of Classmate Homicide on Overall Juvenile Detention



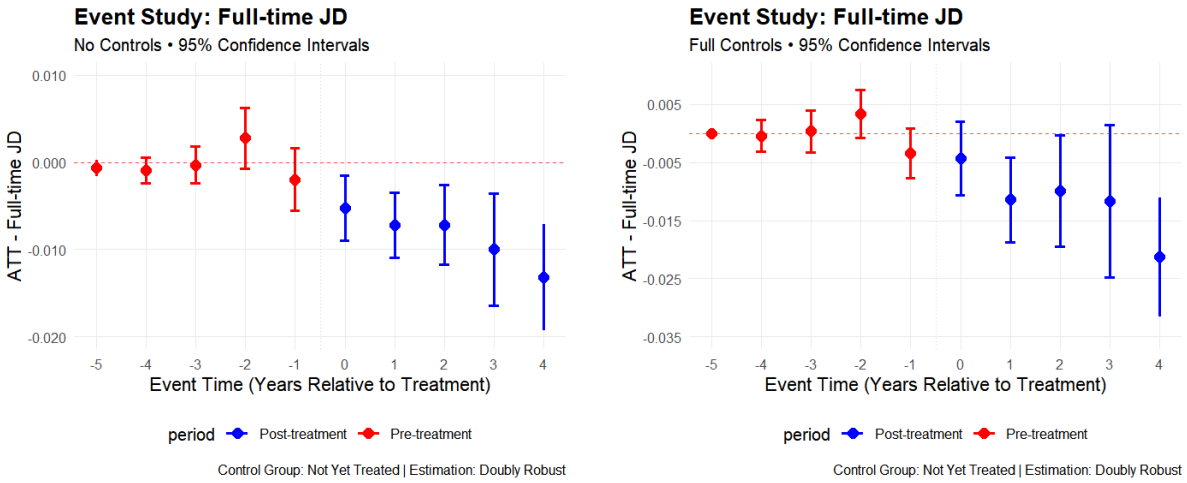
(a) No Controls

(b) Age and Distance Controls

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 the 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. The figure presents confidence intervals at the standard 95% level, and these standard errors are 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.

homicide. While the initial effects are modest, the magnitude of the reduction increases steadily over time. The event-study for part-time detention (11) is consistent with the table results. The estimates point to some decline, but they are less precise. Panel (b) of Table 5 separates the effects by offense type. The decline is strongest for drug-related crimes, with ATT estimates ranging from -0.0035 to -0.0085. Violent crimes also fall significantly, with effects from -0.0020 to -0.0047. For property crimes, the coefficients range from -0.0070 to -0.0093 but lose significance once full controls are added. Figures 12 and 13 show the event-study estimates for violent crimes and drug-related crimes, respectively. For violent crimes, the effect is not immediate. The reduction in detention becomes significant only in later years, suggesting that it takes time for the shock to change behavior. Panel (c) of Table 5 looks at recidivism, defined as having multiple juvenile detention episodes. The results show a reduction in repeat offenses in two of the four specifications. However, this effect loses statistical significance when both age and distance controls are included. Students already in the juvenile justice system may respond less to a classmate's death because they have already been exposed to detention.

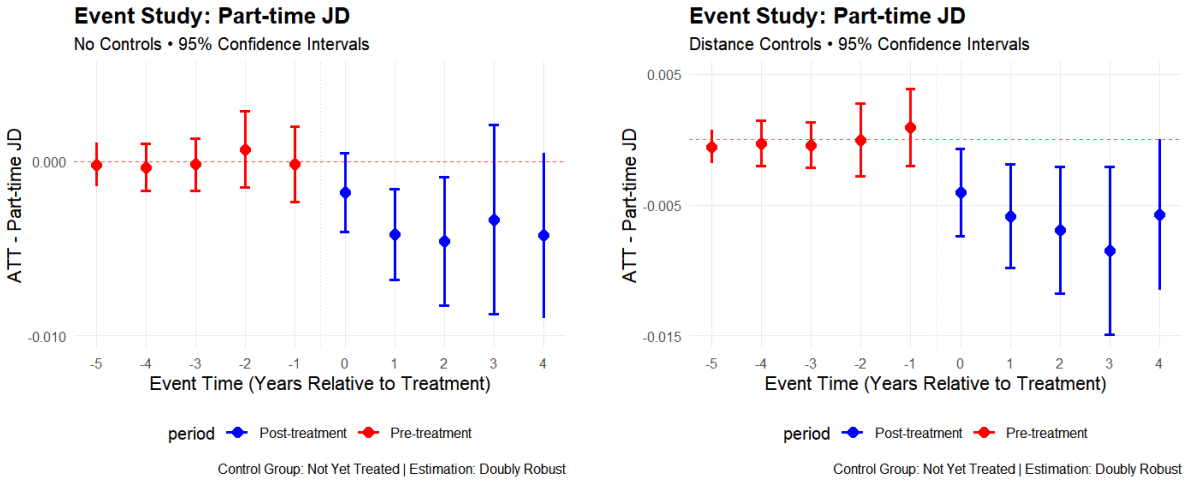
Figure 10: Effect of Classmate Homicide on Full-Time Juvenile Detention



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

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 the age difference between the student and victim (months) and the distance between school and homicide location (km). Red dots represent pre-treatment periods, blue dots represent post-treatment periods. The figure presents confidence intervals at the standard 95% level, and these standard errors are clustered at the school level. The vertical dashed line indicates the treatment period.

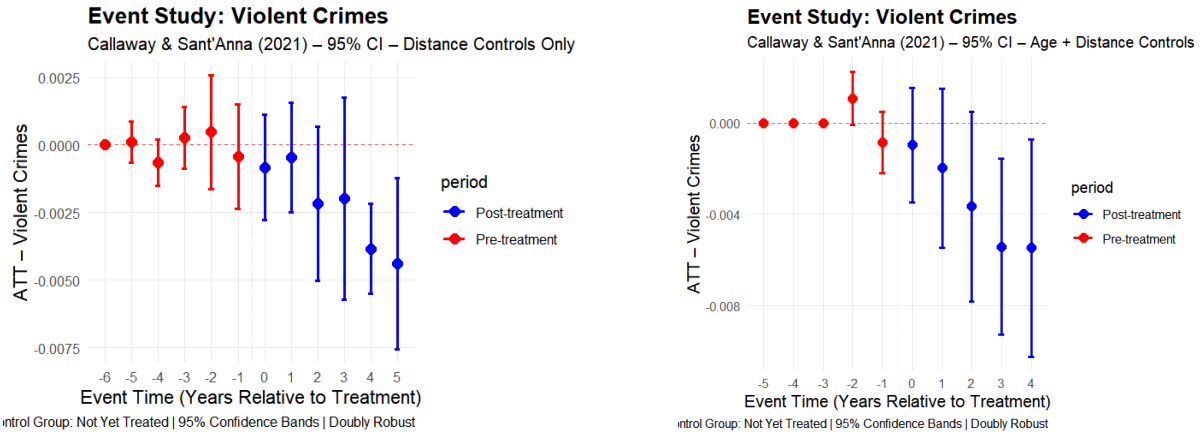
Figure 11: Effect of Classmate Homicide on Part-Time Juvenile Detention



(a) No Controls (b) Distance Controls

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. The figure presents confidence intervals at the standard 95% level, and these standard errors are clustered at the school level. The vertical dashed line indicates the treatment period.

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

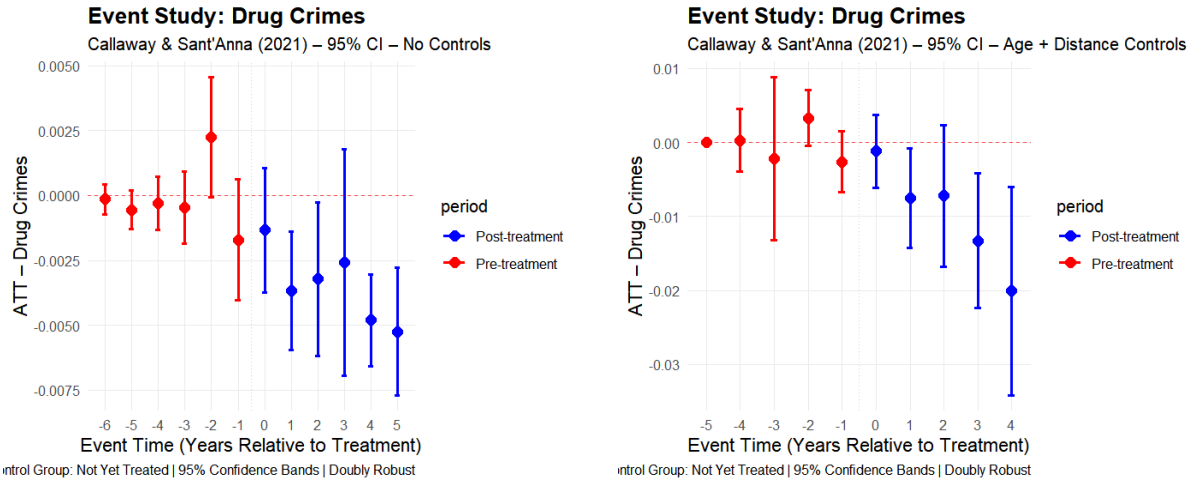


(a) No Controls

(b) Age and Distance Controls

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 the 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. The figure presents confidence intervals at the standard 95% level, and these standard errors are 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.

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



(a) No Controls

(b) Age and Distance Controls

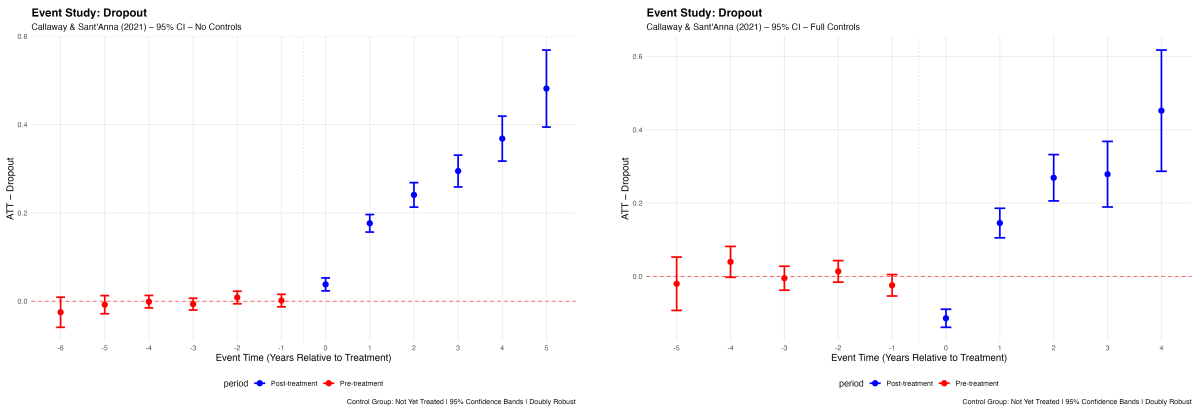
Notes: This figure presents event study estimates for the effect of classmate homicide on juvenile detention for drug offenses using the Callaway and Sant'Anna (2021) difference-in-differences estimator. Panel (a) shows results without controls, while Panel (b) includes controls for the age difference between the student and the victim (months) and the distance between the school and the homicide location (km). Red dots represent pre-treatment periods, and blue dots represent post-treatment periods. The figure presents confidence intervals at the standard 95% level, and these standard errors are 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.

6.2 Effects on Dropout and Grade Progression

Given that the analysis is conducted at the student level, I next examine the effects of exposure to a classmate's homicide on educational progression. Table 6 reports the estimated coefficient for school dropout and grade retention. As in the previous analysis, treatment is defined at the classroom level, and identification exploits variation in the timing of homicides, which is considered exogenous from the perspective of classmates. Column (1) presents the baseline specification. Columns (2) and (3) introduce controls for age proximity between the student and the victim and for the distance between the homicide location and the school, respectively. Column (4) includes both sets of controls.

In Panel (a), the treatment increases the probability of dropout by 20.6 percentage points with all controls included. Figure 14 presents dynamic event-study estimates of the effect of exposure to a classmate's homicide on school dropout. The post-treatment estimates increase gradually over time, but the mechanisms behind this pattern are not immediately clear. In the next section, I examine post-homicide student migration and educational performance outcomes to understand these dynamics. In contrast, Panel (b) shows that grade retention initially decreases, with estimates ranging from -0.0427 to -0.1158 in columns (1-3). The inclusion of both controls together makes it non-significant. Figure 15 presents the event-study estimates for grade retention. Without controls, there is some indication of a decrease in retention, but the pattern does not hold once controls are included.

Figure 14: Effect of Classmate Homicide on School Dropout



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

Notes: This figure presents event study estimates for the effect of classmate homicide on overall school dropout using the Callaway and Sant'Anna (2021) difference-in-differences estimator. Panel (a) shows results without controls, while Panel (b) includes controls for the 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. The figure presents confidence intervals at the standard 95% level, and these standard errors are clustered at the school level. The vertical dashed line indicates the treatment period. The dependent variable is a binary indicator for school dropout.

In contrast, Panel (b) shows that grade retention initially decreases, with estimates ranging from -0.0427 to -0.1158 in columns (1-3). The inclusion of both controls together makes it non-significant. Figure 15 presents the event-study estimates for grade retention, consistent with these results. Without controls, there is some indication of a decrease in retention, but the pattern does not hold once controls are included. Grade retention

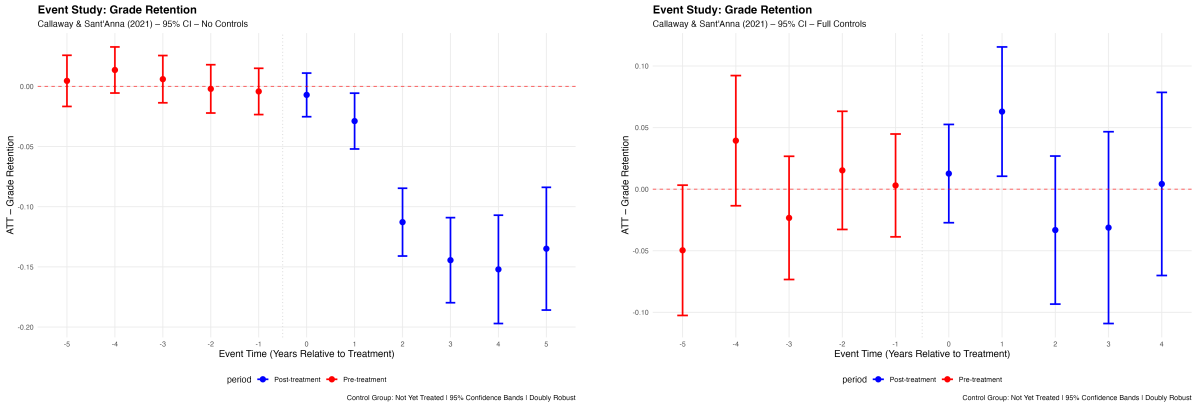
Table 6: Effects on School Persistence and Grade Progression

Dependent Variables: School Dropout and Grade Retention				
	(1)	(2)	(3)	(4)
Panel (a): Probability of School Dropout				
Overall ATT	0.2666***	0.1708***	0.3875***	0.2063***
	(0.0097)	(0.0155)	(0.0123)	(0.0224)
Panel (b): Probability of Grade Retention				
Overall ATT	-0.0967***	-0.0427***	-0.1158***	0.0031
	(0.0068)	(0.0146)	(0.0088)	(0.0138)
Controls and Specification				
Age controls (months)	No	Yes	No	Yes
Distance controls (km)	No	No	Yes	Yes
Observations (Dropout)	187,925	187,925	187,925	187,985
Observations (Grade Retention)	111,370	111,370	111,370	111,370
Number of Students (Dropout)	26,855	26,855	26,855	26,855
Number of Students (Grade Retention)	18,270	18,270	18,270	18,270
Number of Schools	4,096	4,096	4,096	4,096
Time Period	2009–2021	2009–2021	2009–2021	2009–2021

Notes: This table reports overall average treatment effects on the treated from the difference-in-differences estimator proposed by Callaway and Sant'Anna (2021). Panel (a) presents effects on the probability of school dropout, while Panel (b) reports effects on grade retention. Age controls include the age difference (in months) between the student and the homicide victim. Distance controls include the distance (in kilometers) between the student's school and the homicide location. All specifications include individual and year fixed effects. Standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

does not appear to change over time after a classmate's homicide, once confounders are accounted for.

Figure 15: Effect of Classmate Homicide on Grade Retention



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

Notes: This figure presents event study estimates for the effect of classmate homicide on overall grade retention using the Callaway and Sant'Anna (2021) difference-in-differences estimator. Panel (a) shows results without controls, while Panel (b) includes controls for the 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. The figure presents confidence intervals at the standard 95% level, and these standard errors are clustered at the school level. The vertical dashed line indicates the treatment period. The dependent variable is a binary indicator for grade retention.

6.3 Heterogeneity

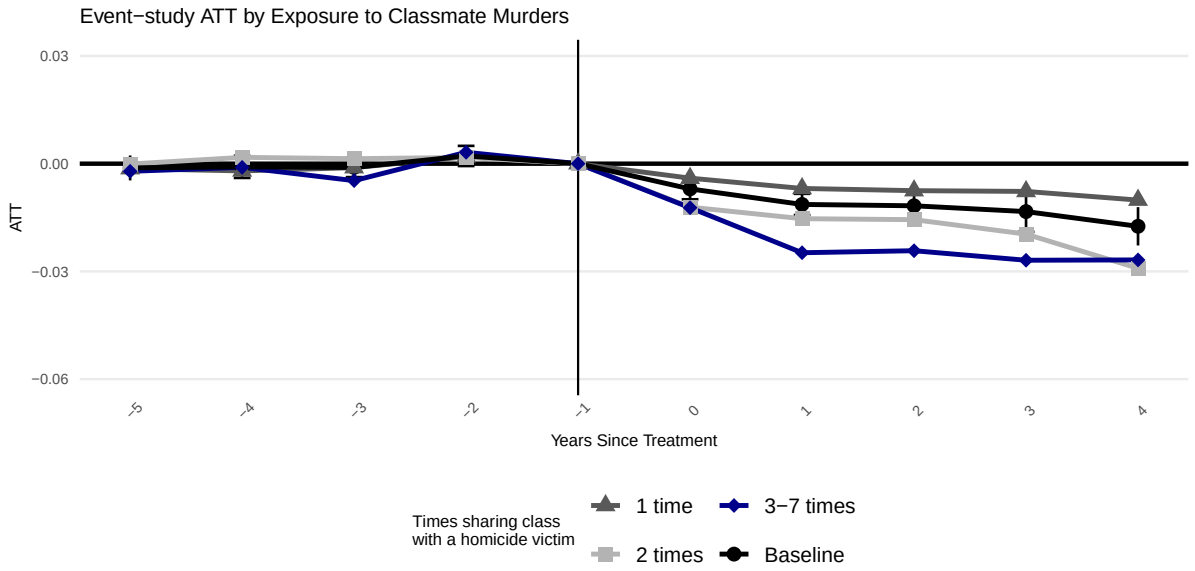
6.3.1 Decomposition by Interaction Intensity

Figure 16 decomposes the dynamic effects of exposure to a classmate's homicide by the number of times a student shared a classroom with the victim. Students who shared a class only once show small post-treatment effects. I also observe that those who shared a classroom several times show larger declines. The biggest effects are among students who overlapped with the victim three or more times, indicating that repeated peer exposure amplifies the effects of the shock. The more time students spent with the victim, the stronger the response.

6.3.2 Decomposition by Age Group

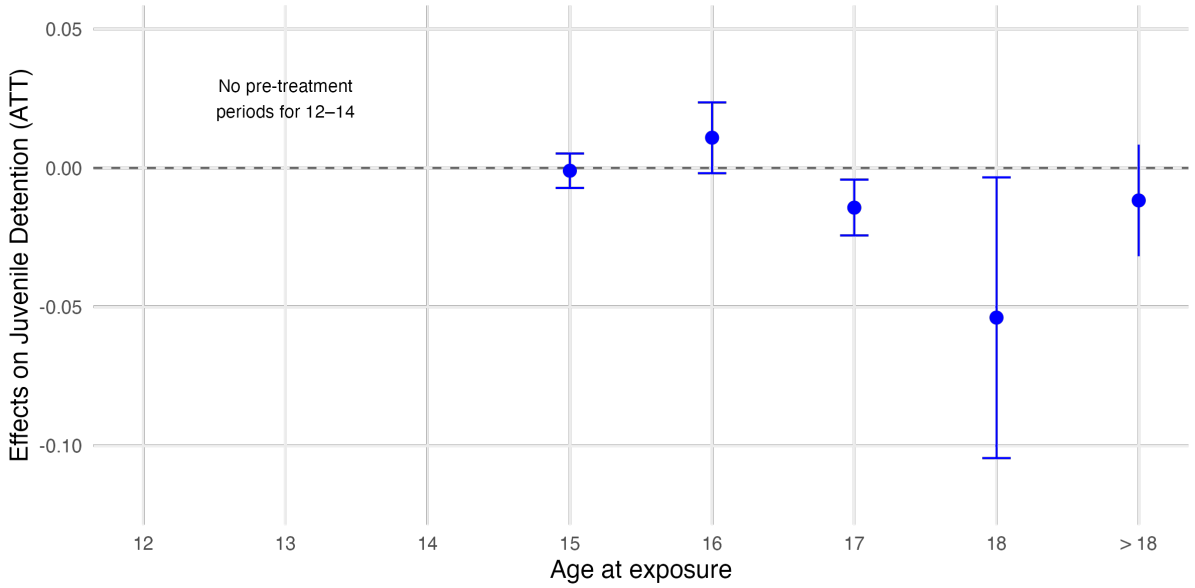
Figure 17 presents the estimated effects of the treatment by students' age at the time of the friend's death. The magnitudes vary across age groups. I restrict this analysis to older cohorts because I do not have pre-treatment observations for students at a younger age. The estimated effects are statistically significant only for students aged 17 and 18, with the magnitude of the effect increasing at age 18. One possible explanation is Brazil's age of majority. When the student reaches 18 years old, they start to face adult criminal penalties, which may make the information they receive from the friend's death significantly stronger. The results for school dropout are also significant but with a different sign (Figure 18). (Figure 18). The effect is concentrated among students aged 16 and older.

Figure 16: Decomposition by Interaction Intensity



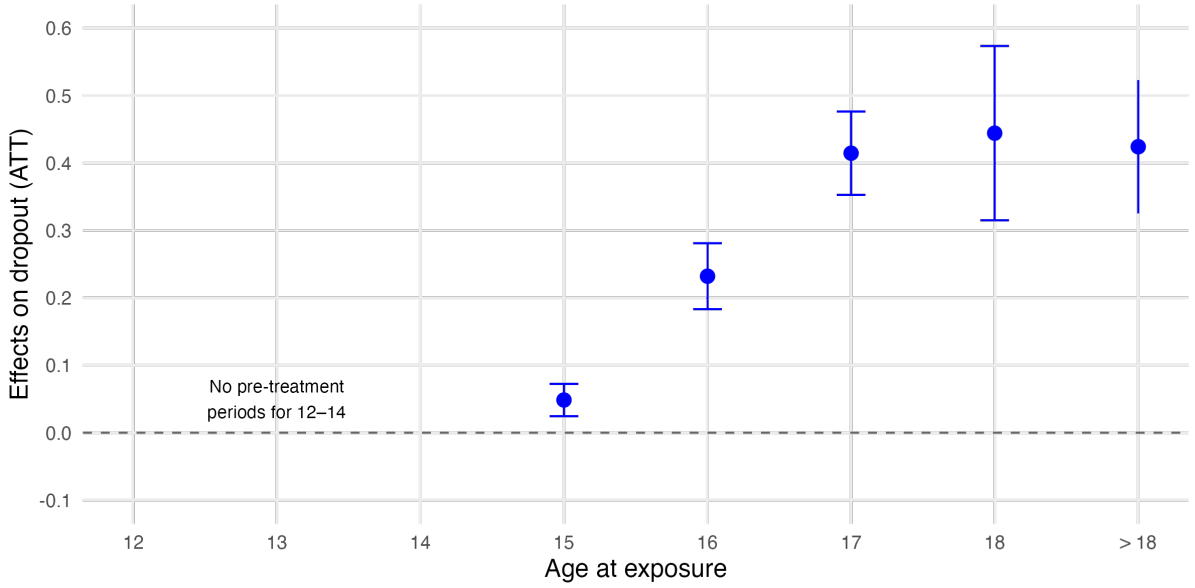
Notes: This figure presents event study estimates for the effect of classmate homicide on overall juvenile detention using the Callaway and Sant'Anna (2021) difference-in-differences estimator decomposing by interaction intensity. Interaction intensity is defined as the number of times an individual shared a classroom with a homicide victim.

Figure 17: Effects on Juvenile Detention by Age Group



Notes: This figure presents estimates of the effect of a classmate's homicide on juvenile detention by age. Ages 12, 13, and 14 did not present sufficient data to allow estimation. The estimation does not include any controls. Estimates follow Callaway and Sant'Anna (2021), with 95% confidence intervals.

Figure 18: Effects on School Dropout by Age Group



Notes: This figure presents estimates of the effect of a classmate's homicide on school dropout by age. Ages 12, 13, and 14 did not present sufficient data to allow estimation. The estimation does not include any controls. Estimates follow Callaway and Sant'Anna (2021), with 95% confidence intervals.

6.3.3 Grade-Level Heterogeneity

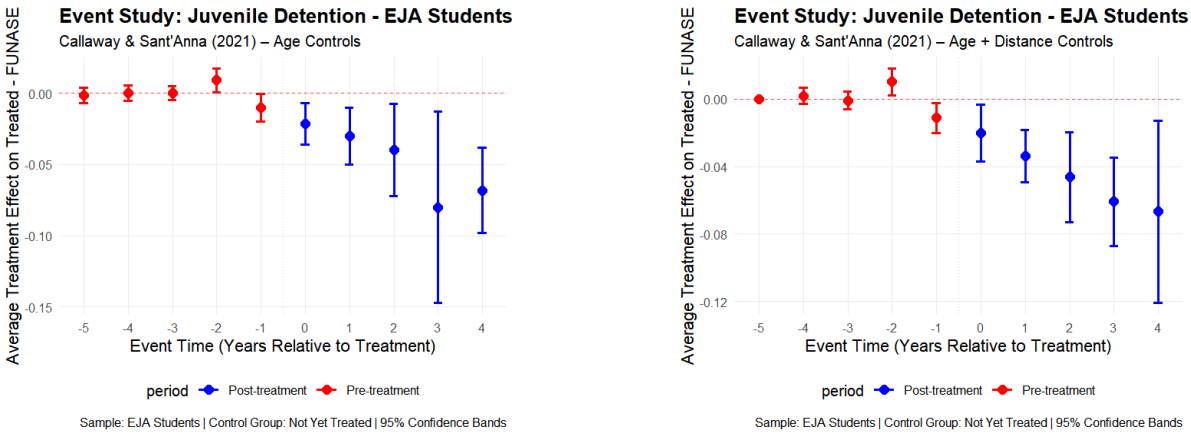
In Table 7, I focus on the decomposition by educational stage. Among 6th-8th-grade students, I find a significant reduction in detention only in the specification with distance controls. While the other specifications are smaller and statistically insignificant. EJA students show large and statistically significant reductions across all specifications. The estimates range from -0.0150 to -0.0479. I also do a test, restricting the sample to students aged 14-18. In this scenario, the estimates range between -0.0081 and -0.0133. Figures **??** and **??** show the event studies. As discussed in the previous section, older students face adult criminal penalties after 18, which may explain why EJA students show the strongest and most immediate reductions.

Table 7: 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 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 the 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.

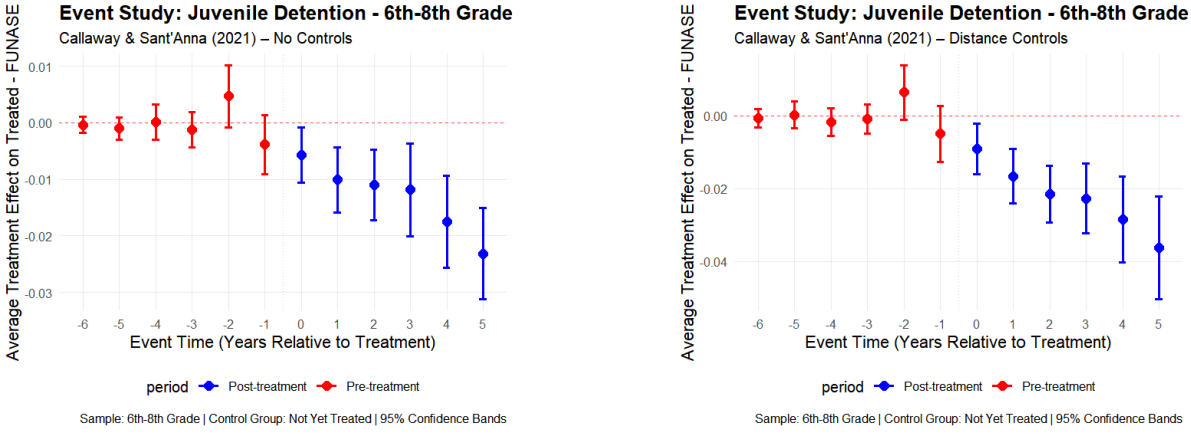
Figure 19: Effect of Classmate Homicide on Juvenile Detention for 6th-8th Grade Students



(a) Age Control (b) Age and Distance Controls

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. The figure presents confidence intervals at the standard 95% level, and these standard errors are 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.

Figure 20: Effect of Classmate Homicide on Juvenile Detention for Students Aged 14-18



(a) Without Controls (b) Distance Control

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. The figure presents confidence intervals at the standard 95% level, and these standard errors are 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.

6.4 Effects on School Performance: Evidence from Test Scores

In this section, I examine whether exposure to student homicides affects educational performance, as measured by standardized test scores. Unlike the previous analyses, which rely on individual-level panel data, this exercise cannot be conducted at the student level because test scores are not observed annually for each student. Instead, I exploit variation at the school level and estimate the impact of homicide exposure on average school performance. A school is considered treated if at least one enrolled student is a homicide victim during the observed period. This allows me to test whether peer violence also affects learning outcomes at the school level.

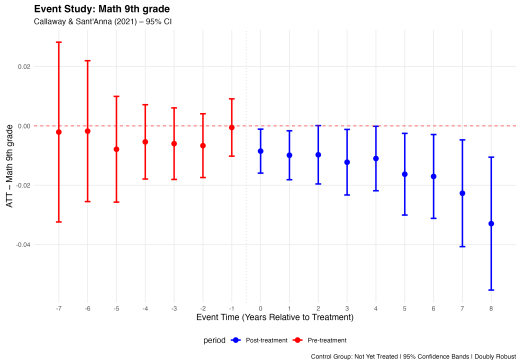
Table 8 presents estimates of the effects of exposure to a student homicide on school-level academic performance, as measured by standardized SAEPE test scores in mathematics and Portuguese. The analysis is conducted separately for 9th- and 12th-grade cohorts and exploits variation in exposure timing. Across all specifications, exposure to a homicide is associated with statistically significant declines in test scores. The effects are larger for older students. For 12th-grade cohorts, test scores decline by approximately 0.04 standard deviations in mathematics and 0.02 standard deviations in Portuguese. The estimated effects for 9th-grade students are still negative and significant, but smaller. Figure 21 presents event-study estimates of the impact of student homicide on school-level test scores, separately by subject and grade. For both mathematics and Portuguese in the 12th grade, as well as mathematics in the 9th grade, the coefficients become increasingly negative after exposure. The negative effects on learning grow over time. Pre-treatment coefficients are close to zero, consistent with the parallel trends assumption. However, the pattern for Portuguese test scores in the 9th grade is less clear.

Table 8: Effects on School Performance

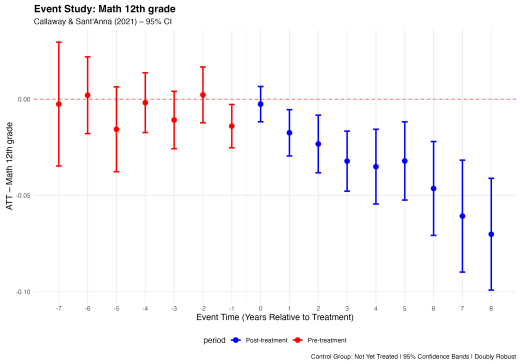
	9th Grade		**12th Grade**	
	Math	**Portuguese**	**Math**	**Portuguese**
	(1)	(2)	(3)	(4)
Overall ATT	-0.0156***	-0.0095***	-0.0355***	-0.0244***
	(0.0032)	(0.0033)	(0.0051)	(0.0046)
Controls	No	No	No	No
Observations	12,580	12,581	5,886	5,886
Schools	1,534	1,534	717	717
Years	2008–2017	2008–2017	2008–2017	2008–2017
Time FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes

Notes: This table reports average treatment effects on the treated estimated using the difference-in-differences approach of Callaway and Sant'Anna (2021). The treatment is exposure to a student's homicide. Outcomes are standardized test scores from the SAEPE assessment in mathematics and Portuguese for 9th- and 12th-grade students. All specifications include school and year fixed effects. Standard errors, shown in parentheses, are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

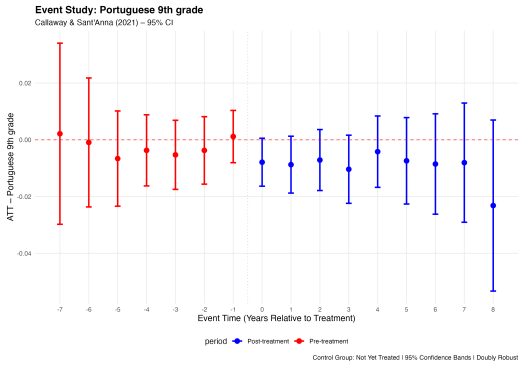
Figure 21: Effect of Student Homicide on Test Scores



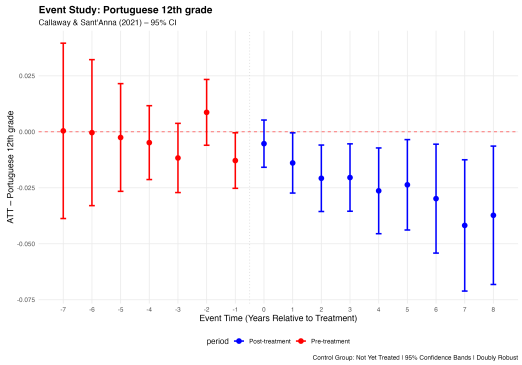
(a) SAEPE Math 9^{th} grade



(b) SAEPE Math 12^{th} grade



(c) SAEPE Portuguese 9^{th} grade



(d) SAEPE Portuguese 12^{th} grade

Notes: This figure presents event study estimates for the effect of student homicide on test scores for schools, using the Callaway and Sant'Anna (2021) difference-in-differences estimator. Red dots represent pre-treatment periods, and blue dots represent post-treatment periods. The figure presents confidence intervals at the standard 95% level, and these standard errors are clustered at the school level. The dependent variable is the standardized test scores from the SAEPE assessment in mathematics and Portuguese for 9th- and 12th-grade students.

6.4.1 Decomposition by the Intensity of Treatment

Table 9 explores whether the effects on school performance vary with the intensity of exposure to student homicides. The baseline estimates present similar effects to those reported before. The biggest changes are in the effect on the 9th-grade students. Where schools exposed to two homicide events show larger declines in mathematics and Portuguese scores than the baseline. Being present in more than three events is also associated with significant declines in 9th-grade Portuguese test scores. However, the situation is a bit different for 12th graders. The estimates across intensity categories are smaller and noisier, so it is hard to say that more exposure makes things worse for older students. Repeated exposure to homicides appears to add up the effects on school performance, especially in earlier grades.

Table 9: Effects of Student Homicide Exposure Intensity on Test Scores

	9th Grade		12th Grade	
	Math	**Portuguese**	**Math**	**Portuguese**
	(1)	(2)	(3)	(4)
Baseline	-0.0156***	-0.0095***	-0.0355***	-0.0244***
	(0.0032)	(0.0033)	(0.0051)	(0.0046)
1 time	-0.0043	-0.0022	0.0037	-0.0040
	(0.0052)	(0.0052)	(0.0091)	(0.0082)
2 times	-0.0245***	-0.0157*	0.0004	0.0044
	(0.0078)	(0.0093)	(0.0128)	(0.0095)
More than 3 times	-0.0078	-0.0186***	-0.0018	-0.0008
	(0.0060)	(0.0070)	(0.0066)	(0.0079)

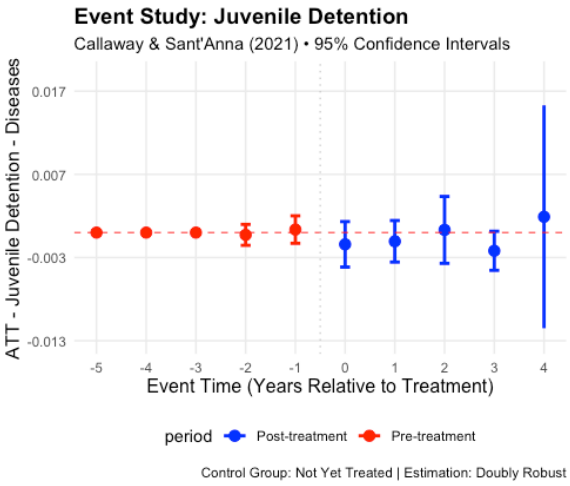
Notes: Each cell reports the overall ATT estimate by exposure group (Baseline, 1 time, 2 times, More than 3 times), based on Callaway and Sant'Anna (2021). All dependent variables are log-transformed standardized test scores (SAEPE). Standard errors are in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.5 Robustness Checks

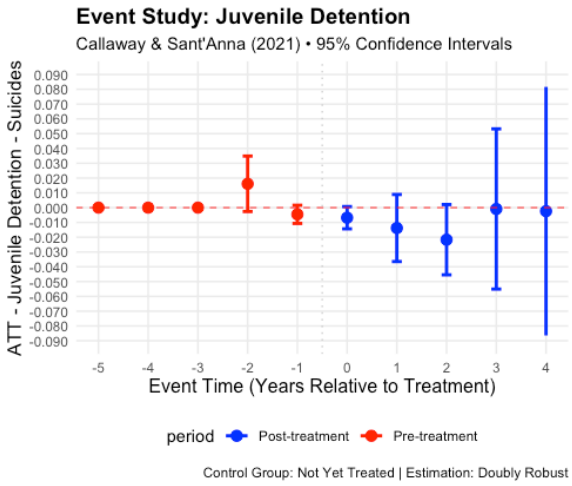
6.5.1 Alternative Treatment Definitions

If the effects I discussed in previous sections are driven by criminality, I should not find significant effects if I define my treatment with non-criminality-related deaths of students. First of all, in Table 10 I report the coefficients for the case where the treatment is defined using different types of classmates' deaths that are non-homicides. I then estimate effects for female students separately, since girls are rarely the target of juvenile justice actions. In all placebo scenarios, the estimated effects on juvenile detention are small and statistically insignificant. The reduction in detention I find in the main analysis does not appear when a classmate dies from disease, suicide, or a traffic accident. It is specific to homicides. Figure 22 plots the dynamic event-studies estimates for these alternative shocks, and they are generally non-significant. The only exception is undetermined causes of death, which yield a small but significant positive effect. This category may include misclassified homicides, which could explain the result. Figure 23 shows the event study for female students. As expected, there are no significant effects. Girls are less often in juvenile detention and less exposed to peer violence in this setting.

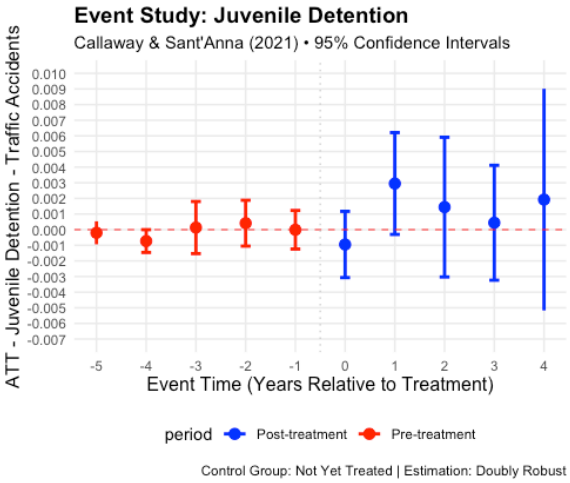
Figure 22: Robustness Check: Effect of Classmate Homicide on Juvenile Detention - Estimates by Alternative Deaths Shock



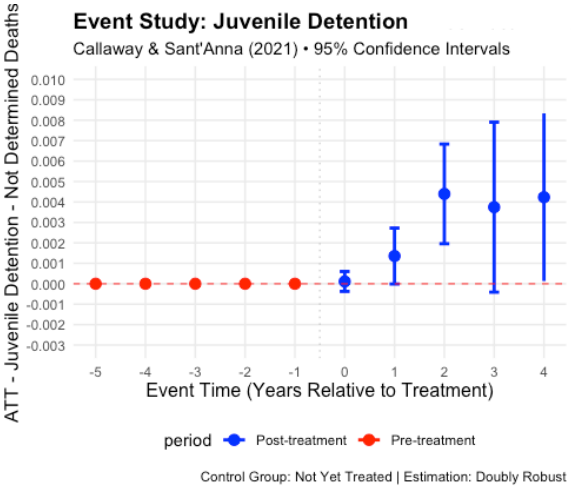
(a) Diseases



(b) Suicides



(c) Traffic accidents



(d) Not determined deaths

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, and Panel (D) for undetermined deaths.

6.5.2 Robustness to Spatial Spillovers

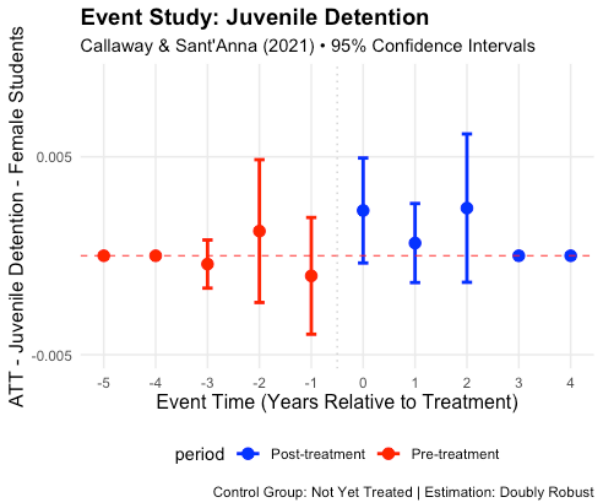
Next, I also test for potential spatial spillover effects across nearby non-treated schools. When schools are close to each other, students could be indirectly exposed to violence at a neighboring institution, which could bias the coefficients. In Figure 24, I redefine the treatment year to account for earlier homicides at schools within a 500-meter radius. If school A experiences a homicide in 2013 but is within 500 meters of school B, which had a homicide in 2010, then school A is assigned the 2010 treatment year. When multiple nearby schools experience homicides, I assign the earliest year. Panel (a) has no additional controls. Panel (b) adds controls for the age difference between the victim and the students.

Table 10: 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 and Sant'Anna (2021). Standard errors (SEs) are shown in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1.

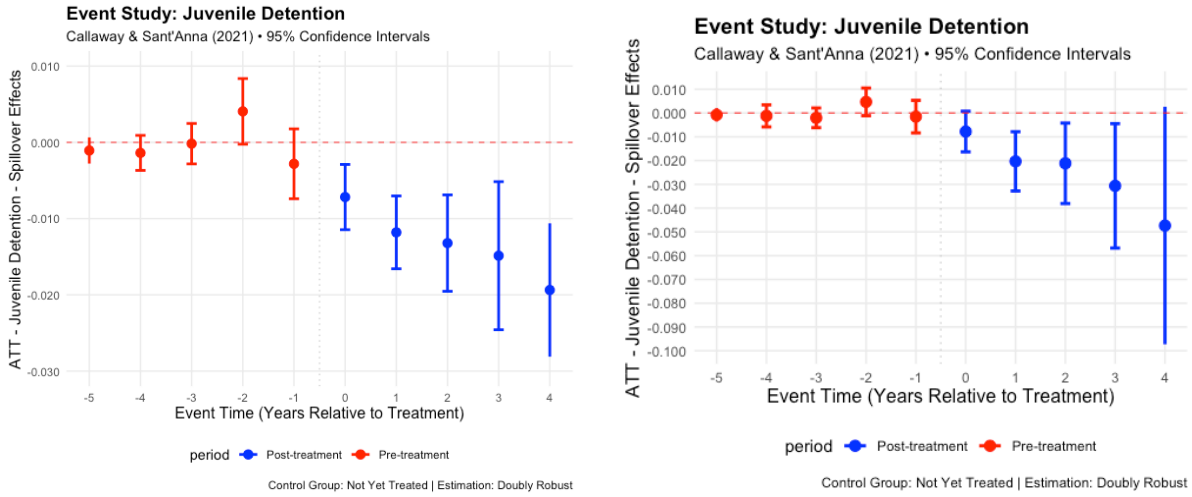
Figure 23: Effect of Classmate Homicide on Female Juvenile Detention



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.

The estimated effects are significant and similar in size in both panels, so accounting for nearby homicides does not change the results. In Figure 25, I take never-treated schools and reclassify them as treated if they are within 500 meters of a treated school, assigning the treatment year based on when the homicide occurred at the nearby school. I find no significant effects on juvenile detention under this approach. Just being near a school where a homicide happened, without a classmate being killed, has no effect on detention. Together, these exercises show that the results are driven by direct exposure to a classmate's death, not by geographic proximity to violence.

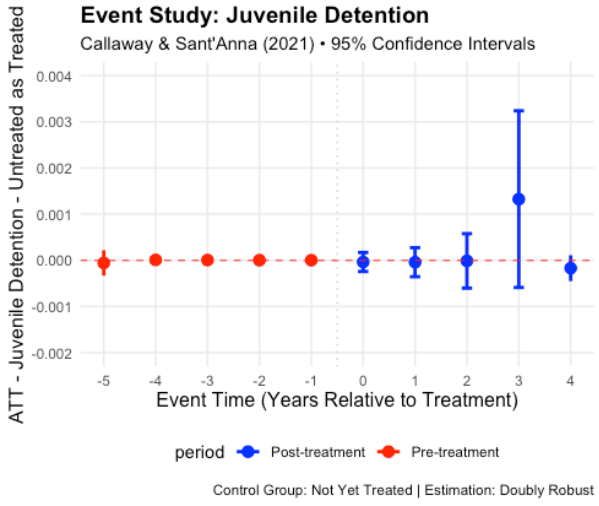
Figure 24: Effect of Classmate Homicide on Juvenile Detention Considering Potential Spillover Effects



(a) No Controls (b) Age Control

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.

Figure 25: Effect of Classmate Homicide on Juvenile Detention Considering Never-Treated Schools as Treated

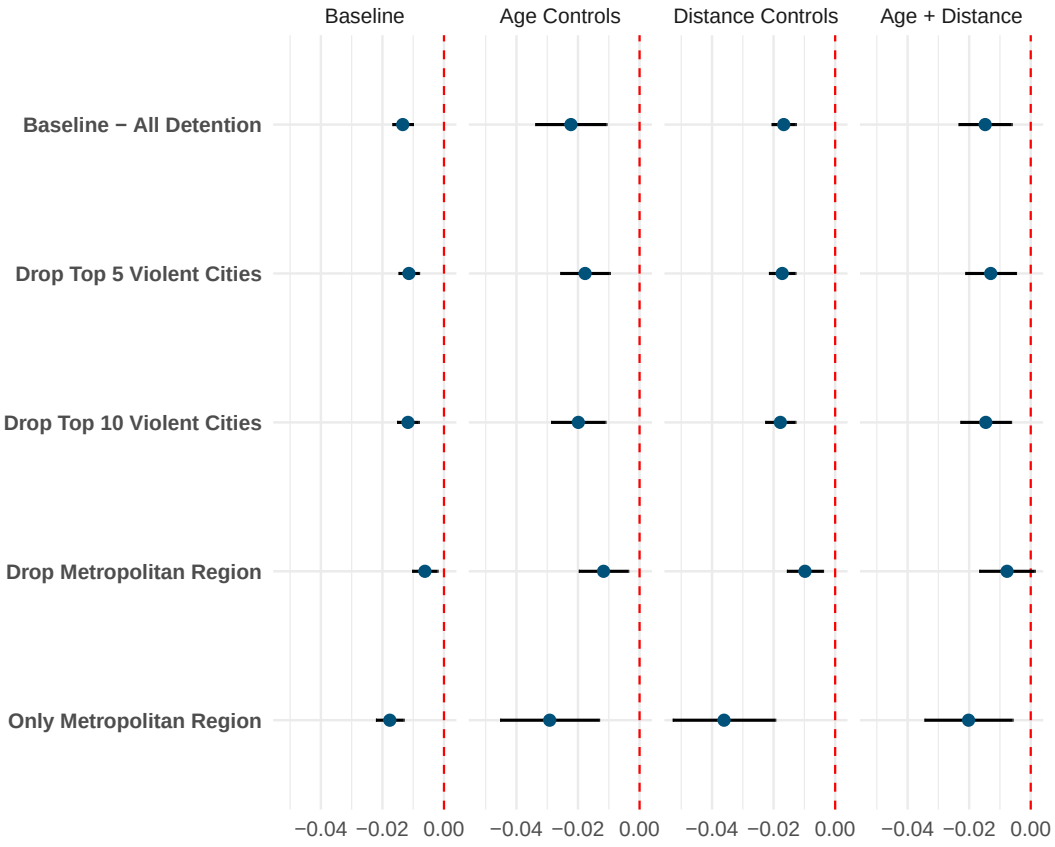


Notes: Event-study estimates for male students attending schools located within 500 meters of another school that had a student who was murdered. Panel (c) does not include any control. Estimates follow Callaway and Sant'Anna (2021), with 95% confidence intervals with standard errors clustered at the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

6.5.3 Robustness to Sample Restrictions

Another concern is that a few highly violent municipalities or the Metropolitan Region may be driving the estimates. To deal with this problem, I re-estimate the regression under different sample restrictions, progressively excluding the most violent cities and the Metropolitan Region, and also estimating the model for the Metropolitan Region alone. Figure 26 presents these exercises. Across all sample restrictions, the estimated effects are negative and similar in size to the baseline. The estimates are larger when the sample is restricted to the Metropolitan Region, which may reflect proximity to violence in urban areas.

Figure 26: Robustness of Treatment Effects to Sample Restrictions



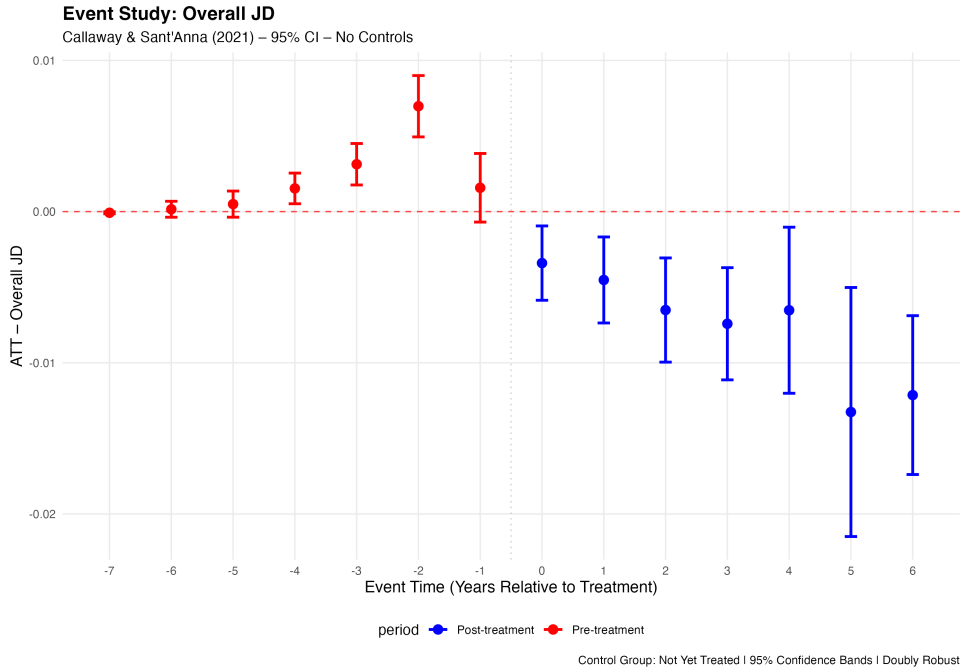
Notes: ATT estimates based on Callaway and Sant'Anna (2021). Treatment: classmate homicide. Columns (1)–(4) correspond to specifications without controls, with age difference (in months), with school–shock distance (in km), and with both controls, respectively. Standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1.

6.5.4 Alternative Control Group

Another concern with the baseline specification is that the control group only includes not-yet-treated students. To test whether this is the main driver behind all the significant results, I re-estimate the event-study, adding never-treated students, those never exposed to a classmate's homicide during the sample period, to the control group. This control

group is not ideal. Never-treated students may differ from treated students in unobserved ways, which weakens the parallel trends assumption. The pre-treatment coefficients are aligned with this, showing evidence of differential trends before exposure. Still, Figure 27 shows that the post-treatment pattern looks similar to the baseline. The effects are negative and persistent over time, though about half the size of the main estimates.

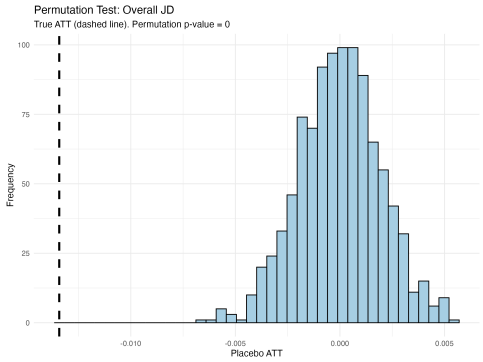
Figure 27: Robustness of Treatment Effects to Alternative Control Group



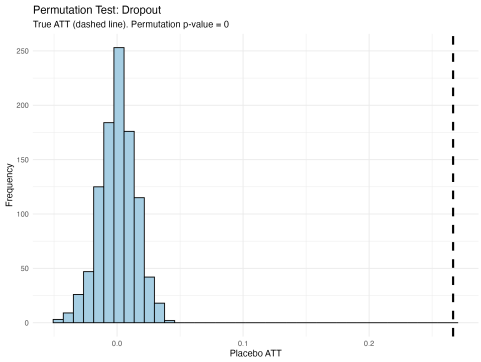
Notes: ATT estimates based on Callaway and Sant'Anna (2021). Treatment: classmate homicide. The control group includes both not-yet-treated students and students who are never exposed during the sample period. Overall ATT: -0.0077 significant at 1%. Standard errors in parentheses. Significance levels: *** p <0.01, ** p <0.05, * p <0.1.

Finally, to ensure that the results are not driven by chance, I perform a permutation test by randomly assigning treatment timing for each student and re-estimating the model using the resulting placebo treatment. This procedure is repeated 1,000 times for each outcome. The empirical distributions of placebo coefficients are presented in Figures 28a through 28g. The true coefficients lie in the tails of the placebo distributions for juvenile detention, dropout, and all test scores (permutation p-value < 0.001), confirming that the estimated effects are very unlikely to be obtained by chance. Only the grade retention outcome has a p-value above 0.1.

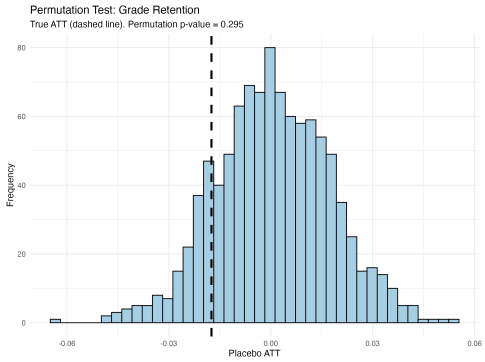
Figure 28: Robustness Check: Permutation Test



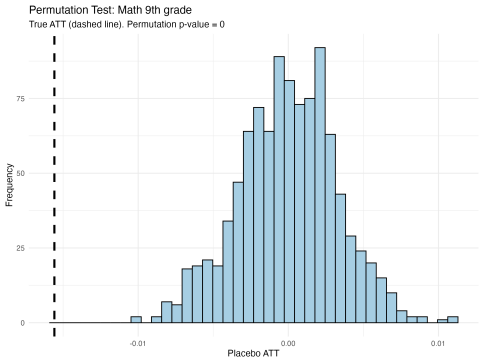
(a) Juvenile Detention



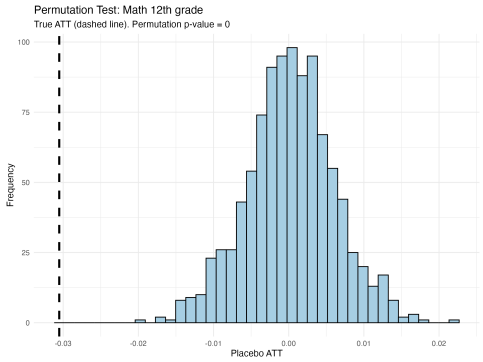
(b) Dropout



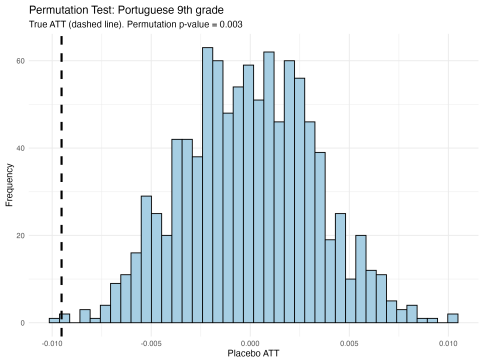
(c) Grade Retention



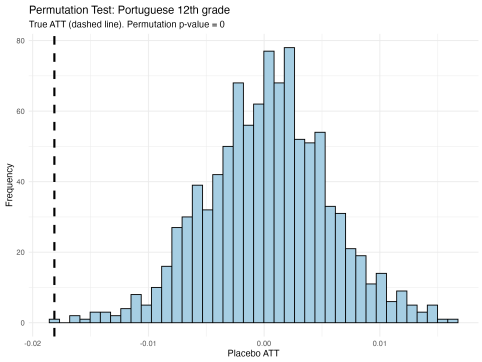
(d) Math 9^{th} grade



(e) Math 12^{th} grade



(f) Portuguese 9^{th} grade



(g) Portuguese 12^{th} grade

Notes: Each panel plots the empirical distribution of 1,000 placebo ATTs obtained by randomly reassigning treatment timing across students. The vertical dashed line marks the true estimate. Permutation p-values are computed as the share of placebo coefficients at least as extreme as the true estimate.

7 Conclusion

This paper provides novel empirical evidence on the responses of adolescents to peer violence by estimating the causal effect of a classmate's homicide on subsequent juvenile detention. I find significant reductions in juvenile detention following the murder of a classmate. Exposure to a classmate's homicide leads to a decline in detention of 1.48 percentage points, a 39% decrease relative to the pre-treatment mean. The effects are especially pronounced for drug-related crimes, violent crimes, and full-time detention. I also detect declines in recidivism, which suggests that the experience may alter long-run behavior for at-risk students. The results are also robust to different potential threats to identification. This paper also presents implications for policymakers. The student's deaths seem to deter crime by making its consequences more real. Then, programs focused on violence prevention education and support for high-risk schools may replicate this deterrent effect before it costs a life. Strategies that both prevent violence and support students exposed to it are needed.

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