

Another Brick in the Wall? The Educational Effects of Repurposed Mafia Properties

Victoria Biagi*

April 2026

Abstract

Italy's anti-Mafia legislation allows confiscated Mafia properties to be converted into educational, cultural, and welfare facilities where local NGOs offer various social activities specifically targeting the youth and other vulnerable groups. This study provides the first causal evidence on how exposure to these repurposed spaces affects students' dropout rates by changing their attitudes toward educational and criminal pathways. Using school-level geo-referenced data from 2015 to 2022 and exploiting the staggered timing of property repurpose, I investigate changes in local dropout rates. Results find a significant reduction in dropout rates of approximately 36% for students living near repurposed properties. I show that this policy reshapes students' beliefs, reducing the appeal of Mafia networks while increasing the value of formal education. The effects are not explained by gentrification, additional educational support, or civic engagement levels.

Keywords: Mafia; property; Italy; education; NGOs; perception; State.

JEL Codes: R23, H72, I25, K42.

Conflict of interest: None.

*University of Liverpool, Liverpool L69 7ZH, United Kingdom; Victoria.Biagi@liverpool.ac.uk. I would like to thank Giuseppe De Feo, Jakub Lonsky, and Balazs Murakozy for their guidance in the project. This paper has also benefited from the suggestions from Sonia Balhota, Jacopo Bregolin, Ian Burn, Enrico Cavallotti, Anand Chopra, Gianmarco Daniele, Giacomo De Luca, Ruben Durante, Rema Hanna, Abhinav Khemka, Gema Lax-Martinez, Noemi Mantovan, Giovanna Marcolongo, Olivier Marie, Bruno Martorano, Giovanni Mastrobuoni, Christian Morabito, Paolo Pinotti, Zachary Porreca, and several presenters met at the Women in State Capacity Conference (Oxford, 2025), NWSSDTP Doctoral Conference (Lancaster 2024), and the 9th Workshop on the Economics of Organised Crime (Edinburgh, 2025). Special thanks go to the confiscated assets director from the association Libera Tatiana Giannone and the NGO Centro Studi Pio la Torre which gave me great knowledge about the practices of reuse of Mafia properties, the context of Mafia strongholds, and allowed me access to their survey data. I thank the Italian Ministry of Education which helped me through the collection of my data as well. All the mistakes are mine.

1 Introduction

The detrimental effects of organised crime on education are well-documented, particularly in areas controlled by Mafia-type groups where these effects are highly localised. Juveniles can be directly recruited by Mafia affiliates, and also affected by criminal social norms and behavioural codes (van Dijk, Kleemans and Eichelsheim, 2019; Kleemans and de Poot, 2008). In Italy, Mafia groups have been shown to systematically distort youth’s aspirations about investing in education versus pursuing criminal alternatives (Acemoglu, De Feo and De Luca, 2020; Coniglio, Celi and Scagliusi, 2010; Caglayan, Flamini and Jahanshahi, 2017), prompting policymakers to develop targeted interventions for Mafia-affected communities. Among these interventions, the most significant is the Mafia Confiscated and Reallocated Assets Reuse Policy (CRR) implemented nationwide since 1996. Under this policy, the confiscated Mafia properties, former symbols of territorial control and criminal activity, are converted into educational, cultural and welfare facilities, where local NGOs offer various social activities specifically targeting young people and other vulnerable groups. These repurposed spaces aim to transform former Mafia strongholds into community assets that foster legitimate social bonds and provide alternative role models (Falcone, Giannone and Iandolo, 2016). The question remains, however, whether this symbolic transformation translates into measurable social and economic benefits for the youth. Existing case studies document positive effects on communities’ social participation and the educational value repurposed spaces (Nazzaro, 2021; Martone, 2020), while establishing that Mafia social bonds may prove resilient to these policy efforts. I address this empirical gap by documenting the evolution of repurposing practices and their subsequent impacts on educational outcomes.

In this paper, I construct a novel dataset and leverage the quasi-experimental variation in the timing and use of repurposed Mafia properties to provide the first empirical evidence on their impact on local education. Moreover, I investigate the mechanisms driving these effects by examining several potential channels. I focus on the ten main urban centres in historically Mafia-ridden regions, which concentrate the majority of confiscated Mafia properties¹. Young people’s educational outcomes tend to be especially low in these regions, with dropout rates reaching concerning levels: 14.6% in Campania and Apulia, and 18.8% in Sicily against a national average of 12.7% (Save The Children, 2022). Local NGOs or municipalities manage these repurposed properties to operate programs focused on education, culture, skills training, and social services, with 45% explicitly targeting the youth. In this setting I exploit the

¹The cities I investigate include Naples, Salerno, Bari, Taranto, Foggia, Reggio di Calabria, Palermo, Messina, Catania, and Siracusa. Focusing on the major Mafia-ridden urban centres allows me to leverage the necessary variation in Mafia real estate reallocation and repurposing practices.

staggered reuse of Mafia properties, conditioning on neighbourhood and municipality-level attributes.

I construct a novel dataset combining information scraped from the website *Confiscati-bene*, internal surveys from the anti-Mafia association Libera, and municipal records, alongside administrative data on the precise locations of confiscated properties and digitised Antimafia Investigative Directory maps measuring baseline Mafia presence. I further draw on Ministry of Education records covering high school enrolment, graduation rates, and student ages, NGO location data from the Ministry of Labour, survey data on students' attitudes toward educational and criminal pathways, and 2011 census data for baseline socio-economic characteristics.

To estimate the effect of this policy on educational outcomes, I employ a DiD design that compares educational outcomes in areas where Mafia properties are repurposed to those located in unaffected areas over the same period. My main outcome variable tracks dropout rates by following the same student cohorts across high school grades, which allows me to focus on students older than 16, which corresponds to the end of compulsory education age in Italy. This exercise allows me to measure students' dropout decisions when continued schooling becomes voluntary. Given the absence of official high school districts in Italy, I construct school catchment areas based on the distance between high schools and census blocks², defining them as treated if they contain at least one repurposed Mafia property and as control otherwise. In this setting, I estimate the average treatment effect on the treated (ATT) with traditional TWFE models as well as modern DiD estimators following [Sun and Abraham \(2021\)](#).

The implementation of social activities in former Mafia properties significantly reduces dropout rates by approximately 36% relative to the mean among students who have reached the age when formal education is no longer compulsory. This effect is consistent with previous research on the effect of the Mafia on education. [Caglayan, Flamini and Jahanshahi \(2021\)](#) find that Mafia presence reduces graduation rates by 25% in Northern Italy. Additionally, I test the intensive margin of the treatment, finding that the results are particularly strong where more than 1 property has been repurposed in the area. I use the count of reused properties rather than the binary treatment indicator and I employ the [de Chaisemartin and D'Haultfoeuille \(2024\)](#) estimator to account for dynamic treatment effects; I find that each additional confiscated property repurposed is associated to a 12% decrease relative to the mean³. The consistency across binary and continuous treatment specifications reinforces

²Census blocks are defined by the Italian Institute of Statistics and typically contain on average 200-400 inhabitants.

³Given that treated municipalities have an average of 2.22 confiscated assets, these estimates are remark-

confidence in the robustness of the intensive margin findings.

The heterogeneity analysis reveals two important patterns. First, the effects I estimate are particularly strong in schools underperforming across multiple domains at the baseline, including both students' performance in national standardised assessments, citizenship competences, the quality of the learning environment, and the local engagement with families and the broader community. This suggests that repurposing interventions are most impactful where institutional weaknesses are most pronounced and where the community environment created by property reuse can most meaningfully complement existing educational resources. Second, technical high schools emerge as the primary beneficiaries of the repurposing interventions, exhibiting sustained reductions in dropout rates that become statistically significant between years 2 and 4 post-treatment and persist throughout the observation period. This contrasts sharply with academic and vocational high schools, which display mixed and statistically insignificant effects. This heterogeneous pattern aligns with the distinct institutional contexts and student populations served by each educational track. Technical schools serve students who often come from backgrounds that value practical skills alongside academic preparation, making them particularly sensitive to localised improvements that enhance educational engagement. Unlike vocational students, who can enter the workforce after three years with a professional certificate, technical high school students are expected to complete the full five-year program, exposing them to a longer period of risk during which dropout becomes increasingly likely. Together, these two dimensions of heterogeneity point to a common mechanism: the enhanced community environment resulting from property reuse is particularly effective in supporting students who face the greatest structural barriers to completing their education.

Estimating the effects of the repurpose of former Mafia properties poses non-trivial challenges. The primary endogeneity concern is that repurposed properties may not be randomly assigned across schools and neighbourhoods, and their allocation could systematically reflect pre-existing differences in educational outcomes or local institutional capacity. Moreover, the multi-stage nature of the CRR policy, spanning confiscation, reallocation to local authorities, and eventual repurpose, raises the question of whether the estimated effects capture the repurposing itself or earlier stages of the process. To confirm that these concerns do not invalidate the results, I conduct a battery of robustness and placebo exercises. I first show that there is no evidence of pre-trends between treated and control schools, ruling out mean reversion as an alternative explanation; then I show that the effects are not driven by the reallocation stage prior to repurposing. I further verify that the treatment is not endogenous

ably consistent ($12\% \times 2.22 \approx 27\%$), providing strong evidence for a linear dose-response relationship where the intensity of reused activities matters proportionally for the magnitude of effects.

to the presence of NGOs, other municipality-level policies, or local rental prices in the years preceding reuse. Additionally, the results are robust to alternative catchment area definitions, the inclusion of municipality-level time trends, and spillover corrections. Sanity checks using future reuse and pre-16 dropout rates yield null effects.

My empirical analysis suggests that the key mechanism is that the repurposing activities provide legitimate role models and opportunities, redirecting youth perceptions from criminal influences toward education in previously Mafia-controlled areas. Survey data on student perception reveal that after their area receives treatment, the students increasingly have a negative view of the Mafia; I perform sentiment analysis over the students' definitions of the Mafia, finding that their language becomes positively correlated with sentiments of fear and negatively correlated with feelings of joy. Simultaneously, students increasingly perceive education and participation in competitive examinations as viable pathways to local employment, while viewing Mafia and political connections as less instrumental for career advancement. These effects are strongest among students from lower socioeconomic backgrounds, consistent with the interpretation that repurposed properties alter the trade off of the youth who would otherwise face more barriers to legitimate career advancement. These findings complement anecdotal evidence from (Nazzaro, 2021; Falcone et al., 2016) gathered through interviews about the potential effects of the repurposing activities on young people. Meanwhile, I find that the treatment effect does not vary with the level of neighbourhood rental prices and thus is unlikely to be driven by gentrification processes. The presence of local NGOs does not mitigate the effect, indicating that activities in repurposed Mafia properties are not easily substitutable by other social and educational programs. Notably, the effect is not driven by properties specifically offering after-school and homework-support activities, but is stronger for properties hosting welfare and cultural activities.

To the best of my knowledge, this is the first paper providing causal estimates on the effects of the repurpose of Mafia properties on local education and social outcomes. Prior research established that the confiscation of Mafia properties increases the prices of commercial real estate located nearby as well as firms' performance, turnover and local market competition (Calamunci, Ferrante and Scebba, 2022; Calamunci and Drago, 2020; Ferrante, Fontana and Reito, 2021a; Operti, 2018). Moreover, the reallocation of such properties increases both market and electoral competition (Ferrante et al., 2021a; Ferrante, Reito, Spagano and Torrisi, 2021b). Boeri, Di Cataldo and Pietrostefani (2023) examines neighbourhood-level effects of Mafia properties' confiscation and reallocation on housing prices. Their findings indicate that while confiscations lead to a decline in nearby housing prices, reallocation drives their increase. I take a step forward from these works in two key directions. First, I leverage the staggered effect of the reuse of Mafia properties, demonstrating how this process translates

policy into action by providing social activities, unlike reallocation, which remains a purely bureaucratic step. Second, I explore the impact of these activities on educational outcomes and the students' social outcomes, an area that has been entirely unexplored until now. For this purpose, the creation of a novel database of the reuse practices of Mafia properties represents an essential contribution. Furthermore, this paper builds on the insights of [Nazzaro \(2021\)](#) and [Martone \(2020\)](#), who offer qualitative case studies on the social effects of reusing Mafia properties in Apulia and Campania, respectively. These studies focus on outcomes related to education and the labour market, enabling me to identify credible mechanisms behind the effects I estimate.

Second, I contribute to the extensive literature investigating the relationship between neighbourhood-specific factors and human capital accumulation. Previous studies from [Ludwig, Duncan, Gennetian, Katz, Kessler, Kling and Sanbonmatsu \(2013\)](#), [Chetty and Hendren, 2018](#)), and [\(Bergman, Chetty, DeLuca, Hendren, Katz and Palmer, 2024\)](#) show that community environment profoundly shapes children's educational trajectories and life outcomes. These studies have been typically focused on poverty, segregation, or physical neighbourhood quality. My contribution shows that public policies reshaping the institutional and social environment can make education a more viable pathway for the local youth. This extends our understanding of neighbourhood effects to contexts where criminal governance is a key social barrier to human capital investment.

Last, this study provides new evidence on how educational and social activities shape juveniles' perceptions of future opportunities, ultimately influencing their choices and life trajectories. Prior work in experimental economics shows that localised, tailor-made programs can play a transformative role not only in improving educational outcomes but also in reducing crime ([Heller, Shah, Guryan, Ludwig, Mullainathan and Pollack, 2017](#); [García, Heckman and Ziff, 2019](#)), as well as in strengthening students' interpersonal trust and self-esteem ([Kenney and Godson, 2002](#)). Other studies highlight how targeted policies can counteract parental incentives to involve children in illegal markets, thereby reducing pathways into criminality. For instance, Conditional Cash Transfer (CCT) programs increase the opportunity cost of a criminal career and enhance the relative benefits of pursuing education ([Sviatschi, 2022a,b](#)). This study advances the literature by focusing on Mafia-ridden areas as a novel setting, showing how educational and social programs can alter juveniles' beliefs about the trade-offs between illicit involvement and educational opportunities.

This paper offers important policy implications for the future of youth living in Mafia-affected communities. First, the results show that this policy effectively provides alternative role models, shaping students' information sets, expectations, and beliefs in areas where the Mafia has long-standing social influence. By acting as a credible signal that legitimate op-

opportunities exist within their own communities, the policy alters youth perceptions of the returns to education relative to criminal involvement, and shapes decisions regarding career advancement in contexts where simple educational support may not be sufficient. While leaving school does not necessarily lead students to join the Mafia, redirecting youth trajectories proves particularly significant in such environments. Second, the paper underscores the importance of not only confiscating Mafia properties but ensuring their active and sustained repurpose for social activities. This paper shows that confiscation prove insufficient, while it is the repurposing of these properties into spaces for community engagement that drives the estimated effects. Increased governmental funding for these initiatives, along with greater recognition of the local NGOs working to renovate Mafia-affected areas, would contribute substantially to improving educational outcomes for local youth. Notably, the heterogeneity results reveal that the policy is most effective precisely where it is most needed: among students attending technical and underperforming schools, and in more deprived areas where young people face the greatest structural barriers to legitimate career advancement. In this sense, the policy operates as an equalising force, targeting its benefits toward those with the fewest alternatives.

The remainder of the paper is structured as follows: Section 2 illustrates the relevant institutional background, while Section 3 frames the conceptual framework that informs the key mechanisms. Section 4 describes the data, while the empirical strategy is developed in Section 5; in Section 6, I present the results articulated in the main results and robustness checks. The mechanisms are detailed in Section 7. Finally, Section 8 summarises the conclusions and introduces the policy implications related to the main findings.

2 Institutional background

In this section, I first introduce the institutional framework of the Mafia Confiscated and Reallocated Assets Repurpose Policy (CRR) in Italy; second, I provide an overview of the current repurpose practices of Mafia properties in Italy, their scope, and their main beneficiaries.

2.1 The Mafia Confiscated and Reallocated Assets Repurpose Policy (CRR) Policy

Mafia groups have been playing a substantial role in affecting Italy's economy and social development for more than a century. As criminal syndicates, Mafia groups mainly reinforce

their power through the accumulation of both economic resources and social consensus (Sciarrone, 1998). The economic sources of Mafia power were historically neglected until 1982,⁴ when the politician Pio La Torre and the Minister of the Interior Virginio Rognoni drafted a Bill to target the Mafia's economic assets. In 1976, Pio La Torre described the purpose of their effort stating that

The path of simple repression - which strikes at the outgrowth, but does not change the economic, social and political humus in which the mafia has its roots - did not and could not lead to definitive results.

In September 1982, after Pio La Torre was murdered by the Sicilian Mafia, the Bill he proposed passed and became the main turning point in the Italian fight against the Mafia. The law introduced two key innovations: first, it established Mafia association as a crime under the article 416-bis, making Mafia groups directly liable for specific criminal activities⁵; second, since Mafia families' economic assets serve to reinforce their criminal sovereignty (Operti, 2018; Mosca, 2017), the La Torre-Rognoni law strategically enforced the confiscation of these symbols of power. By targeting criminal assets, this Bill was intended to send a clear message to local populations: the State is stronger than the Mafia and can hinder its economic resources.

Yet, the Rognoni-La Torre law did not provide any regulations for the management of the confiscated Mafia assets, especially real estate and land properties (Menditto, 2013; Nazzaro, 2021). In 1995, after an intense period of Mafia killings, several CSOs reacted against Mafia groups by joining a new Italian network to counter the Mafia: *Libera. Associazioni, nomi e numeri contro le mafie*. *Libera* proposed law - the Law 109 of 1996 - to allow confiscated Mafia properties to be reused for urban and social recovery, specifically targeting the most Mafia-infiltrated areas (Nazzaro, 2021; Falcone et al., 2016). This proposal represented a significant shift from repression-oriented anti-Mafia policies toward policies aimed at compensating local communities and providing alternative role models for the local population. *Libera* and the NGOs part of such a network put into practice the beliefs of the Sicilian judge Paolo Borsellino, who was murdered by the Sicilian Mafia in 1992:

The fight against the Mafia must first and foremost be a cultural movement that accustoms everyone to smell the beauty of the fresh scent of freedom, which is opposed to the stench of moral

⁴Some preventive measures against people connected to Mafia groups have been previously introduced in 1965 through the Bill 575/1965: *Provisions against mafia-type criminal organisations, including foreign ones*. These measures only targeted criminals without addressing the management of their economic assets.

⁵The Rognoni-La Torre bill (n. 646 in 1982) stated that "Anyone who is part of a Mafia-type association consisting of three or more persons shall be punished by imprisonment from three to six years. Those who promote, direct or organise the association are punished with imprisonment from four to nine years."

compromise, indifference, contiguity and therefore complicity.

Following the formulation of Law 109/1996, a standardised procedure for repurposing confiscated Mafia properties was established under the CRR policy. As shown in Figure 1, such policy consists of three main phases: first, Mafia families are arrested as the outcome of antimafia investigations, and their properties confiscated upon conviction; second, the ANBSC⁶ determines how confiscated properties are repurposed, allocating them either for institutional use (properties are retained by the State or assigned to law enforcement agencies) or for social purposes (properties get transferred to local authorities). Local NGOs or local municipalities then use properties designated for social purposes to carry out cultural and social activities.

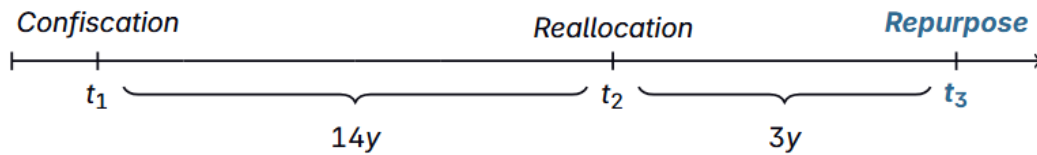


Figure 1 The CRR policy timeline

Figure 2 shows the number of confiscated, reallocated, and repurposed properties in the historically Mafia-ridden municipalities in my sample. Confiscations and reallocations begin rising from the 1990s, while repurposing practices, first established in the late 1990s, increase dramatically in the late 2010s. On average, it takes 14 years for confiscated Mafia properties to be effectively reallocated, and a further 3 years for them to be repurposed once reallocated. This staggered timing between reallocation and repurposing allows me to disentangle the two effects and assess whether the effects I measure are driven by the reallocation of properties or by their active repurposing.

⁶The National Agency for the Administration and Destination of Properties Seized and Confiscated from Organised Crime (ANBSC) is an executive body which determines how to repurpose confiscated assets, with decisions aimed at compensating local communities. Being a direct government agency, its operations are monitored by the Court of Auditors (ANBSC, 2019).

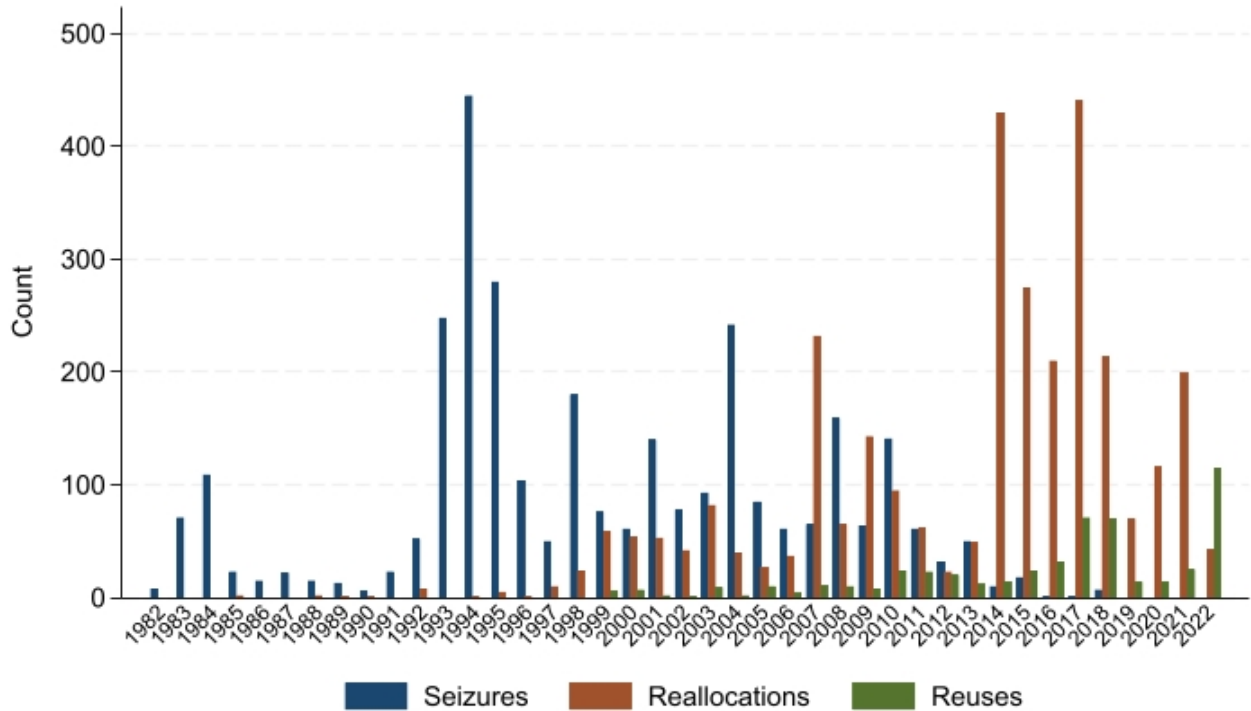


Figure 2 Number of confiscations, reallocations and reuses from 1982 to 2022

2.2 The importance of reurpose practices

In this paper, I focus on the final step of the CRR policy: the effect of repurposing confiscated Mafia properties for social activities. While existing literature demonstrates that the reallocation of Mafia properties affects several economic outcomes, such as housing prices and market concentration (Boeri et al., 2023; Ferrante et al., 2021b), a critical gap remains in two main directions: first, in evaluating the effective social reuse of these properties, second, in assessing the social outcomes of these practices (Ferrante et al., 2021a). From a conceptual standpoint, the administrative transfer of properties from the ANBSC to local municipalities represents merely a bureaucratic procedure. Although this transfer may signal the clear removal of Mafia control, it does not constitute tangible social renewal of the local social fabric (Falcone et al., 2016).

In this context, the distinction between the reallocation and the repurpose phases is crucial. Once reused, the property previously owned by the Mafia families transforms into public spaces and community centres managed by local NGOs. These spaces serve as hubs for social activities, youth programs, and community development initiatives, involving direct

citizen participation by promoting trust, social cohesion, and sustainable local development (Nazzaro, 2021; Falcone et al., 2016). Residents of all ages participate in recreational and educational activities aimed at reclaiming neighbourhood spaces, rebuilding social bonds, and fostering anti-Mafia resilience. The properties hold particular educational significance as centres that represent safe spaces for young people during after-school hours and weekends, with participants often sharing their positive experiences in schools and throughout the wider community (Nazzaro, 2021). The transformative power of the repurpose activities is perhaps most strikingly demonstrated by the behaviour of Mafia affiliates, as they frequently attempt to occupy or vandalise their former properties, revealing their deep concerns about the potential for these spaces to start serving the community’s benefit (Italian Ministry of Justice, 2018).

3 Conceptual framework

In this section, I develop the conceptual framework motivating my empirical analysis. I first draw on the opportunity cost framework from the economics of crime and education literature to explain how Mafia presence shapes juveniles’ educational incentives, particularly in historically Mafia-ridden neighbourhoods. I then review existing evidence on how Mafia groups leverage their properties to sustain juvenile recruitment and establish alternative authority structures. Finally, I examine qualitative evidence from NGOs operating in repurposed Mafia properties to illustrate how their activities may shift juveniles’ beliefs about the returns to education. Rather than presenting formal model predictions, this section aims to motivate the economic mechanisms underlying the estimated treatment effects.

Building on the crime choices literature, which extends the work from Becker (1968) on the trade-offs between crime and education (Lochner, 2004, 2011; Lochner and Moretti, 2004; Machin and Meghir, 2004), I discuss how students weigh investing in education against joining Mafia networks. This trade-off depends on the legitimate educational pathways available when individuals face such a choice relative to the perceived benefits and social status offered by Mafia affiliation. I argue that the repurpose of Mafia properties creates a local shock to the perception of the Mafia, altering the opportunity cost of this trade-off in favour of education. On the one hand, individuals face the choice between pursuing education and joining Mafia activities, with Mafia affiliation involving both legal risks, such as the probability of arrest, and unobserved factors, such as risk preferences. Crucially, Mafia groups offer not only monetary returns but also non-monetary benefits such as local power, reputation, and social status, which are essential for maintaining their territorial and social control (Gambetta,

1993; Sciarrone, 1998).

On the other hand, young people living in areas dominated by the Mafia often view the Mafia as a viable path to success, with powerful bosses serving as role models (Caglayan et al., 2017). The absence of legitimate opportunities reinforces Mafia’s appeal, making Mafia affiliation appear as a reliable pathway for career advancement (Catozzella, 2011; Balestrini, 2004).

Anti-Mafia policies can alter the cost-benefit calculation of joining the Mafia. Since Mafia strength relies heavily on social consensus, civil society interventions can effectively erode this accumulated power (Arlacchi and Chiesa, 1987). Repurposing confiscated properties for social use directly targets one of the key functions these assets serve within Mafia organisation: that of *positional goods*, namely visible symbols of territorial control and legitimacy (Hirsch, 1976; Baldascino and Mosca, 2012). By acting as tangible manifestations of power and wealth, these properties help Mafia families project authority and maintain their role model status within local communities (Mosca, 2017). Their conversion into community spaces readdresses this symbolic economy, undermining the Mafia’s capacity to present itself as a legitimate and aspirational force. While the reuse activities might not affect the monetary gains of joining the Mafia, which are mostly affected by the confiscation of the Mafia’s properties, they directly undermine the Mafia-related non-monetary benefits by transforming symbols of their dominance into community-led social amenities. This weakens the Mafia’s social control and reduces the appeal of joining their networks.

Through what mechanism does the repurposing of such properties weaken the social influence of Mafia networks? The effect is likely to operate through several channels, which I discuss in greater detail in Section 7. First, the concentration of repurposed properties in specific urban areas may improve overall neighbourhood conditions and stimulate local economic activity (Datcher, 1982; Ludwig et al., 2013). Second, the educational support programs offered by local NGOs — such as after-school and weekend initiatives — may themselves be the primary driver of the estimated effects (Heller, 2014; García et al., 2019). Third, and perhaps most symbolically, transforming former Mafia properties into community spaces may shift public perceptions of the Mafia’s strength and legitimacy: when properties that once served as visible symbols of criminal power are reclaimed by civil society, they may generate renewed social capital and erode the Mafia’s authority in the eyes of residents (Chiodo, 2021; Mosca, 2017; Heller et al., 2017).

4 Data

4.1 Schools data

I use school-level data covering the public upper secondary schools in the major Italian urban areas with significant historical Mafia presence. School-level data were provided by the Italian Ministry of Education, allowing me to geocode each specific school’s location to cover the period from 2015 to 2022. The data present information about the number of students completing each academic year in each grade, graduating at the end of the educational cycle, as well as their age and gender. Additionally, the data provide information about the school-specific educational track: *Licei* or Academic High Schools focus on academic subjects and mainly prepare students to enrol in tertiary education, *Istituti Tecnici* or Technical High Schools provide a more practical and technical education, while *Istituti Professionali* or Vocational High Schools offer vocational training. From each track, we know students can specialise in different subjects; the specialisations offered to date count to 14 and are summarised in Table 1, as outlined by the Italian Ministry of Education⁷. The universe of possible high school tracks is described in more detail in Figure A1. To provide clarity to the analysis, I first omit schools that changed address across the years, unless they were relocated within the same specific census block⁸. Second, to reduce measurement error, I double-check that schools that merged at some point in the panel were located at the same address. Last, I exclude from my sample private high schools, which in the Italian context target a specific subgroup of the population and only represent 5% of the entire country’s enrollment preferences (ISTAT, 2021).

⁷The organisation of Italian high schools can be found online on the website of the [of Education \(2024\): Organisation of upper secondary education in Italy](#).

⁸As explained later in this Section, since the treatment is defined by aggregating census blocks into schools’ catchment areas, any change of the school’s location occurring within the same census block is insignificantly affecting my identification strategy.

Table 1 The types of high school tracks

HS Tracks	Description	Specialisations	Sample %
<i>Academic</i>	Provide students with the skills and knowledge for higher education in classical studies, scientific studies, linguistic studies, humanities, music, and fine arts.	6	0.411
<i>Technical</i>	Provide practical and technical skills related to key sectors such as administration, marketing, and industrial development.	2	0.371
<i>Vocational</i>	Provide vocational skills for industrial, commercial, and social development, as well as agricultural, maritime and hospitality skills.	6	0.101

Italian upper-secondary schools offer a five-year educational program spanning from grade 9 to grade 13. Students typically complete grade 9 in their first year at the age of 14 or 15, and graduate at grade 13 when they are 18 or 19, respectively. The Italian academic year begins in September, with all students born in the same calendar year enrolling together regardless of their month of birth. However, the successful completion of each academic year is measured in May. Figure 3 illustrates the expected age of enrolled students measured at the end of each academic year. Students born between January and May will be 15 years old when they complete grade 9 and 19 years old at the time of graduation, while those born between June and December will be 14 when they complete grade 9, and 18 years old at the time of graduation.

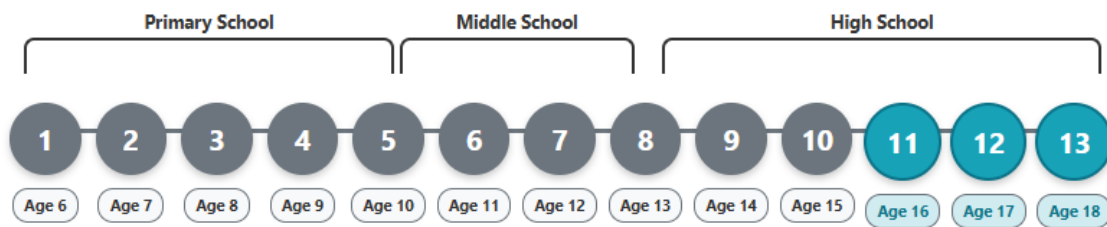


Figure 3 Each academic year starts in September and students born in the same calendar year get enrolled regardless their month of birth. The number of students who completed each academic year is measured in May. This Figure represents the scenario where students do not start school later and do not repeat any year.

Compulsory education lasts 10 years, from ages 6 to 16, creating a critical threshold for school attendance. Before the age of 16, students have limited discretion, making dropouts

very rare⁹. However, once students turn 16, they gain legal freedom to discontinue their studies. This legal framework leads to specific dropout patterns, which typically happen in the transition between the third and the fourth year of the upper secondary cycle, namely from grade 11 to grade 12. Indeed, as shown in Figure 3, after completing grade 11, all students are at least 16 years old. Existing empirical evidence support this pattern: in 2015, the Italian average rate of students dropping out from high schools before turning 16 was only 3.3%, while the rate of students who dropped out after turning 16 was 8.2%. Similar patterns persist over time: in 2022, just 2% of the students dropped out before turning 16, compared to 5.41% who dropped out after reaching this age threshold (ISTAT, 2023). This paper focuses on the dropout behaviour after grade 11 has been completed, specifically when all students are 16 or older and have gained the legal autonomy to discontinue their education. Educational decisions at this juncture are particularly sensitive to contextual influences, as students weigh the costs and benefits of continued schooling against immediate alternatives (Angrist and Krueger, 1991). This is precisely when local environmental factors exert their strongest influence on educational persistence (Oreopoulos, 2006). Transforming former Mafia properties into educational or community resources is likely to reshape students’ attitudes and beliefs during this formative stage, allowing me to distinguish the effects of reuse practices from the constraints imposed by earlier compulsory schooling.

The main outcome variable is the cumulative dropout rate among students aged 16 and older, calculated by tracking the same cohorts over time. I focus on transitions between grades 11 and 13, since this is when students typically turn 16 or older. The measure of dropout is built as follows: I track the number of students who completed grades 11, 12 and 13 in year $t - 1$ and measure how many of them completed grades 12 and 13 in year t . From this, I subtract those who graduated after completing grade 13 in time t . The remainder is then calculated as the share of the baseline cohort of students who completed grades 11, 12 and 13 in year $t - 1$.¹⁰ This share tells me how many students from the same cohorts

⁹In Italy, Law 296/2006 extended compulsory education from ages 6–15 to 6–16 and raised the minimum working age accordingly. Compliance is overseen by local authorities under Legislative Decree 297/1994: mayors track enrollment, identify non-attending students, and issue warnings, with persistent violations leading to legal action. As a result, leaving school before 16 is both legally prohibited and actively monitored, making it very unlikely for students to not attend school before turning 16 without facing institutional scrutiny within an entire academic year.

¹⁰Dropout in the final year, namely grade 13, is quantitatively negligible, as students who reach this stage have already demonstrated sustained persistence and are unlikely to leave before graduation. An additional concern is that this measure may capture exam-related attrition, namely students who complete grade 12 but fail or choose not to sit the final exam. To address both concerns, in Figure A2 I re-estimate the main specification using a narrower dropout measure that tracks only whether students who completed grade 11 in year $t1$ subsequently enroll in grade 12 in year t , and whether students who completed grade 12 in year $t1$ subsequently enroll in grade 13 in year t . This way the measure only captures the decision to continue or abandon schooling at each grade transition, without conflating voluntary dropout with failure to complete

successfully enroll in the following years after turning 16. The cumulative dropout measure is defined as follows:

$$D_{g11-13ct} = \frac{C_{g11-13ct-1} - G_{g13ct} - C_{g12-13ct}}{C_{g11-13ct-1}} \quad (1)$$

where D_{g11-13} represents the cumulative dropout rate for students aged 16 or above in year t for school catchment area c , C_{g11-13} represents the number of students enrolled in grades from 11 to 13 in year $t - 1$, G_{g13} is the number of students who completed grade 13 and therefore graduated in year t , and C_{g12-13} represents the number of students from the same cohorts who remain enrolled in grades 12 and 13 in year t . This approach ensures by construction that dropout rates reflect genuine dropout patterns from the same cohorts of students rather than demographic changes between different cohorts. By isolating graduation as a separate category, the measure also provides an accurate assessment of educational dropout that distinguishes between students who leave due to the successful completion of the five-year program versus those who drop out before finishing their studies. Moreover, to address the concern of students' migration and internal retention for grades 11, 12 and 13, I show in Section 5 that my results are robust while controlling for these factors. It is possible that students born between January and May turn 16 during grade 11 and drop out before its completion, meaning they would not be captured by my main outcome measure. This could lead to a downward bias, causing me to underestimate the true effect of the policy on dropout rates. However, Section 6 addresses this concern directly by estimating the effect of the policy on dropout rates across grades 10 to 13, thereby including these students. The results remain unchanged, suggesting that this source of bias is negligible in practice. Another concern is that changes in enrollment between grades 11 and 13 may partly reflect students transferring to another school rather than genuinely dropping out. However, the Italian Ministry of Education (2017) show that schools' transfers and other motivated exits account for only 6.4% of all student departures from upper secondary school, while 89.1% represent genuine unmotivated abandonment. This suggests that school transfers constitute a quantitatively minor component of enrollment changes, and that controlling for retention rates at grades 11 and 12, which absorbs the main driver of mobility, makes the estimated effects more plausibly reflecting genuine decisions to discontinue education.

the final high-school examination.

4.2 Mafia properties data

I create a novel database covering the universe of reused Mafia properties by scraping various institutional sources and collaborating with the Italian Antimafia Association *Libera*. The data collection represents a novel contribution to the literature, addressing previously fragmented sources that have never been systematically compiled and employed for empirical analysis.

I start the dataset construction from the list of reallocated Mafia properties released online by the ANBSC (2023). The data comprise a unique identifier for each Mafia property, the type of real estate, its usage before confiscation, the recipient and purpose of the reallocation, and the dates of confiscation and reallocation. I was able to geocode 3119 of the total count of 3667 Mafia properties ¹¹, with 42% and 41% of them being reallocated for social and institutional purposes, respectively. Crucially for my analysis, 66% of the properties have been reallocated to the jurisdiction of the nearest municipality, as only these properties can undergo the full transformation from confiscated Mafia properties to community resources. Finally, 83% of the reused properties are identified as housing estate - such as villas and flats - while the 10% consists of commercial and industrial estate, and the 12% of lands. Additional information about the attributes of repurposed properties which have been effectively repurposed is reported in Appendix B.

Second, I scrape information from the website *Confiscatibene*, which is managed by the Association *Libera* in collaboration with the ANBSC. On this platform, both *Libera* and several users update the current state of the properties, flagging whether they have been reused for any social activity. Additional information are provided about the description of the activities, and the name of the local NGO managing the property. In a few cases, the website also reports the year and the month when the reuse experience started. Since the website releases reuse-related information up to 2018, I collaborated with the *Libera* national managers of confiscated Mafia properties, who allowed me access to their yearly survey targeting the NGOs managing reused Mafia properties, giving me additional information about the reuse practices to date. Finally, to minimise missing information, I cross-referenced my data with the information shared by every single municipality about the current status of Mafia properties under their jurisdiction. ¹². Table B2 reports several attributes of the

¹¹The majority of the properties which I failed to geocode due to incomplete information represents lands in rural areas, which will less likely affect the dropout rates of the urban areas I investigate.

¹²According to the Art. 48 of the Antimafia Code (2011), municipalities are obliged to address transparency regarding the management of Mafia properties under their jurisdiction, and they are expected to share a monthly updated list of the properties and their current state of use. Data limitations imply that it is possible to have some missing information about some repurposed properties from municipal archives and *Libera's* website, implying that my measure of reused Mafia properties would likely be an undercount. Any resulting attenuation bias would suggest my estimates represent a lower bound of the true effect.

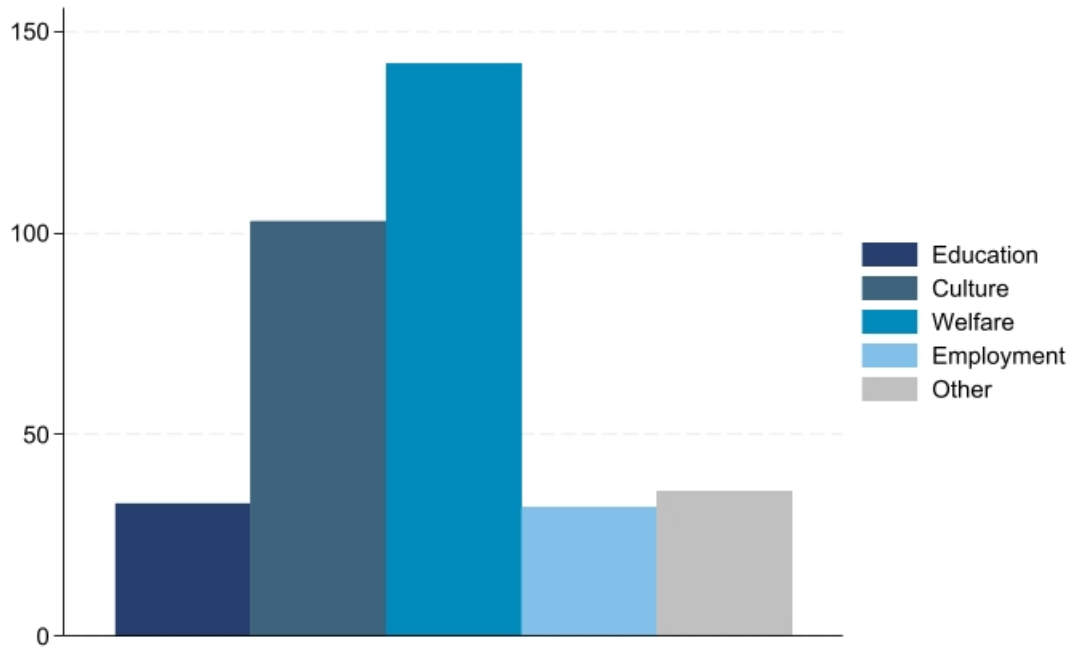


Figure 5 Repurpose categories

Table 2 The types of reuse activities described

Activity	Description	Reused Mafia properties %
Education	After-school activities and schooling support, socio-educational activities for at-risk juveniles	9.5%
Culture	Cultural activities to raise awareness about organised crime, the rule of law and self-responsibility	29.8%
Welfare	Places for housing emergency, activities to assist the homeless and people in need, social activities targeting vulnerable groups	41.1%
Employment	Support and training activities for unemployed people or fragile groups	9.2%
Other	Activities in the agricultural industries aiming to sell organic products and other	8.9%

4.3 Treatment allocation

Given the localised nature of the analysis, it is necessary to identify which students attend which school by linking their residential addresses and the schools' locations. To address this issue, I would need to employ student-level educational data, which are not easily released to the public. To systematically assign students to schools in the absence of formally defined school districts - a common challenge while using educational data - I build school catchment areas using an adapted distance-based location-allocation method. My approach follows established practices in the spatial economics analysis for defining catchment areas when administrative boundaries are unavailable (Pearce, 2000; Singleton, Longley, Allen and O'Brien, 2011). The main approaches to address this issue are either the use of weighted-Voronoi polygons, which address this issue from a geometric perspective, or the location-allocation method, which frames the problem in terms of student demand, based on the students' residential distribution, and school supply. Pearce (2000) shows that while the former offers computational simplicity, the latter performs better in predicting the dimensions of schools' catchment areas in real-world applications.

I construct school catchment areas following the location-allocation method in three main steps: first, I consider the Euclidean distance between each school and each residential census block to select the closest schools for each of them, which is the main factor influencing enrollment preferences (Mandic, Sandretto, García Bengoechea, Hopkins, Moore, Rodda and Wilson, 2017). The geometry of each census blocks is obtained from the 2011 Italian census data (ISTAT, 2011). Second, I differentiate catchment areas by educational specialisation sub-track, acknowledging that families' and students' choices also depend on the type of track offered and preferred. I ultimately created catchment areas for 14 distinct sub-tracks that map onto the three main tracks described in Table 2. Rather than imposing arbitrary distance constraints, the sub-track-specific assignment approach naturally determines appropriate catchment boundaries by ensuring each census block is matched to its nearest school within each educational specialisation. This method avoids the problem of unassigned blocks while acknowledging that students' choices are defined by program availability rather than arbitrary distance thresholds. I work with a total of 10556 census blocks, with an average area of 0.05 square kilometres, an average population of 200 individuals, of which 11.64% is aged 14 to 19. I compute 334 schools' catchment areas aggregating on average 580 census blocks per school ¹³. Each catchment area has an average population of around ten thousand individuals, with 570 individuals aged between 14 and 19 years old. Additionally, I construct a second set of school catchment areas where I account for the baseline number of students

¹³Because catchment areas are calculated for each school sub-track, the census blocks sum up only within each sub-track and not across the entire dataset

enrolled in each school. This approach captures the fact that students' allocation to schools depends not only on geographic proximity but also on school capacity. Appendix D provides the details of this procedure, while Section 6 presents the results according to this alternative construction method.

To define treated schools' catchment areas, I employ the precise address of each repurposed Mafia property, and I compute two main treatment measures: first, to investigate the extensive margin of the treatment, I create a dummy variable which is equal to 1 whenever at least one Mafia property has been repurposed within the boundaries of the school catchment area in a specific year. Areas which have been treated before the beginning of the panel are coded as always treated. Second, I compute an intensive margin measure as the count of the properties reused for each catchment area in each specific year; this measure provides a continuous treatment intensity measure that varies both spatially and temporally. To better control for demographic confounders, I additionally compute area-specific weights based on the local student population. As a robustness check, I weight each catchment by the average distance of repurposed properties from the population-weighted centroids of each school catchment area ¹⁴. These weighted measures capture both the localised nature of property reuse and the expected decay in its effect with distance from the treated sites (Boeri et al., 2023; Damm and Dustmann, 2014).

Figure 6 provides an ad-hoc example of how the catchment areas for each school track are computed. Each school, shown as a filled coloured circle, is assigned a set of census blocks based on the Euclidean distance between the blocks' centroids (grey dots) and each school. Each block is assigned to the nearest school for its specific school sub-track. The colored regions represent the resulting schools' catchment areas: School A (blue), School B (green), and School C (orange). The grey lines connecting each census block to its assigned school represent the relative Euclidean distance and allow to visualise the distance-based assignments. Figure 6 also shows the presence of repurposed Mafia properties within the catchment areas for a specific year, marked by the purple diamonds. School A serves as *control*, while Schools B and C are *treated* under the extensive margin of the treatment; notably, Schools B and C differ in treatment intensity, as two properties are reused within School C's catchment area, whereas only one property is reused within School B's catchment area.

¹⁴Population-weighted centroids are calculated by taking the weighted average of the coordinates of all census block centroids within each catchment, where the weights are the high school-age population (ages 14-19) in each block, resulting in a single centroid per catchment that reflects the spatial distribution of the residential student population

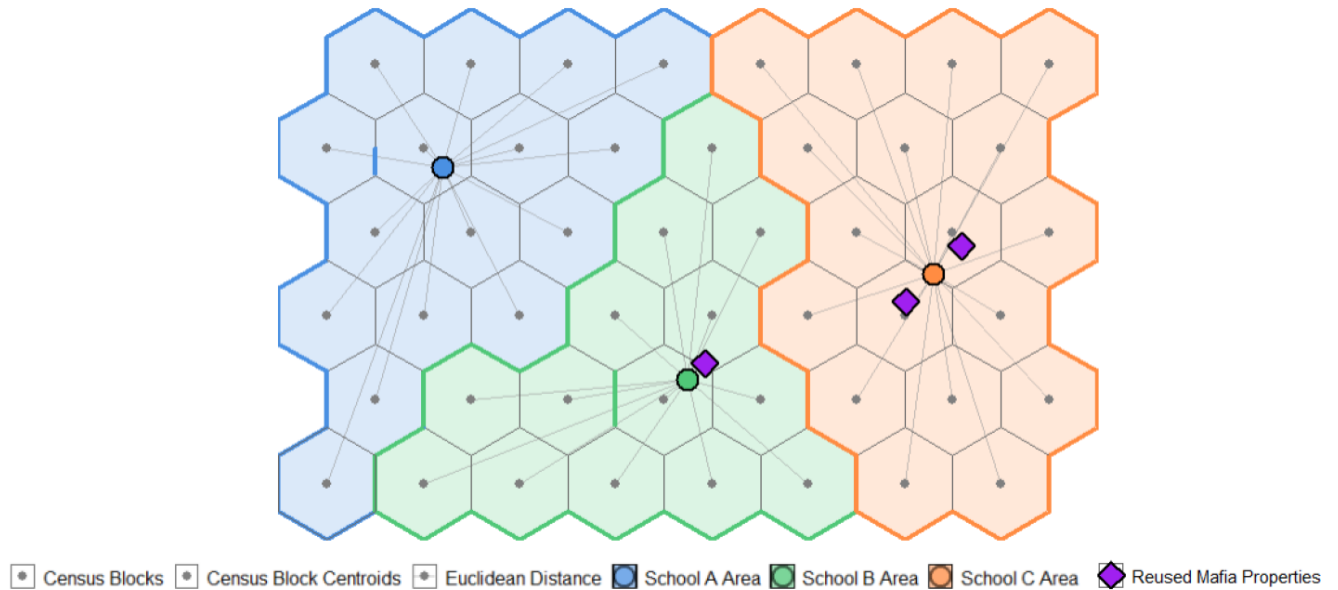


Figure 6 Ad-hoc example of schools' catchment areas construction

4.4 Survey on youth's perception of the Mafia

I employ survey data from the *Survey of the Perception of the Mafia* to investigate changes in the perception of the Mafia and its role in shaping youth's attitudes. The survey data are created and provided by the Sicilian NGO [Centro Studi Pio La Torre \(2025\)](#), targeting students enrolled from grade 11 to grade 13, roughly aged between 16 and 19. Some responses are aggregated at the school level, which I can identify with a unique code, while others provide a unique identifier per respondent. The survey, which spans from 2009 to 2024, is administered to students through a collaboration between the schools and the NGO. While this creates a selected sample, it allows me to directly test whether changes in the perception of the Mafia serve as a mediating channel for the treatment effect¹⁵. For this purpose, I focus on the answers collected from 2011 to 2022, a time frame for which consistent questions can be examined.

The students' questionnaire comprises a battery of questions focusing on several key dimensions of the perception of the Mafia: students' perception of the relationship between the State and the Mafia (V32), and their beliefs about whether the Mafia could be useful or not for career advancement (V28); moreover, student-level definitions of the Mafia are

¹⁵Results reported in Section 7 also account for the baseline quality of school performance and for students' socio-economic background to address any related concern.

provided (V12). Table A1 offers a complete list of the answers I employ. Considering the school-level answers, I create dummy variables for each specific option of the multiple-choice questions the students have been asked to answer. Regarding the student-level answers, I perform a simple text analysis and calculate sentiment scores for the words used by the students to describe the Mafia, which is further discussed in Section 7. I use these indicators to assess whether the reuse of Mafia properties leads students to change their perception and sentiments towards the Mafia and educational investments.

4.5 Other data

I collect information about the socio-economic conditions of the local community around the schools; understanding these contextual factors is crucial, as community socio-economic conditions can affect educational outcomes through multiple pathways.

I first collected information about rental prices from 2016 to 2022 from [Immobiliare.it](#) as a proxy for deprivation at the neighbourhood level; second, from the [National Registry of the Third Sector](#)¹⁶, I scraped information about local NGOs, such as their legal address, the time the NGOs were created, the type of activity they pursue and the number of people which engage in their activities. As with the Mafia properties, I geocode the NGOs' addresses to map them at the street level. Moreover, I digitise on GIS the historical maps about the neighbourhood-level distribution of Mafia families in Italy published by the Italian Antimafia Directorate [DIA \(2015a,b\)](#). Last, I employ the educational data as described in Section 4.1 to construct proxies for student migration and grade retention at the school level. I define student migration as the average annual rate of students who do not complete the grades 9 and 10, typically aged between 13 and 15. This variable captures students who leave the school where they first enrolled before turning 16, when they are unlikely to be dropping out of the educational system and are more likely to transfer to another institution. I define grade retention as the share of students who complete grades 11 and 12 being older than the expected age for their grade cohort, indicating they have repeated a grade or experienced delayed academic progression. Controlling for both student migration and grade retention is essential, as these factors can directly affect dropout rates and may be correlated with changes in school catchment areas, potentially biasing the estimated effects. Appendix D presents how these measures are built in more detail.

Table 3 shows descriptive statistics of the observable socioeconomic attributes for both treated and control areas measured at the baseline, before the reuse of any Mafia property occurs. First, treated and control areas exhibit virtually identical baseline educational out-

¹⁶The registry is offered online by the Italian Ministry of Labour and Social Policies (MLPS)

comes, both in terms of students’ migration and grade retention, which supports the validity of using dropout rates as the primary outcome measure in this specific setting. Moreover, treated areas show higher historical Mafia presence, which is expected given that this intervention specifically targets areas with confiscated Mafia properties. These areas also exhibit greater NGO activity and marginally lower rental prices, suggesting they might represent working-class neighbourhoods where both criminal organisations and civil society have historically been active. Because the reuse of properties may be influenced by the local availability of NGOs, I further examine whether pre-existing NGOs’ presence is associated with future dropout patterns in Section 7. I report that NGO activity measured at times t , $t - 1$, $t - 2$, and $t - 3$ shows no systematic relationship with subsequent dropout rates, indicating that the baseline NGO presence is unlikely to drive the estimated effects. Crucially, once standard errors are clustered at the school level to account for spatial autocorrelation, any baseline difference loses statistical significance, indicating that treated and control areas are virtually comparable across all the observed dimensions.

Table 3 Descriptive statistics

	Reused Mafia property in the school’s area						Robust SE	Δ Clustered SE
	No			Yes				
<i>Baseline covariates</i>	N	mean	sd	N	mean	sd		
Mafia presence	573	0.644	0.479	1,234	0.703	0.457	-0.059** (0.023)	-0.059 (0.061)
NGOs presence	561	37.43	54.26	1,207	45.45	83.01	-8.015** (3.837)	-8.015 (8.801)
Rental prices	561	7.450	2.251	1,207	7.261	1.756	0.189* (0.098)	0.189 (0.278)
Students’ migration	556	0.355	0.0242	1,155	0.351	0.0398	0.003* (0.002)	0.003 (0.004)
Grade retention 3rd year	559	0.0248	0.0253	1,185	0.0247	0.0303	0.000 (0.001)	0.000 (0.004)
Grade retention 4th year	559	0.0156	0.0158	1,190	0.0133	0.0145	0.002*** (0.001)	0.002 (0.002)

Notes: Descriptive statistics of baseline covariates. The last column presents standard errors clustered at the school level.

5 Empirical strategy

Estimating the effect of reusing confiscated Mafia properties on dropout rates is complicated by the involvement of multiple institutional actors in the reuse process. As discussed in Section 4.5, reused properties tend to be located in more deprived areas with higher civil engagement and baseline Mafia presence. Additionally, the presence of NGOs and unob-

served municipality-level characteristics may influence reuse decisions. Although baseline differences between treated and control areas become statistically insignificant once standard errors are clustered at the school level, I take a further step by systematically control for the individual determinants of reuse decisions. I demonstrate that, conditional on these factors, the variation in reuse timing and implementation is plausibly uncorrelated with other determinants of dropout dynamics.¹⁷ As discussed in Section 2, when a Mafia property is reused for social purposes - becoming a community, after-school facility, or social services centre - it transforms from a symbol of Mafia power into a symbol of community resistance (Mosca, 2017). These spaces may improve neighbourhood support and educational services while reshaping local perceptions of the Mafia as an alternative career path. Students at critical dropout ages might rationally weigh the expected returns from education versus criminal careers. The potential effects of reuse activities are therefore twofold: reducing dropout rates by increasing returns to education through enhanced services, or by diminishing the perceived attractiveness of criminal careers as symbols of Mafia power become symbols of State authority and community resilience. My empirical strategy proceeds as follows: First, I identify the socio-economic determinants of Mafia property reuse. Table B2 in Appendix B shows that even including controls and time trends for such determinants, my results hold. Second, I estimate a difference-in-differences model comparing school catchment areas exposed to reuse practices with unexposed areas. Last, I investigate dynamic treatment effects by examining the intensive margin of the treatment.

5.1 DiD model

I estimate a TWFE model under a DiD design with staggered treatment adoption. The first model estimates the extensive margin of the treatment comparing treated and control schools before and after the first Mafia property get reused. I define as *treated* schools catchment areas which have at least one reused Mafia property within their boundaries, and *control* those who do not¹⁸. The sample comprises a total of 1807 observations with 256 unique

¹⁷It is still possible that reused Mafia properties differ based on unobserved factors from those that remain unused - such as specific acts of resistance or vandalism, or unobserved municipal political dynamics - which could bias the estimated effects in either direction. If reused properties are systematically located in areas with greater unobserved criminal resistance, political instability, or social tensions that make reuse more contentious, this could lead to underestimation of the true effect by creating additional challenges for educational improvement that are not captured in the analysis; if reused properties are located in areas with stronger unobserved community mobilization or political commitment to anti-Mafia efforts, this would lead to overestimation of the treatment effect.

¹⁸I estimate an additional model where I restrict the sample to the schools which already host at least one reallocated property, to make sure the areas are comparable according to the policy process. Results are reported in Figure A2.

school catchment areas for which the dropout information is not missing¹⁹; of those, 58 were never treated, while 198 have been treated at some point in the sample. The first model is specified as:

$$DropoutG11 - 13_{cnmt} = \beta_1 Repurpose_{ct} + \beta_2 X'_{ct} + \delta_c + \eta_t + \epsilon_{cnmt} \quad (2)$$

where $DropoutG11 - 13$ is the share of students dropping out during grade 11 of high school in schools catchment area c , neighbourhood n , and municipality m measured in time t ; $Repurpose$ is a binary indicator equal to 1 if there is at least one Mafia property repurposed within the school catchment area in time t and after the first repurpose. Since schools are treated at different points in time, the coefficient of interest β_1 captures the average treatment effect on treated (ATT) comparing treated school catchment areas to never or not yet treated ones. X is a vector of controls at the catchment area level, including migration dynamics and grade retention rates for grades 11 and 12, which account for additional educational disruptions that could be captured by the dropout measure²⁰. Additionally, δ_c captures the catchment areas fixed effects, and η_t captures the year fixed effects. Standard errors are clustered at the school catchment area level to account for spatial autocorrelation.

As shown in Table 4, treated areas seems to be located where there are higher levels of Mafia presence and NGOs and slightly lower rental prices, while educational patterns are virtually the same. When clustering standard errors at the appropriate level, these baseline differences become statistically insignificant, suggesting that treated and control areas are reasonably comparable. The DiD design relies on the parallel trends assumption, which states that in the absence of treatment, dropout rates for treated and control schools would follow similar trends. The fact that baseline differences are not statistically significant once we account for clustering suggests that treated and control areas are more similar than they initially appear, strengthening confidence in the comparability of these groups. Additionally, I employ an event study approach to partially relax the concern of differential trends. The event study estimation based on Equation (1) may yield biased results due to the well-

¹⁹The dropout measure has several missing values for the years 2015 and 2016. The measure tracks students from the same cohorts from grade 11 to graduation after the completion of grade 13. Dropout rates cannot be computed for 2015 cohorts (data for 2014 are not available) and some 2016 cohorts (due to missing data in 2015 preventing complete cohort tracking). Despite this, the staggered policy implementation provides sufficient treatment variation for identification.

²⁰I confirm that the treatment does not affect student migration or grade retention, indicating that these controls capture pre-existing school characteristics rather than treatment effects. Results are reported in Table A2.

documented limitations of TWFE models in settings with staggered treatment adoption and heterogeneous treatment effects (Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and Sant’Anna, 2021). To address this concern, I employ the solution proposed by Sun and Abraham (2021), which creates an interaction-weighted estimator of the average treatment effect (ATT) including dummies for the interactions of each treated cohort with their treatment times²¹.

5.2 DiD dynamic model

The underlying assumption that students are homogeneously affected by the treatment across catchment areas may not reflect reality. The impact of reused Mafia properties likely depends on the intensity of the repurposed activities as well as the location of the repurposed properties themselves. To capture the intensive margin of the treatment effect, I employ the number of properties getting reused per catchment area as a continuous treatment measure, using the dynamic DiD estimator from de Chaisemartin and D’Haultfoeuille (2020). This estimator extends the traditional two-way fixed effects framework to handle continuous treatment variables by comparing changes in outcomes for schools experiencing different *doses* of treatment exposure. Traditional event study approaches assume binary treatment and cannot handle the continuous variation in exposure intensity that characterises this setting. Moreover, the classic TWFE estimator assumes linear dose-response relationships, and cannot properly identify dynamic treatment effects. This estimator addresses these issues by allowing for non-linear dose-response functions and heterogeneous treatment effects across the distribution of treatment intensity. Finally, I re-estimate the treatment intensity by weighting the continuous treatment measure by the catchment area’s student population (ages 14-19) and by the average distance between the properties and the population-weighted centroids of the catchment areas; these adjustments are crucial since the intensity of the treatment effect depends not only on the number of reused properties but also on how many students could potentially be affected by the treatment.

6 Results

After the first Mafia property get repurposed within the school catchment area, dropout rates for students aged 16 or older fell on average. The estimated ATTs are presented in Table 5, where all specifications include schools and time FEs, and standard errors are clustered at

²¹I employ the Sun and Abraham (2021) estimator as my preferred specification as it is particularly well-suited to properly manage the large number of time trends and fixed effects included in the exercises reported in Appendix B

the school level. Column (1) shows that having at least one reused Mafia property within the catchment area reduces the dropout rate of 1.9 percentage points. Given the baseline dropout rate, this represents a relative 36% reduction in the dropout rate. Columns (2), (3), and (4) demonstrate that the estimated effects are robust to the introduction of controls for both migration dynamics and grade retention among students older than 16.

Table 4 Impact of reusing Mafia real estate on the share of students dropping out from grades 11 to 13

	Dropout rates G11-G13			
	(1)	(2)	(3)	(4)
Repurpose = 1	-0.019** (0.009)	-0.020** (0.009)	-0.019** (0.009)	-0.020** (0.009)
clustered SE	yes	yes	yes	yes
school FE	yes	yes	yes	yes
time FE	yes	yes	yes	yes
migration	no	yes	no	yes
retention	no	no	yes	yes
Observations	1,296	1,292	1,274	1,272
Number of schools	235	234	234	234
Mean dep. var.	0.054	0.053	0.053	0.053

Notes: TWFE model. The treatment variable is equal to 1 whenever there is at least one reused Mafia property within the school catchment area. Column (1) represents the baseline accounting for school and time fixed effects, while in Columns (2) and (3) I control for students' migration and grade retention rate, respectively. Column (4) reports the complete specification. Standard errors are clustered at the school level.

Figure 7 shows the event study of my preferred specification, namely Column (4), which accounts for school FEs, time FEs, and controls. The event study does not show any evidence of pre-trend, and I cannot reject the hypothesis that the pre-treatment coefficients are jointly zero, as shown by the F-tests with a p-value of 0.991. The event study reveals that the estimated effects are predominantly long-term in nature. Dropout rates become significantly lower between the second and third year of implementation, with downward trends persisting for up to six years following the onset of the first reusing activities. This gradual pattern is consistent with the inherent delays in the treatment variable's timing: the indicator switches to 1 at the moment local NGOs and municipalities sign a collaboration agreement to reuse the property, which does not yet reflect the time required to develop and deliver meaningful activities for local communities. It is therefore reasonable to expect that the full impact of

repurposing activities appears only once such activities are sufficiently established. These insights follow what suggested by previous literature: [Nazzaro \(2021\)](#) explains that NGO projects in Mafia confiscated properties face substantial obstacles before becoming fully operational. Moreover, the long-term effect I find aligns with the theoretical understanding of cultural change processes driven by anti-Mafia policies, where meaningful change occurs through the gradual buildup of small interventions and sustained community engagement over several years. ([Nazzaro, 2021](#)).

Moreover, Figure 8 shows heterogeneity in the treatment based on the basic attributes of repurposed properties. Following [Operti \(2018\)](#), I define *operational properties* all those residential real estate which belonged to the Mafia family signaling their local sovereignty, and *economic properties*, such as real estate units used for commercial purposes. Figure 8 reveals that the effect is driven by school catchment areas treated by the presence of at least one operational property, while those treated by economic properties alone show no statistically significant effect. The results are further concentrated among independent residential units and agricultural land, rather than industrial deposits or garages.

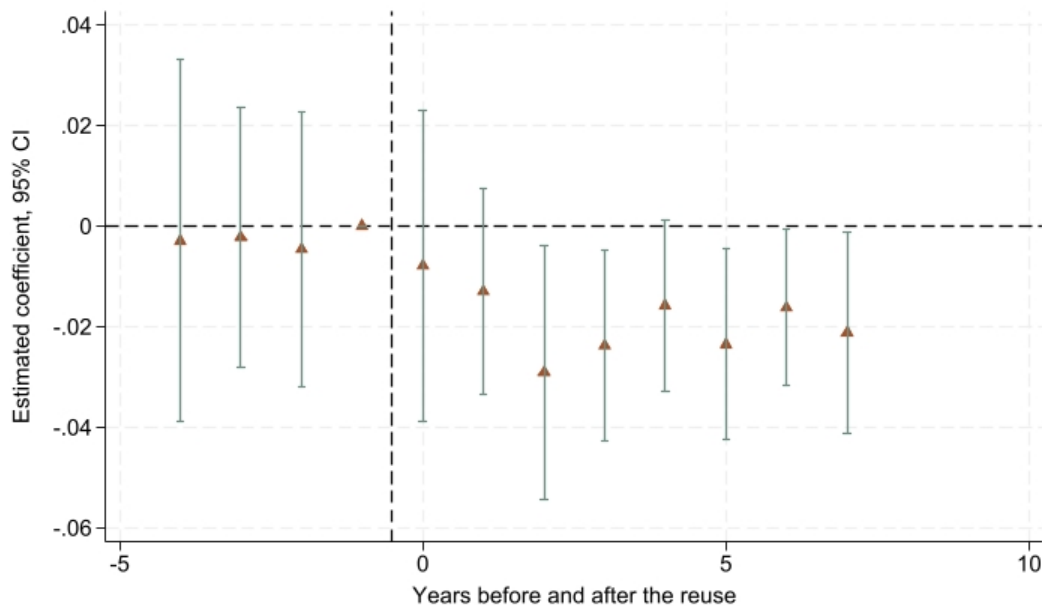


Figure 7 Estimated effects of reusing practices on dropout rate before and after the first reuse starts

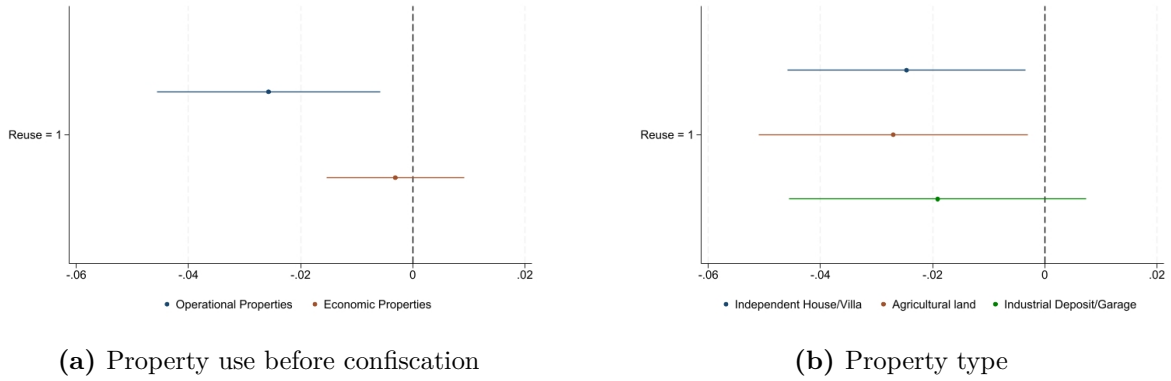
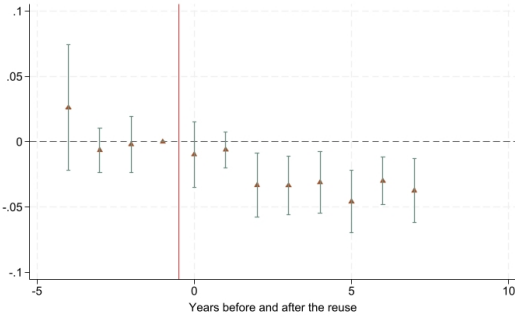


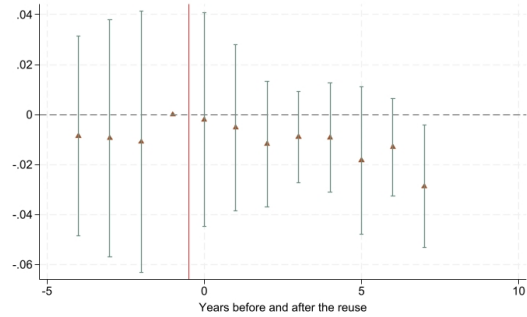
Figure 8 Estimated effects of reusing practices on dropout rates before and after the first reuse starts by properties' features

Figure 9 presents the heterogeneous treatment effects across school catchment areas by baseline school quality. I construct a composite school quality indicator by first averaging standardized scores across academic outcomes and organizational and social processes, and then taking the row mean of these two sub-indices into an overall school performance measure. This index thus captures institutional effectiveness along both the outcome and process dimensions of school quality²². Figure 9a and 9b report the treatment effects separately for schools below and above the median of the composite quality index. Both subsamples pass the parallel trends test, with F-test p-values of 0.143 and 0.941 respectively, lending credibility to the identifying assumption in each group. The effects are concentrated among low-performing schools, which exhibit larger point estimates and stronger statistical significance beginning two years after the first property reuse, while the estimates for high-performing schools remain small and imprecise. This heterogeneity suggests that the intervention operates through channels that are particularly effective in resource-constrained educational environments, where the marginal improvement in the surrounding social context translates into comparatively larger reductions in dropout rates.

²²Appendix D discusses more in detail what the sub-indices measures.



(a) Low Performing Schools



(b) High Performing Schools

Figure 9 Estimated effects of reusing practices on dropout rates before and after the first reuse starts by the baseline quality of schooling

I also explore heterogeneity by school track type. As explained in Section 4.1, the Italian secondary educational system is divided in 14 specific high school sub-tracks, which can be grouped into three main tracks: academic, technical, and vocational high schools. I estimate three separate event studies to investigate whether the treatment effect shows different patterns for different tracks. The respective F-tests reveal p-values of 0.421, 0.651, and 0.333, confirming that I cannot reject the hypothesis that pre-treatment coefficients are jointly zero.

The results reveal substantial heterogeneity across educational tracks in response to the repurpose intervention. Academic high schools, shown in Figure 10a, exhibit consistently small and statistically insignificant coefficients throughout the observation window, while vocational schools, shown in Figure 10c, display a similar pattern, which is consistent with their institutional structure, whereby students obtain a professional qualification upon completing grade 11 rather than a full five-year diploma. Technical high schools, shown in Figure 10b, by contrast, show a more pronounced and sustained response, with negative effects on dropout rates that become statistically significant between two and four years after the first property repurpose. This differential response likely reflects the distinct student populations and institutional contexts of each track. Technical schools occupy an intermediate position between academic preparation and vocational training, and their students appear particularly sensitive to the improved educational environment generated by the intervention. Research on the Italian education system documents that technical schools have experienced sharper declines in tertiary transition rates relative to other school types (Contini and Salza, 2020), suggesting these students face particular challenges in their educational trajectories. Unlike vocational students, who can enter the labour market with a three-year professional certificate, technical students require a full five-year diploma to meaningfully improve their employment prospects, making early dropout especially costly for this group. The improved

educational incentives stemming from repurpose practices may therefore be especially valuable for students enrolled in technical programs. Importantly, this pattern is not driven by compositional shifts in enrollment. Table A3 shows that enrollment in technical schools does not change significantly following the treatment, indicating that the estimated effects operate through reduced dropout rather than student sorting across school tracks.

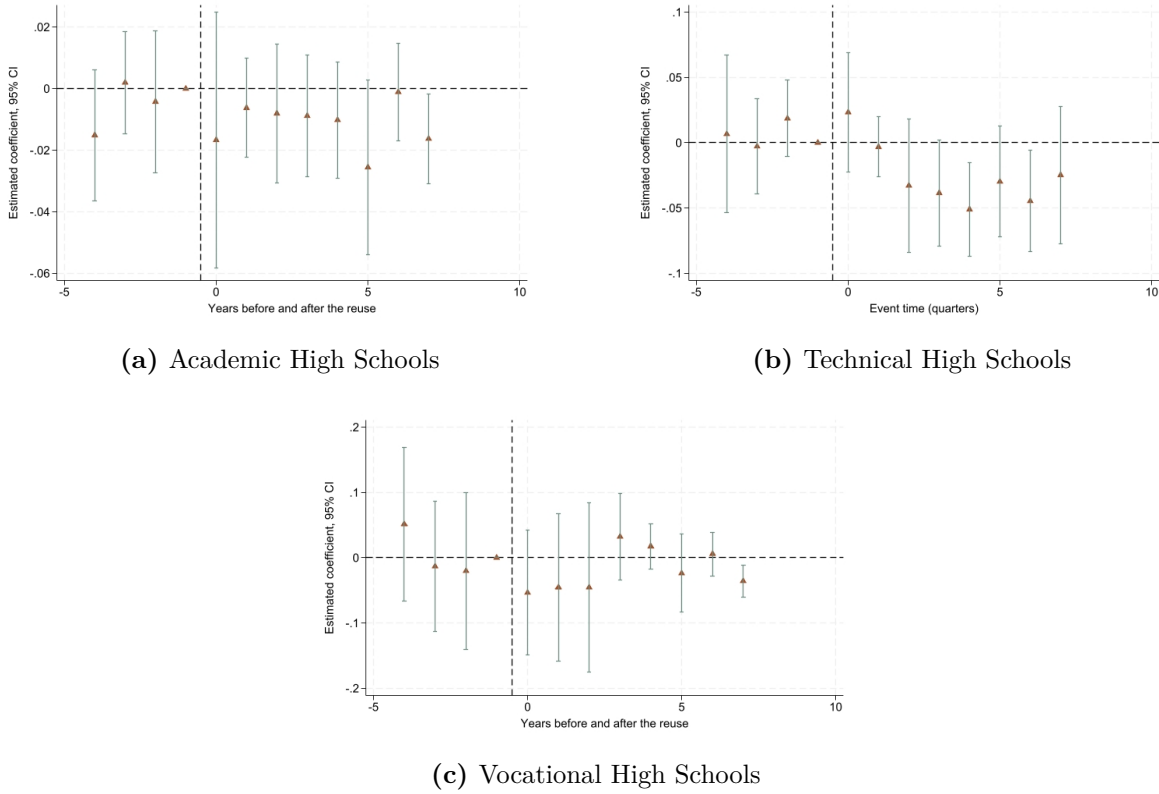


Figure 10 Estimated effects of reusing practices on dropout rates before and after the first reuse starts by school track

Beyond school characteristics, the treatment effect may also vary with the number of confiscated properties repurposed within a given catchment area and their spatial distribution relative to the student population. I therefore examine whether the estimated effects are driven solely by the first reuse event or whether they intensify with cumulative exposure to multiple repurposed properties over time. The underlying hypothesis is that the impact of reuse practices on student outcomes need not materialise immediately upon first treatment, but may instead unfold gradually, shaped by both the timing of individual reuse events and the accumulating density of repurposed properties within the catchment area. In particular, treatment effects are expected to grow stronger as the stock of reused properties increases and as their locations overlap more closely with where students actually reside. To investigate

this, I split the sample into schools whose catchment area experienced at most one repurpose event over the entire observation period and those exposed to multiple repurpose practices. Table 5 reports the results, revealing a potential dose-response relationship between reusing practices and dropout reduction. Columns (1) and (2) show that schools whose catchment areas experienced only a single reuse event exhibit small and statistically insignificant effects on dropout rates. By contrast, schools exposed to multiple repurposed properties, which are reported in Columns (3) and (4), display substantially larger and precisely estimated reductions, corresponding to declines of 51% and 48% relative to the mean, respectively. This pattern suggests that cumulative exposure to repurpose practices amplifies the treatment effect, pointing to a dose-response relationship whereby the educational benefits of the treatment intensify as the number of repurposed properties within the catchment area grows.

Table 5 Impact of reusing Mafia real estate on the share of students dropping out from grades 11 to 13 by intensity of exposure

	(1)	(2)	(3)	(4)
Dep: Dropout 3-5 years	Properties reused = 1	Properties reused = 1	Properties reused > 1	Properties reused > 1
Reuse = 1	-0.00284 (0.0133)	-0.00466 (0.0139)	-0.0293** (0.0123)	-0.0277** (0.0119)
Observations	541	522	755	750
Number of codd clustered SE	101	101	134	133
school FE	yes	yes	yes	yes
time FE	yes	yes	yes	yes
migration retention	no	yes	no	yes
Observations	541	522	755	750
Number of schools	101	101	134	133
Mean dep. var.	0.0485	0.0477	0.0574	0.0568

Notes: TWFE model. The treatment variable is equal to 1 whenever there is at least one reused Mafia property within the school catchment area. Columns (1) and (3) do not include controls while Columns (2) and (4) include them. Standard errors are clustered at the school level.

I take a step forward and I directly estimate the dynamic evolution of the treatment effect generated by the repurpose of confiscated Mafia properties. I perform three subsequent exercises: first, I estimate a dynamic DiD model using an event study approach. This framework allows me to follow the evolution of the treatment effect relative to the timing of the repurpose and to assess whether the observed impacts arise from a gradual buildup

of exposure to reusing activities. I employ the estimator proposed by [de Chaisemartin and D’Haultfoeuille \(2024\)](#), which computes the cumulative effect of each treatment dose across all time periods and determines how long these effects persist on average. Figure 11 displays the event study of the dynamic evolution of the treatment effect. The control and treated groups do not appear to exhibit differential pre-trends, as indicated by the F-test on the pre-treatment coefficients with a p-value of 0.330. Figure 11 displays the average cumulative treatment effect per additional reused property on dropout rates, where each coefficient captures the total impact of one further reuse event accumulated over all subsequent periods. The overall average effect is negative and equal to 0.64 percentage points, implying that each additional repurposed property reduces dropout rates by approximately 12% relative to the mean. Importantly, the magnitude of this effect varies considerably with the timing of reuse: properties repurposed in the first and second year of treatment are associated with reductions of 0.04 and 1.9 percentage points respectively, whereas those reused four and five years after the initial treatment generate substantially larger reductions of 3.8 and 5.2 percentage points. This monotonically increasing pattern suggests that the educational returns to property reuse compound over time, with sustained, long-term programs hosted in repurposed Mafia assets generating substantially greater benefits than early or isolated activities.

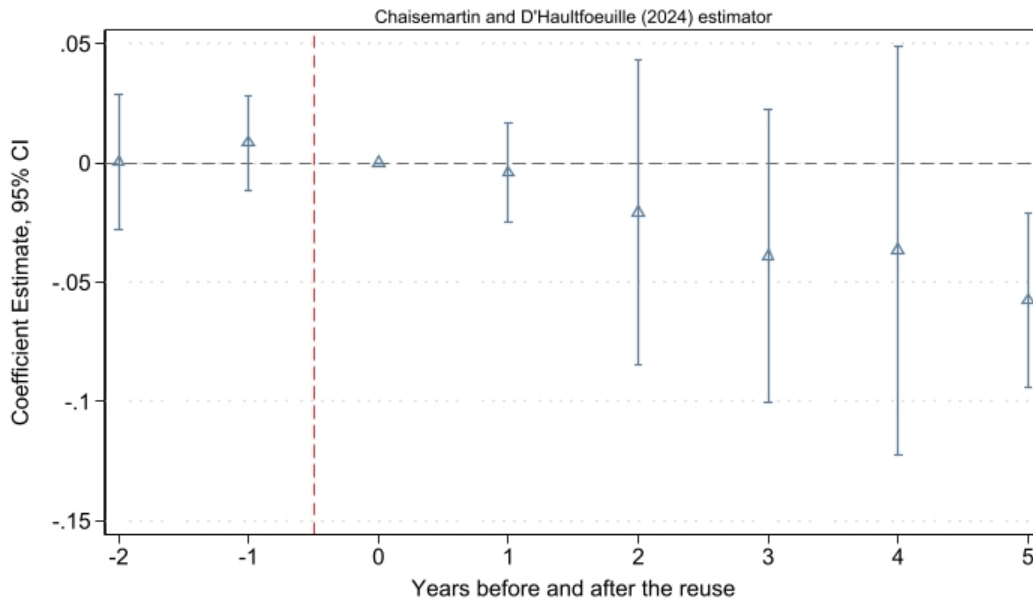


Figure 11 Average cumulative treatment effect of confiscated property reuse on dropout rates, by reuse intensity and timing

I next re-estimate the event study by weighting the count of reused assets by the stu-

dent population within each school catchment area. While the count-based measure captures the overall intensity of repurpose activities, it does not account for the size of the student population that could potentially benefit from them. The results, reported in Appendix A, closely mirror those obtained under the simple count specification and are if anything stronger. Figure A3 shows a reduction of 4.5 percentage points in dropout rates, suggesting that treatment intensity matters: repurpose activities generate larger educational returns when concentrated relative to the local student population rather than dispersed across larger catchment areas. I further validate these findings through a distance-weighted specification, in which the treatment measure is weighted by the average distance of repurposed properties from the population-weighted centroid of each catchment area. Figure A4 confirms the previous results, yielding an estimated reduction in dropout rates of 5 percentage points. Taken together, both alternative specifications reinforce the conclusion that the spatial concentration of repurpose activities relative to the student population is a meaningful determinant of treatment effectiveness.

6.1 Robustness and Falsification Checks

The estimated effects are robust to a series of specification checks and alternative treatment assumptions. This section proceeds as follows. First, I test for additional confounding factors that may represent sources of omitted variable bias. Second, I investigate whether pre-treatment reallocations or anticipation effects could be confounding the estimated results. Third, I assess whether the treatment allocation is subject to spatial selection bias. Fourth, I test for spatial spillover effects onto neighbouring schools.

6.1.1 OVB and Alternative Explanations

In the main specification, I control for unit-specific and time-specific characteristics, as well as the time-varying rates of retention and migration among students. By controlling for these factors, I find no pre-trends in any of the estimated event study. Nevertheless, it is still possible that the repurpose of confiscated properties is part of a broader policy plan implemented at the municipality level, or that it coincides with other educational or social cohesion programs implemented in the same time window. Additionally, previous trends in the presence of NGOs and civic engagement might play a substantial role in how and when the policy is implemented locally. To address these concerns, I first show that controlling for contemporaneous programmes leaves the main estimates unchanged, with coefficients on the additional controls close to zero. Second, I test whether the policy’s impact complements or substitutes for other civil society activities by estimating the effect of the number of NGOs

present at the street level on dropout rates, net of the effect of the policy itself. I further confirm the absence of differential pre-trends when including these as covariates, with the corresponding event studies presented in Figures A5 and A6.

I first collect data on the number of educational and social cohesion projects implemented in each municipality for each year from the Italian Department for Cohesion Policy²³. The data offer detailed information on projects targeting various developmental goals for local administrations between 2007 and 2022. I focus on projects related to education and social inclusion, measured as the share of completed and ongoing projects relative to the total number of projects implemented in each municipality per year. This allows me to test whether the estimated effect of the repurpose of properties reflects concurrent policy activity rather than the intervention itself. Table 6 presents results controlling for the presence of educational and social inclusion initiatives implemented at the municipal level over the same period. The coefficient on the repurpose treatment remains statistically significant and virtually the same across all specifications, ranging from 1.9 to 2.1 percentage points. Neither educational nor social inclusion projects show any significant association with dropout rates, with coefficients close to zero and large standard errors. These results suggest that the dropout reduction effect is specifically attributable to the repurpose intervention, rather than reflecting broader municipal development strategies or coincidental policy activity targeting education and social outcomes.

²³The data have been collected from opencoesione.gov.it.

Table 6 Alternative explanations: controlling for concurrent municipal programs

	(1)	(2)	(3)	(4)
Dropout rate G11-G13				
Repurpose = 1	-0.0193** (0.00903)	-0.0203** (0.00918)	-0.0198** (0.00867)	-0.0210** (0.00876)
Educational programmes	-0.000777 (0.0146)	-0.00533 (0.0139)	0.00289 (0.0151)	-0.00136 (0.0144)
Social cohesion programmes	-0.000929 (0.0157)	-0.00334 (0.0153)	-0.00755 (0.0185)	-0.00869 (0.0184)
Clustered SE	yes	yes	yes	yes
Catchment school FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Migration controls	no	yes	no	yes
Retention controls	no	no	yes	yes
Observations	1,269	1,265	1,248	1,246
Number of schools	235	234	234	234
Mean dep. var.	0.0538	0.0535	0.0530	0.0531

Notes: TWFE model. The treatment variable is equal to 1 whenever there is at least one Mafia property within the school catchment area. Column (1) does not include controls while Columns (2) includes controls for migration. Column (3) includes only the controls for grade retention rate, while Column (4) include them all. Standard errors are clustered at the school level.

A natural question arises when interpreting these results: is there something uniquely valuable about conducting activities in former Mafia properties, or would any NGO operating in the area produce similar reductions in dropout rates? To disentangle the specific contribution of repurposed properties from the broader effect of civil society presence, I test whether the main estimates are sensitive to controlling for the number of NGOs active within each school’s catchment area. If the observed effects were simply driven by the availability of social services nearby, regardless of whether they operate from repurposed Mafia properties, the main coefficient should diminish substantially once I account for the local presence of NGOs. Conversely, if the main coefficient remains stable while the proxy for the presence of NGOs shows little independent effect, this would suggest that the symbolic and contextual significance of operating within former Mafia properties generates distinctive value that conventional NGO activities might not be able to replicate. Table 7 supports this last interpretation. Columns (2) and (5) show that the presence of other NGOs in school catchment areas has negligible and statistically insignificant effects on dropout rates, indicating that general NGO activity alone does not meaningfully reduce educational dropout. Moreover, the repurposing effect remains remarkably stable when controlling for NGO presence.

Comparing the baseline specifications in columns (1) and (4) with the full specifications in columns (3) and (6), the reuse coefficients are virtually unchanged in magnitude and remain statistically significant at the 5% level throughout. These results provide compelling evidence that the observed effects stem not from general social service provision in the area, but from the particular significance of conducting activities within former Mafia properties.

Table 7 Impact of reusing Mafia real estate and NGO presence on dropout rates for G11-G13

	(1)	(2)	(3)	(4)	(5)	(6)
	Dropout rate G11-G13					
Reuse = 1	-0.0192** (0.00934)		-0.0191** (0.00960)	-0.0196** (0.00945)		-0.0194** (0.00963)
NGOs presence		-0.000590 (0.000392)	-0.000626 (0.000389)		-0.000542 (0.000351)	-0.000583 (0.000354)
clustered SE	yes	yes	yes	yes	yes	yes
catchment school FE	yes	yes	yes	yes	yes	yes
time FE	yes	yes	yes	yes	yes	yes
migration	no	yes	no	yes	no	yes
retention	no	yes	no	yes	no	yes
Observations	1,296	1,487	1,296	1,272	1,447	1,272
Number of schools	235	293	235	234	288	234
Mean dep. var.	0.0537	0.0552	0.0537	0.0531	0.0541	0.0531

Notes: TWFE model. The treatment variable is equal to 1 whenever there is at least one Mafia property within the school catchment area. Columns (1), (3), and (5) do not include controls while Columns (2), (4), and (6) include them all. Standard errors are clustered at the school level.

6.1.2 Policy Effects before the Repurpose

As explained in Section 2, the reuse of Mafia property represents the final stage of the CRR policy, which requires first confiscating and then reallocating confiscated assets under the jurisdiction of local authorities. [Boeri et al. \(2023\)](#) demonstrate that the confiscation of nearby Mafia properties depresses housing prices by signalling the local presence of the Mafia, while reallocation sends the opposite signal, restoring property values. A potential concern is therefore that my treatment variable captures a recovery process following multiple confiscations that negatively affected neighbourhoods, reduced local economic activity, and contributed to higher dropout rates.

A related concern is that the reuse treatment merely captures dropout reductions driven by the reallocation stage rather than the repurposing itself. I argue this is implausible for two reasons. First, reallocation is a purely administrative process whereby confiscated properties

are formally transferred to local authorities. While this may signal a municipality’s intention to repurpose former Mafia assets, it generates no tangible changes at the community level and no social activity that could plausibly alter youth behaviour or educational decisions. Second, Table 8 provides direct empirical evidence: Columns (3) and (4) show that reallocation alone has no independent effect on dropout rates, with coefficients close to zero and consistently insignificant across specifications. Columns (5) and (6) show that the reuse coefficient remains stable in magnitude and statistically significant at the 5% level even after controlling for reallocations. Taken together, this evidence supports the interpretation that meaningful educational impacts arise when properties are actively repurposed for community use, rather than simply transferred to public ownership. The event study reported in Figure A5 corroborates these findings, showing no differential pre-trends and estimates closely in line with the main specification.

Table 8 Impact of reusing Mafia real estate on the share of students dropping out at the age of 16 - including previous policy stage

	(1)	(2)	(3)	(4)	(5)	(6)
Dropout rate G11-G13						
Reuse = 1	-0.0192** (0.00934)	-0.0196** (0.00943)			-0.0193** (0.00936)	-0.0199** (0.00948)
Reallocation = 1			0.00477 (0.00653)	-0.000235 (0.0101)	0.00290 (0.00653)	-0.00238 (0.0102)
clustered SE	yes	yes	yes	yes	yes	yes
school FE	yes	yes	yes	yes	yes	yes
time FE	yes	yes	yes	yes	yes	yes
migration	no	yes	no	yes	no	yes
retention	no	yes	no	yes	no	yes
Observations	1,296	1,272	1,286	1,262	1,286	1,262
Number of schools	235	234	233	232	233	232
Mean dep. var.	0.0537	0.0531	0.0537	0.0531	0.0537	0.0531

Notes: TWFE model. The treatment variable is equal to 1 whenever there is at least one reused Mafia property within the school catchment area. Standard errors are clustered at the school level.

6.1.3 Anticipation Effects

A potential threat to the identification strategy is that families and students may anticipate the repurpose of confiscated Mafia properties before it formally takes place. If information about upcoming activities spreads through informal networks or institutional channels, households could adjust their educational decisions in advance, and the estimated treatment effect

would partly capture these anticipatory responses rather than the direct impact of the intervention. To test for this, I examine whether the reuse of confiscated properties in period $t + 1$ affects dropout rates measured in period t . A significant coefficient on the lead of treatment would indicate that behavioural changes precede the intervention, undermining the causal interpretation of the main results. Table 18 shows that the estimated coefficients are consistently small and statistically insignificant across all specifications, providing no evidence of anticipation effects. This reinforces the credibility of the main identification strategy: the reduction in dropout rates occurs only after properties are effectively repurposed and local NGOs begin offering social activities in the treated area.

Table 9 Impact of reusing Mafia real estate on the share of students dropping out after the age of 16 - Reuse $t + 1$

	(1)	(2)	(3)	(4)
	Dropout rate G11-G13			
Reuse $t + 1$	-0.0119 (0.00884)	-0.0137 (0.00866)	-0.00994 (0.00880)	-0.0116 (0.00859)
clustered SE	yes	yes	yes	yes
catchment school FE	yes	yes	yes	yes
time FE	yes	yes	yes	yes
migration	no	yes	no	yes
retention	no	no	yes	yes
Observations	1,062	1,060	1,052	1,050
Number of schools	232	231	232	231
Mean dep. var.	0.0508	0.0509	0.0509	0.0510

Notes: TWFE model. The treatment variable is equal to 1 whenever there is at least one reused Mafia property within the school catchment area. Column (1) represents the baseline accounting for school and time fixed effects, while in Columns (2) and (3), I control for students' migration and grade retention rate, respectively. Column (4) reports the complete specification. Standard errors are clustered at the school level.

6.1.4 Selection Bias

A primary concern is that never-treated schools may be fundamentally different from eventually-treated schools. Although Table 3 shows broadly comparable pre-treatment characteristics across groups, the never-treated areas may differ along unobserved dimensions, such as the degree of institutional engagement with confiscated assets and the level of local support for antimafia policies, making them an inappropriate control group. To address this, I only ex-

exploit the timing of the treatment by restricting the comparison to treated and not-yet-treated schools, excluding never-treated units entirely. This ensures that the control group consists only of schools that eventually receive treatment, and therefore plausibly belong to the same population of Mafia-affected areas undergoing institutional repurpose processes.

Table 9 reports the results from this restricted sample. The estimates are remarkably stable and, if anything, slightly larger in magnitude than the main specification, while remain statistically significant at the 5 percent level throughout. This stability is reassuring on two fronts. First, it suggests that the main results are not inflated by the inclusion of never-treated schools as being structurally different from treated areas. Second, the fact that the effect is preserved and marginally strengthened when identification comes solely from variation in treatment timing among eventually-treated schools lends further credibility to the causal interpretation. The reduction in the number of schools from 232 to approximately 182 does not meaningfully affect precision, indicating that the never-treated units are not driving the main statistical power of the baseline estimates.

Table 10 Impact of reusing Mafia real estate on the share of students dropping out at the age of 16 - different catchment areas assumptions

	(1)	(2)	(3)	(4)
Dropout rate G11-G13				
Repurpose = 1	-0.0220** (0.00951)	-0.0232** (0.00965)	-0.0212** (0.00956)	-0.0227** (0.00968)
clustered SE	yes	yes	yes	yes
catchment school FE	yes	yes	yes	yes
time FE	yes	yes	yes	yes
migration	no	yes	no	yes
retention	no	no	yes	yes
Observations	1,028	1,025	1,014	1,013
R-squared	0.094	0.108	0.092	0.106
Number of schools	183	182	182	182
Mean dep. var.	0.0566	0.0562	0.0558	0.0558

Notes:

A further concern relates to spatial selection bias arising from the method used to construct school catchment areas. Treatment allocation may be sensitive to the baseline assumption that students attend their geographically closest school regardless of its size or capacity. Since catchment areas are constructed by assigning each census block to the nearest school,

the boundaries between adjacent catchment areas are determined purely by proximity. This rule may misclassify treatment status for schools near those boundaries: if larger schools in practice serve students living closer to a neighbouring smaller school, then a reused property near such a boundary could be assigned to the wrong catchment area, generating a measurement error in treatment that is correlated with school characteristics. I re-estimate the main results under alternative assumptions about the construction of schools' catchment areas. If the effect were spuriously driven by the specific rule used to assign treatment status, changing that rule should produce meaningfully different treatment allocations and consequently different estimates. Specifically, I weight the Euclidean distance between each census block and the closest school by the school capacity, namely the enrollment in the first year for each school measured at the baseline. This capacity-weighted approach allows larger schools to draw students from greater distances and have more extensive catchment areas; this provides a more realistic representation of how students are distributed across urban areas (Pearce, 2000).²⁴ Under the capacity-weighted construction, only 18 schools switch treatment status relative to the baseline assignment. The small number of switchers is itself reassuring, suggesting that the two approaches yield largely consistent treatment allocations. To further ensure that the main results are not driven by schools with inherently ambiguous treatment assignment, I re-estimate the main specification excluding these 18 schools. Table 7 shows that the coefficients of interest are virtually unchanged across all specifications, whether estimated on the full sample or on the restricted sample. The stability of the estimates across both the alternative weighting scheme and the restricted sample jointly suggests that the treatment effect is not an artifact of how catchment areas are constructed. The somewhat wider confidence intervals in the restricted sample are expected given the reduction in sample size, and if anything underscore the importance of retaining the full sample for statistical precision without compromising identification.

²⁴Appendix D explains in detail how the areas have been computed.

Table 11 Impact of reusing Mafia real estate on the share of students dropping out at the age of 16 - different catchment areas assumptions

	(3)	(4)	(7)	(8)
Dep Var: Dropout rate G11-13	All sample	Non-switchers only	All sample	Non-switchers only
Reuse = 1	-0.0192** (0.00934)	-0.0206* (0.0122)	-0.0196** (0.00943)	-0.0207* (0.0123)
clustered SE	yes	yes	yes	yes
school FE	yes	yes	yes	yes
time FE	yes	yes	yes	yes
migration	no	no	yes	yes
retention	no	no	yes	yes
Observations	1,296	1,192	1,272	1,174
R-squared	0.093	0.117	0.098	0.123
Number of schools	235	217	234	216
Mean dep. var.	0.0537	0.0558	0.0531	0.0552

Notes:

6.1.5 Spillover Effects

In the main results, I compare treated and control schools without accounting for potential spillover effects. However, it is plausible that the treatment also reduces dropout rates in nearby schools that are not formally treated. In such cases, the estimates would violate the Stable Unit Treatment Value Assumption (SUTVA), which requires that each unit’s potential outcomes are independent of other units’ treatment status (Cunningham, 2021). To address this concern, I follow a standard approach in the difference-in-differences literature: either excluding potentially affected controls or introducing an indicator for spillover exposure to separate the direct and spillover components of the treatment effect (Kline and Moretti, 2014; Butts, 2023). Because my sample includes only a limited number of control schools located far from treated areas, I opt for the second option and construct a time-varying spillover dummy. This variable equals 1 if a school’s catchment area shares at least one boundary with a treated area after treatment occurs, and zero otherwise.

Table 9 reports the results. Column (1) is the baseline, which ignores spillover effects. Column (2) controls for spillovers, estimating a direct effect which is slightly smaller, around 1.6 percentage points; the spillover effect appears to be insignificant, but with a substantial reduction of the dropout rate of nearby untreated areas of 1.6 percentage points. In Columns (3) and (4), I re-estimate the same specifications but including controls, showing similar

patterns. This test indicates that ignoring spillovers leads to a modest overestimation of the direct treatment effect, but the overall results remains robust.

Table 12 Impact of reusing Mafia real estate on the share of students dropping out at the age of 16 - controlling for spillover effects

	(1)	(2)	(3)	(4)
	Dropout rate from years 3 to 5 (16-19yo)			
Reuse = 1	-0.0192** (0.00934)	-0.0177** (0.00892)	-0.0201** (0.00910)	-0.0184** (0.00874)
Spillover = 1		-0.0116 (0.0136)		-0.0132 (0.0149)
clustered SE	yes	yes	yes	yes
catchment school FE	yes	yes	yes	yes
time FE	yes	yes	yes	yes
migration	no	no	yes	yes
retention	no	no	yes	yes
Observations	1,296	1,296	1,272	1,272
Number of schools	235	235	234	234
Mean dep. var.	0.0537	0.0537	0.0531	0.0531

Notes: TWFE model. The treatment variable is equal to 1 whenever there is at least one reused Mafia property within the school catchment area. Columns (1) and (3) do not include controls while Columns (2) and (4) include them. Standard errors are clustered at the school level.

7 Mechanisms

Repurposing Mafia properties for social purposes helps lower dropout rates in the areas where they are located. These effects are particularly pronounced in technical high schools and academically weaker schools. Moreover, a dose-response pattern emerges, with each additional repurposed property amplifying the reduction in dropouts. I then turn to the mechanisms behind these effects, proposing three arguments: first, gentrification is not the main driver; second, the results cannot be explained solely by greater educational support that improves academic outcomes; third, repurposed Mafia properties can serve a transformative function signalling a local social change and reshaping how students view the value of education, while diminishing Mafia’s appeal. I support this discussion with both empirical and anecdotal ev-

idence.

7.1 Gentrification

First, I rule out gentrification as the main channel driving the estimated effects by employing a triple difference-in-differences design. I interact the treatment dummy with a continuous indicator of rental prices in euros per squared meter measured at the neighbourhood level. The analysis is specified as:

$$DropoutG11 - G13_{cnmt} = \beta_1 Repurpose_{ct} \times Princes_{nt} + \beta_2 Repurpose_c + \beta_3 Princes_n + \beta_4 X'_{ct} + \delta_c + \eta_t + \epsilon_{ct} \quad (3)$$

where $DropoutG11 - G13_{cnmt}$ is the main outcome as specified before, and $Reuse$ is the main treatment dummy equal to 1 whenever there is at least one reused property in the school catchment area c in time t , and 0 otherwise. $Prices$ measures the average rental prices in neighbourhood n at time t , while β_1 is the coefficient of interest which captures how the impact of repurposed Mafia properties on dropout rates varies with local property price dynamics. $X'_{c,t}$ is a vector of time-varying community-level variables controlling for students' migration and grade retention dynamics. δ_c is school fixed effects and η_t is time fixed effects. If the main effect operates through the upgrading and gentrification of the neighbourhood, I would expect the effect of treatment to be stronger in areas experiencing increases in rental prices. Table 13 shows the results; the coefficient of the interaction term is very close to zero and not statistically significant, making the effect of rental price changes on dropout rates virtually identical in areas with and without repurposed properties. Moreover, the results are robust to the inclusion of migration and grade retention controls. These results support the argument that specific activities and programs do not reduce dropout rates through a general gentrification effect at the neighbourhood level.

Table 13 Impact of reusing Mafia real estate and NGO presence on dropout rates for G11-G13 interacted with rent price

	(1)	(2)	(3)	(4)
	Dropout rate G11-G13			
Repurpose = 1	-0.0144 (0.0375)	-0.0208 (0.0383)	-0.0137 (0.0372)	-0.0213 (0.0380)
Rental Prices	-0.000801 (0.00709)	-0.00469 (0.00695)	-0.00128 (0.00691)	-0.00475 (0.00681)
Repurpose =1 × Rental Prices	-0.000566 (0.00382)	0.000127 (0.00390)	-0.000626 (0.00375)	0.000191 (0.00383)
clustered SE	yes	yes	yes	yes
school FE	yes	yes	yes	yes
time FE	yes	yes	yes	yes
migration	no	yes	no	yes
retention	no	no	yes	yes
Observations	1,296	1,292	1,274	1,272
Number of schools	235	234	234	234
Mean dep. var.	0.0537	0.0534	0.0530	0.0531

Notes: TWFE model. The treatment variable is equal to 1 whenever there is at least one Mafia property within the school catchment area. Column (1) does not include controls while Columns (2) includes controls for migration. Column (3) includes only the controls for grade retention rate, while Column (4) include them all. Standard errors are clustered at the school level.

7.2 Educational and Training Premium

Having ruled out gentrification as the primary driver of the estimate results, it is worth examining whether the effects operate mainly through improved educational support. If repurposed properties were simply adding educational resources, we would expect those dedicated to education to have a greater impact than those used for other social and cultural purposes. To test this, I decompose the treatment effect by the type of activity offered in the repurposed property. Since categories are not mutually exclusive, meaning that a school catchment area may contain properties offering different types of activities, I estimate separate specifications for each category. In each regression, I distinguish between treated areas where at least one property offers activities of a given type (Category = 1) and treated areas where no property offers that type of activity (Category = 0), comparing both against control

areas. I specify the test as follows:

$$DropoutG11-G13_{cnmt} = \beta_1(Category = 1)_{ct} + \beta_2(Category = 0)_{ct} + \beta_3X'_{ct} + \delta c + \eta_t + \epsilon_{cnmt} \quad (4)$$

where $(Category = 1)_{ct}$ equals 1 when the school catchment area contains at least one repurposed property offering activities of the relevant type, and $(Category = 0)_{ct}$ equals 1 when the area is treated but none of its repurposed properties offer that type of activity. Everything else is defined as before.

The results, presented in Table 14, reveal several important findings. Column (1) shows that areas with educational repurpose and areas treated without any education activities both display negative coefficients of similar magnitude, with the latter being statistically significant, suggesting that educational-related activities might not be the main driver of the effect. Column (2) shows a similar pattern for employment-related activities. Crucially, Columns (3) and (4) indicate that welfare and cultural activities drive stronger and statistically significant effects on dropout reduction. In particular, areas with properties repurposed for cultural activities exhibit a significant reduction in the dropout rate of about 30%, while areas with welfare reuse show a significant reduction of 34%. This pattern suggests that the dropout reduction benefits do not operate primarily through direct educational or vocational resource provision, but rather through welfare and cultural activities that foster broader community-level change.

Table 14 Impact of reusing Mafia real estate on dropout rates for G11-G13

<i>Types of repurpose</i>	(1)	(2)	(3)	(4)
	Dropout rate G11-G13			
Education = 1	-0.0170 (0.0114)			
Education = 0	-0.0206* (0.0105)			
Employment = 1		-0.0141 (0.0140)		
Employment = 0		-0.0188** (0.00936)		
Culture = 1			-0.0162** (0.00767)	
Culture = 0			-0.0222 (0.0140)	
Welfare = 1				-0.0183* (0.00951)
Welfare = 0				-0.0252** (0.0114)
clustered SE	yes	yes	yes	yes
catchment school FE	yes	yes	yes	yes
time FE	yes	yes	yes	yes
migration	yes	yes	yes	yes
retention	yes	yes	yes	yes
Observations	1,274	1,274	1,274	1,274
R-squared	0.091	0.091	0.091	0.091
Number of codicescuolas	234	234	234	234
Mean dep. var.	0.0530	0.0530	0.0530	0.0530

Notes:

7.3 Students' Perception and Beliefs

These findings carry important implications for understanding the mechanism at work. The absence of stronger effects from either gentrification or education-specific repurposing suggests that dropout reductions are not primarily driven by neighbourhood upgrading or direct educational resource provision. Rather, the results point to repurposed Mafia properties generating broader community-level benefits, by fostering cultural change and reshaping social

norms within affected areas. Recent conversations with *Libera's* Mafia real estate managers and social workers from the NGOs managing the reused Mafia real estate, together with the interviews conducted by [Nazzaro \(2021\)](#) and [Falcone et al. \(2016\)](#), support this interpretation. Social workers and volunteers working at repurposed properties describe these places as gathering centres for the local community, attracting people of all ages to take part and put efforts into transforming the previously infiltrated area; renovating social bonds and reclaiming the local area through the participatory redevelopment of the Mafia real estate seems to address a local change of perspective.

Interviews conducted by [Nazzaro \(2021\)](#) highlight that

Directly involving citizens in various activities for the redevelopment of former Mafia properties is important in the perception of that space as a newly acquired common space that had previously been taken away for criminal purposes. - Interview from the NGO *AGESCI*, Apulia, Italy

Moreover, especially considering the juveniles' experiences, [Nazzaro \(2021\)](#) reports that

"On properties and lands confiscated from the Mafia [...] we find experiences featuring many young people, who were the first to decide to participate, aware of the importance of what was at stake." - *Carlo Borgomei, President of Fondazione Con il Sud*

On the same topic, [Falcone et al. \(2016\)](#) reports that

This policy has served to develop NGOs gathering juveniles who work in the sector of sustainable agriculture and develop new markets that did not exist until the day before, and has introduced and consolidated in our society a strong and open message: it is indeed possible to build a different future, where many and many different people in terms of culture, profession and age participate to make it happen. - *Lucio Cavazzoni, president of Alce Nero*, interview from *Libera*

To provide related empirical evidence, I examine how these interventions alter students' perceptions about educational and criminal pathways to career development in their communities. I employ TWFE models using data from the survey *The Perception of the Mafia*, which was collected from a subsample of schools. The survey covers 54 schools with an average of 110 students per school. Out of the total sample, 24 schools are treated while 30 serve as controls. I exploit responses to the question: *What of this options you think will be more useful for you to find a job in your town?*. Students were asked to rate the following different pathways to the job market on a scale from 1 - as the most useful - to 7 as the most useless: embark in an educational programme, refer to a job centre, take a competitive examination, ask the Mafia, ask a politician, ask family, or ask a friend. If the reuse of Mafia properties successfully reduces the attractiveness of criminal pathways and strength-

ens incentives for education, students in treated areas should place greater value on formal employment channels. Conversely, they should show diminished reliance on informal or illegitimate networks when seeking job opportunities. Table 16 presents the ATT estimated under a DiD design that includes school fixed effects and time fixed effects; I also weight each school by the number of students replying to the survey to account for varying school sizes in the survey sample. The outcome variables represent the percentage of students for each school who rated each pathway as a *very useless* or *very useful* option, allowing me to identify whether repurposed Mafia properties systematically alter the distribution of student perceptions within schools. Following previous literature (Villa, 2025), I focus on the extreme categories of student responses to better capture meaningful shifts in perceptions²⁵ Finally, standard errors are clustered at the school level across all specifications.

The results reveal compelling evidence of altered student perceptions consistent with a weakened criminal influence and a strengthened belief in legitimate pathways. Panel A examines the effect of the reusing activities on the probability of rating each pathway as *very useless*. Most notably, students in areas with repurposed Mafia properties are significantly more likely to rate the option to ask for help from the Mafia as very useless by 24% relative to the baseline mean of 0.564, indicating that a substantial portion of students already viewed Mafia connections as unhelpful, but the intervention further reinforces this belief. Similarly, students are more likely to rate the option to ask for help from a politician as very useless, representing a 26% increase from the baseline. Panel B examines the effect of the reusing activities on the probability of rating each pathway as *very useful*. Students in treated areas are significantly more likely to view education as very useful, with a substantial 34% increase relative to the baseline, indicating that the intervention meaningfully enhances students' perception of education as a pathway to employment success. Additionally, while students become more likely to opt to participate in a competitive examination, this effect is not statistically significant, even though the magnitude might suggest a potential strengthening of trust in formal institutions. Table A4 also suggests that the reuse of Mafia properties may be associated with a shift in trust away from Mafia groups toward formal institutions. The coefficients for other formal and informal networks remain small and insignificant, suggesting the intervention's effects are specifically concentrated on reducing reliance on illegitimate networks while enhancing the perceived value of education. This fundamental shift in how students perceive opportunity structures likely contributes directly to the observed reduction in dropout rates, as students who believe education leads to better job prospects have stronger incentives to remain in school.

²⁵I measure the most useful choices as the percentage of students that rate each option with 1 or 2, and the most useless choices as the percentage of students that rate each option with 6 or 7.

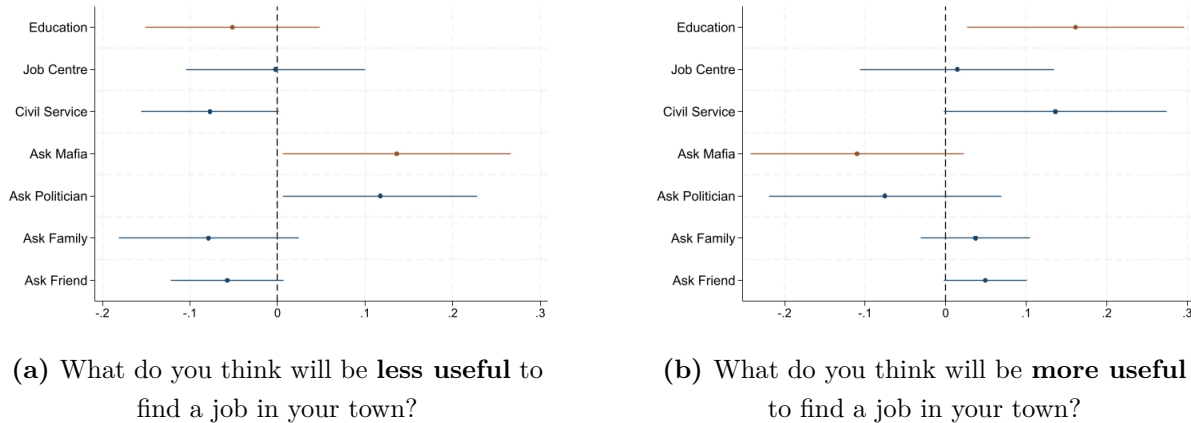


Figure 12 Estimated effects of reusing practices on students’ survey answers about career development

Additionally, I analyse open-ended survey responses where students were asked to give their own definition of the Mafia. This approach provides deeper insights into students’ emotional and cognitive associations with the Mafia, moving beyond structured survey questions to capture more nuanced attitudinal changes. The survey collected written definitions of the Mafia from students across 46 schools, yielding 3,242 observations across 11 years. I employ natural language processing (NLP) techniques to perform sentiment analysis of students’ definitions. I show the results employing two established sentiment analysis algorithms, namely Syuzhet and AFINN, and I extract sentiment scores that capture the overall emotional valence of each response. While Syuzhet scores are well-suited for analysing the narrative structure of students’ written definitions, the AFINN lexicon provides fine-grained intensity measures with distinct methodological advantages. Syuzhet assigns sentiment values between -1 and +1 with 16 gradients, and it has been developed specifically for narrative text analysis (Silge and Robinson, 2017). In contrast, AFINN scores words on a scale from -5 to +5; originally developed for Twitter sentiment analysis, it enables stronger differentiation between extreme positive and negative expressions (Isasi, 2021; Kim, 2022). The aggregated sentiment score for each Mafia definition is calculated by summing the individual word scores, with AFINN’s broader range providing greater sensitivity to intensity variations in student responses. Additionally, I apply the NRC emotion lexicon to investigate specific emotional dimensions: anger, disgust, fear, sadness, joy, trust, surprise, and anticipation expressed in students’ definitions. This lexicon comprises English words and their associations with these eight basic emotions. Moreover, the lexicon was developed by human annotators rather than relying on automated methods (Mohammad and Turney, 2013). Following the same approach used for analysing the survey answers, I employ a TWFE estimator to investigate how the implementation of reuse activities affects the sentiments extracted from Mafia definitions. If

the reuse of Mafia properties alters students' perceptions of the Mafia, we would expect to observe systematic differences in how students in treated versus control areas conceptualise the Mafia. Specifically, successful interventions might lead to more negative sentiment scores. Table 17 reports the results where all standard errors are clustered at the school level and both school and time FEs are included. Students seem to have more negative sentiments towards the Mafia after the implementation of reuse activities in their area. Column (1) reveals a statistically significant decrease in the syuzhet score of 37% relative to the mean, representing a meaningful shift towards more negative narrative construction about the Mafia. The AFINN algorithm, which provides more granular intensity measures, shows an even stronger effect, suggesting students in areas with repurposed Mafia properties express more intense negative emotions when describing the Mafia. The event studies reported in Figures A8 and A9 confirm these results are driven by the treatment itself rather than pre-existing trends: coefficients in the pre-treatment period are statistically indistinguishable from zero and show no systematic pattern, while post-treatment effects emerge sharply following repurposing and persist over time. This dynamic pattern reinforces that the shift in narrative sentiment reflects a causal response to property repurposing rather than differential pre-trends between treated and control areas.

Table 15 Impact of reusing Mafia properties on students' sentiment scores

Sentiment analysis outcomes		
	(1)	(2)
	Syuzhet Score	AFINN Score
Reuse = 1	-0.266** (0.112)	-0.417** (0.195)
Clustered SE	yes	yes
Time FE	yes	yes
Schools FE	yes	yes
Observations	3,242	3,242
Number of schools	46	46
Mean dep. var.	-0.710	-2.349

Notes: TWFE models. Standard errors are clustered at the school level.

Finally, I employ the NRC emotion lexicon to analyse how reuse activities affect the per-

ception of the Mafia across eight distinct emotional categories: anger, disgust, fear, sadness, joy, trust, surprise, and anticipation. Table A5 reports the most common terms appearing in the top 25% of responses for each emotion. Students expressing high levels of negative emotions frequently employ concrete terms directly related to violence and criminality; fear-based definitions prominently feature words which reflect an understanding of the Mafia's coercive power, while anger-related responses include terms that show the students' awareness of how the Mafia infiltrates democratic institutions. Disgust-associated language features words indicating moral repugnance toward Mafia practices, while sadness-related terms demonstrate emotional responses to the costs related to the Mafia presence. The positive emotion categories reveal an interesting picture. Across joy, trust, and surprise categories, the term *money* emerges as the most frequent, suggesting that students are aware of the monetary gains and social status that make the Mafia attractive for career development purposes.

Table 18 presents the results. Among negative emotions, fear emerges as the most consistent and robust response to the intervention. Students in treated areas show increases in fear-based language of 23% relative to the mean, even including school and time fixed effects. This suggests that exposure to repurposed Mafia properties genuinely enhances students' understanding of the Mafia's threatening and coercive nature. The analysis of positive emotions reveals a drop in the emotion of joy of 36% relative to the mean, suggesting that the intervention may actively reduce any romanticised or positive associations students might harbour toward the Mafia. Trust, surprise, and anticipation all show negative but insignificant coefficients, suggesting these emotional dimensions are less affected by exposure to repurposed Mafia properties.

These findings collectively suggest that the reuse of confiscated Mafia properties serves as an effective intervention for reshaping young people's emotional responses to the Mafia and the perception of the Mafia network as a career development pathway. The intervention appears to work primarily by intensifying fear-based understanding of the Mafia's harmful nature while simultaneously reducing any positive emotional associations, creating a more critical perception of the Mafia's impact on society.

Table 16 Impact of reusing Mafia properties on students’ emotional sentiments towards the Mafia

Sentiment analysis outcomes				
	(1)	(2)	(3)	(4)
	Anger	Disgust	Fear	Sadness
Panel A: Negative sentiments				
Reuse = 1	-0.0151 (0.140)	-0.0637 (0.0705)	0.254** (0.125)	0.0764 (0.120)
Clustered SE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
School FE	yes	yes	yes	yes
Observations	3,242	3,242	3,242	3,242
Number of schools	46	46	46	46
Mean dep. var.	0.895	0.687	1.060	0.483
	(1)	(2)	(3)	(4)
	Joy	Trust	Surprise	Anticipation
Panel B: Positive sentiments				
Reuse = 1	-0.136* (0.0694)	-0.0221 (0.104)	-0.0180 (0.0777)	-0.0153 (0.0772)
Clustered SE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
School FE	yes	yes	yes	yes
Observations	3,242	3,242	3,242	3,242
Number of schools	46	46	46	46
Mean dep. var.	0.369	0.708	0.271	0.399

Notes: TWFE models. Standard errors are clustered at the school level.

7.3.1 Students’ Heterogeneity

I further investigate heterogeneity in the sentiments expressed by students about the Mafia by examining differences across socio-economic backgrounds. Since further information on household income or educational level are not accessible at the student level, I construct a proxy of socio-economic background based on the level of each student’s linguistic complexity. I build on rich evidence from developmental linguistics showing that children from lower socio-economic backgrounds tend to produce shorter and less lexically diverse sentences, reflecting differences in the quantity and quality of language input received during early development (Huttenlocher, Waterfall, Vasilyeva, Vevea and Hedges, 2010; Spencer, Clegg and Stackhouse, 2012). For simplicity, I use the word count of each student’s open-ended

definition of the Mafia as a measure of syntactic complexity. Specifically, I compute the number of words in each response, standardise the measure into z-scores using the sample mean and standard deviation, and assign each student to a quartile rank from 0 (bottom 25%) to 3 (top 25%). Students with empty responses are assigned to the lowest rank. I then split the sample at the median, classifying students in ranks 0–1 as proxied lower socio-economic status and those in ranks 2–3 as proxied higher socio-economic status. I report some examples of what type of definitions fall in which rank in Table A6. Figure 11 presents the treatment effects on sentiment scores separately for the two groups, estimated with school and time fixed effects. A clear pattern emerges: students with lower syntactic complexity express significantly more negative sentiment toward the Mafia following the repurpose intervention, with both the Syuzhet and AFINN scores shifting downward.²⁶ By contrast, students with higher syntactic complexity show no significant change in either sentiment measure. Since the specification includes school fixed effects, these results capture within-school variation, meaning that the differential response is not driven by differences across schools but rather by heterogeneity among students attending the same institutions. Overall, the results show that the intervention is most effective in reshaping perceptions among students from more disadvantaged backgrounds, precisely the group most exposed to Mafia influence and for whom the provision of alternative role models and community engagement is likely to carry the greatest marginal value.

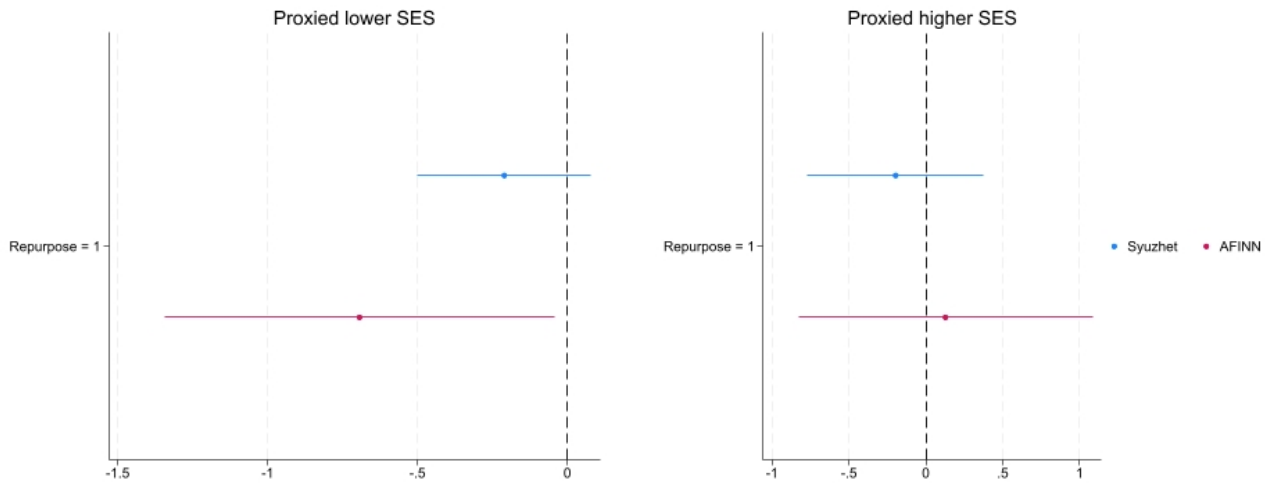


Figure 13 Estimated effects of reusing practices on students' survey emotions in defining the mafia by proxied SES

²⁶Although the Syuzhet coefficient does not reach conventional significance levels ($\beta = -0.21$ and p-value = 0.150), it displays a more precise estimate than the corresponding coefficient for higher socio-economic background students ($\beta = -0.19$ and p-value = 0.497).

8 Conclusions

This study provides the first causal evidence that converting seized Mafia properties into community spaces yields tangible educational benefits for youth in historically Mafia-affected areas. I construct a comprehensive dataset tracking the implementation of the CRR policy across major urban areas from 2015 to 2022; additionally, I leverage several sources of administrative and survey data by following student cohorts from grade 9 to grade 13. I build school catchment areas by matching census blocks to their closest high school for each schooling track, and I exploit the time and the location of repurposed Mafia properties within those areas. School catchment areas are defined as treated whenever there is at least one Mafia real estate repurposed within the area boundaries. I compare school catchment areas affected by the repurpose of Mafia properties to those unaffected or not yet affected before and after the first experience of repurpose.

Using a difference-in-differences approach, I demonstrate that transforming former criminal strongholds into hubs for social activities reduces high school dropout rates by approximately 36% relative to baseline levels among students beyond the age of compulsory schooling. The findings reveal nuanced patterns in how this policy intervention operates. Low-performing and technical high school students benefit most substantially, experiencing a sustained decrease in dropout rates that persists up to 5 years after the start of the treatment. Additionally, the magnitude of impact scales with intensity: each additional repurposed property in a school’s catchment area corresponds to an approximate 12% reduction in dropout rates. This intensive marginal effect decreases as the distance to the student population-weighted centroids increases, and is stronger when weighted by the average catchment area student population.

I further investigate the mechanisms underlying the estimated effects, ruling out several alternative explanations. First, triple difference-in-differences estimates interacting the treatment indicator with neighbourhood rental prices yield coefficients that are virtually zero and statistically insignificant, indicating that the dropout reduction does not operate through gentrification or neighbourhood upgrading. Second, controlling for the presence of other NGOs in school catchment areas leaves the reuse coefficient unchanged, while the NGO variable itself has no significant effect, demonstrating that the activities hosted in repurposed Mafia properties are not easily substitutable by conventional civil society provision. Third, the inclusion of municipality-level controls for concurrent educational and social cohesion programmes does not alter the main estimates, confirming that the effects are not part of a broader development strategy. To shed further light on the channel through which repurposed properties reduce dropout rates, I decompose the treatment by the type of activity offered.

If the mechanism operated primarily through additional educational or vocational support, properties dedicated to these purposes should exhibit the strongest effects. The evidence points in a different direction: education- and employment-related activities do not drive the largest reductions. Instead, the strongest effects are associated with properties hosting welfare and cultural activities, suggesting that what matters is the broader transformation of the social environment rather than the direct provision of academic resources.

Survey evidence on students' perceptions corroborates this interpretation. Students exposed to repurposed properties increasingly define the Mafia with greater fear and diminished positive emotions, while viewing educational achievement and meritocratic pathways as more viable routes to employment. This shift in students' beliefs appears central to the policy's effectiveness. The cultural and welfare activities hosted in former Mafia properties seem to operate by offering alternative social frameworks and role models, reshaping how young people perceive the trade-off between criminal affiliation and educational investment.

These findings carry substantial implications for anti-Mafia policy design, both in Italy and in comparable settings internationally. Most fundamentally, they demonstrate that effective crime prevention requires moving beyond asset confiscation toward the active construction of legitimate alternatives within affected communities. The challenge lies not in seizing criminal property but in ensuring its rapid and effective deployment as a community resource. At present, more than half of all reallocated properties remain not yet repurposed, representing missed opportunities to weaken Mafia recruitment and strengthen educational retention. This paper underscores the need to accelerate the bureaucratic transition from reallocation to active reuse, and to provide sustained financial support to the local NGOs that manage these spaces. Enhanced funding mechanisms, streamlined administrative procedures, and stronger partnerships between local authorities and civil society organisations would amplify the policy's reach and impact.

SUPPLEMENTARY APPENDICES

Appendix A: Additional Figures and Tables

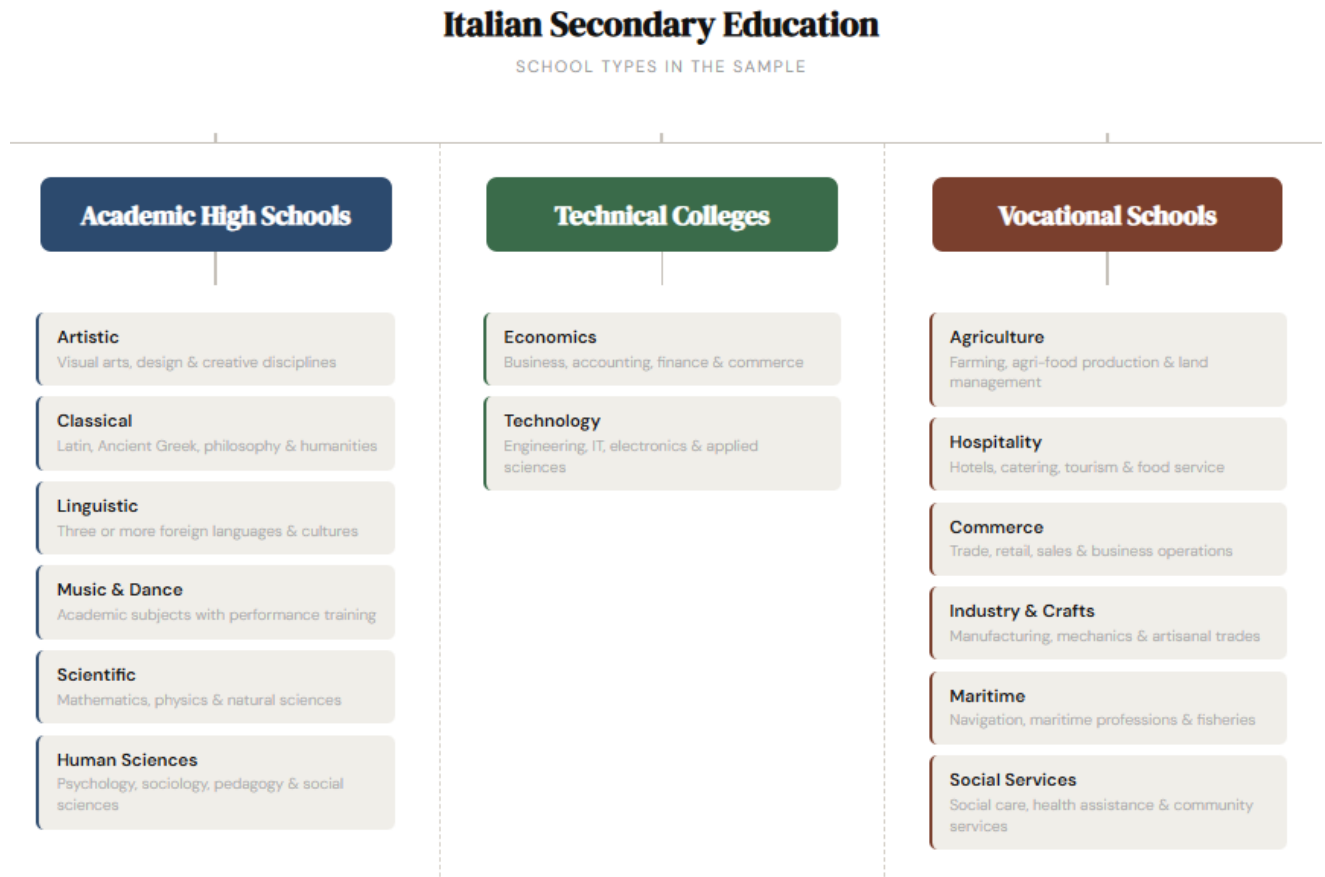


Figure A1 The universe of possible high school sub-tracks in Italy.

Table A1 Survey Questions from the Survey of the Perception of the Mafia

ID	Question	Answer Type	Unit
V12	How would you define the Mafia?	Open-ended text	Student
V28	<p>According to you, when young people are looking for a job in your city what can they do?rate the following options from very useful (1) to very useless (7)</p> <p>Invest in education</p> <p>Participate in a public competition</p> <p>Turn to job centre</p> <p>Turn to the Mafia</p> <p>Turn to a politician</p> <p>Ask family</p> <p>Ask a friend</p>	<p>Index 1-7</p> <p>Index 1-7</p> <p>Index 1-7</p> <p>Index 1-7</p> <p>Index 1-7</p> <p>Index 1-7</p> <p>Index 1-7</p>	<p>School</p> <p>School</p> <p>School</p> <p>School</p> <p>School</p> <p>School</p> <p>School</p>
V32	<p>In your opinion, who is stronger between the State and the Mafia?</p> <p>Choose an option</p> <p>The Mafia</p> <p>The State</p> <p>Equally</p> <p>I don't know</p>	<p>Multiple choice</p> <p>Multiple choice</p> <p>Multiple choice</p> <p>Multiple choice</p>	<p>School</p> <p>School</p> <p>School</p> <p>School</p>

Notes: The answers to the Survey on the Perception of the Mafia have been provided by [Centro Studi Pio La Torre \(2025\)](#)

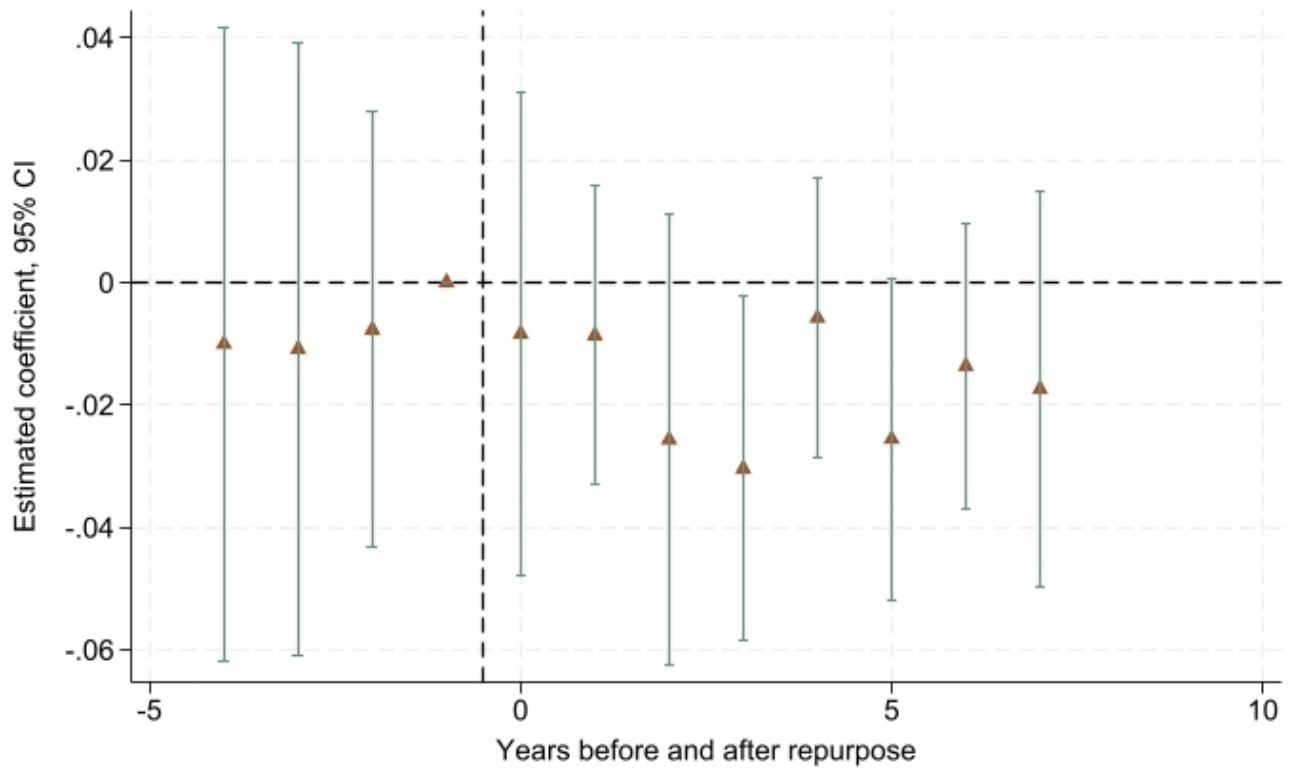


Figure A2 Estimated effects of reusing practices on dropout rate before and after the first reuse starts - excluding dropout from grade 13

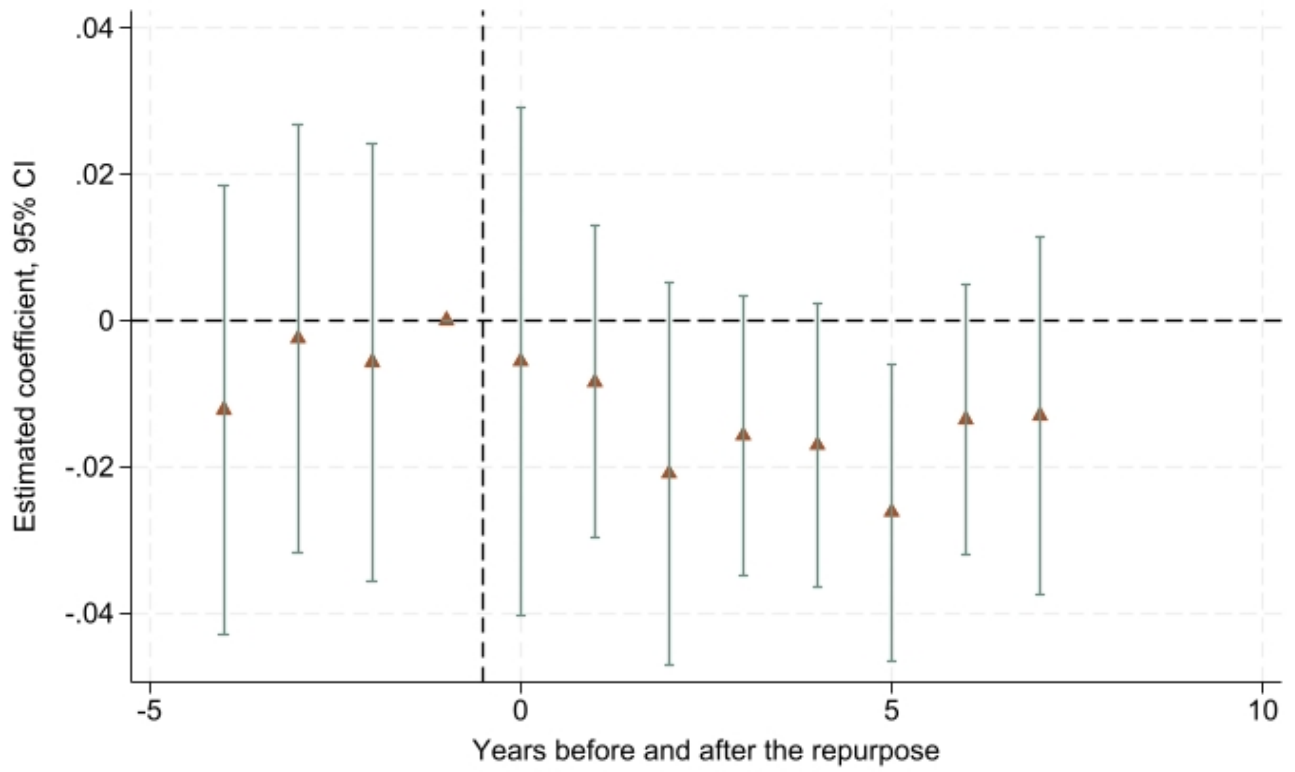


Figure A3 Estimated effects of reusing practices on dropout rate before and after the first reuse starts - event study of areas already hosting reallocated properties

Table A2 Testing the effect of the treatment on the main controls

	(1)	(2)	(3)	(4)
	Student migration		Grade retention	
Reuse = 1	0.00160 (0.00182)	0.00159 (0.00182)	-0.000460 (0.00120)	0.000469 (0.00114)
clustered SE	yes	yes	yes	yes
School FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Student migration	no	no	no	yes
Grade retention	no	yes	no	no
Observations	1,294	1,292	1,542	1,292
Number of schools	234	234	244	234
Mean dep. var.	0.349	0.349	0.0108	0.0105

Notes: TWFE model. The treatment variable is equal to 1 whenever there is at least one Mafia property within the school catchment area. Standard errors are clustered at the school level.

Table A3 Effect of the treatment on selection in enrollment preferences

	(1)	(2)	(3)	(4)
	Enrollment Share			
Reuse = 1 X Technical	-0.00723 (0.0127)	-0.0117 (0.0121)	-0.00778 (0.0125)	-0.0116 (0.0115)
Reuse = 1 X Academic	0.0120 (0.0148)	0.0240 (0.0145)	0.0121 (0.0147)	0.0235* (0.0140)
Reuse = 1 X Vocational	-0.0638** (0.0250)	-0.0647** (0.0266)	-0.0637** (0.0246)	-0.0645** (0.0258)
clustered SE	yes	yes	yes	yes
school FE	yes	yes	yes	yes
time FE	yes	yes	yes	yes
migration	no	yes	no	yes
retention	no	no	yes	yes
Observations	1,496	1,254	1,471	1,235
Number of schools	236	228	235	228
Mean dep. var.	0.232	0.230	0.232	0.230

Notes: TWFE model. The treatment variable is equal to 1 whenever there is at least one Mafia property within the school catchment area. Standard errors are clustered at the school level.

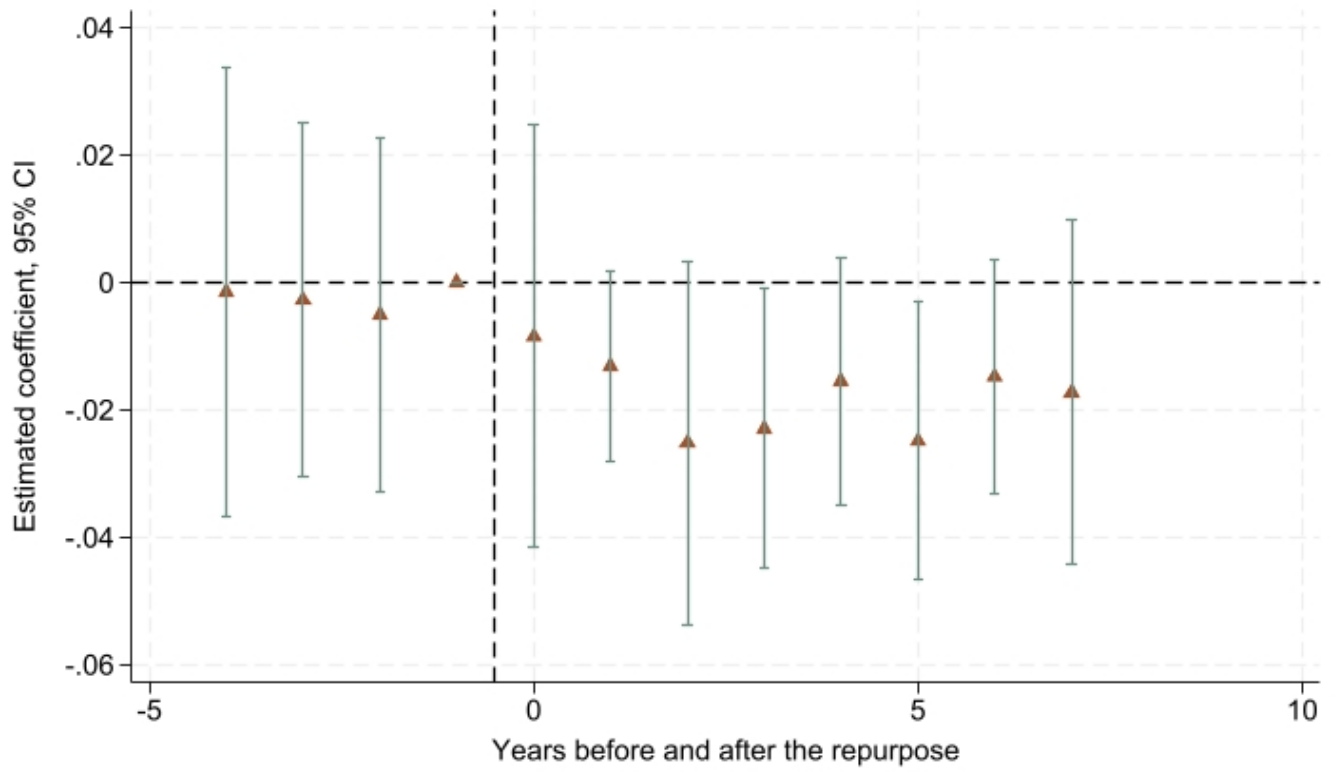


Figure A4 Estimated effects of reusing practices on dropout rate before and after the first reuse starts - event study controlling for the presence of educational- and urban-related programmes at the municipality level

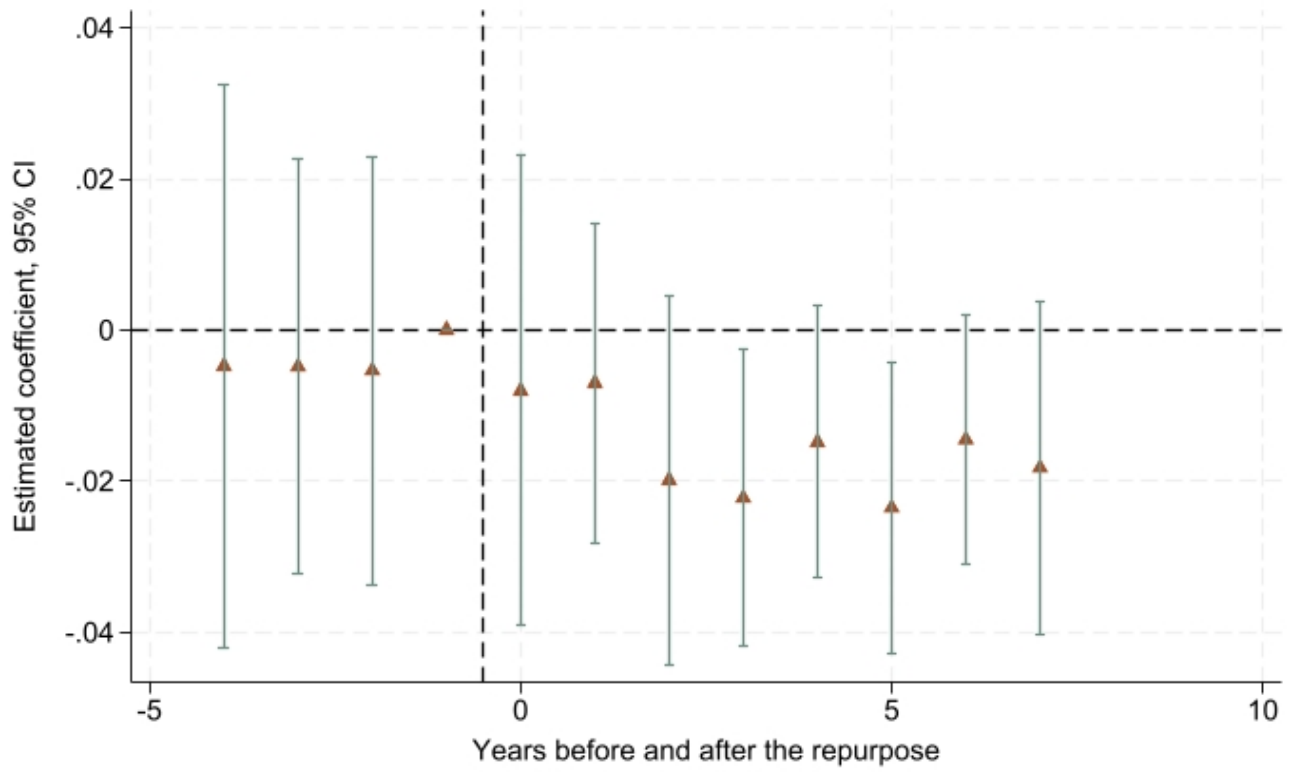


Figure A5 Estimated effects of reusing practices on dropout rate before and after the first reuse starts - event study controlling for the presence of NGOs

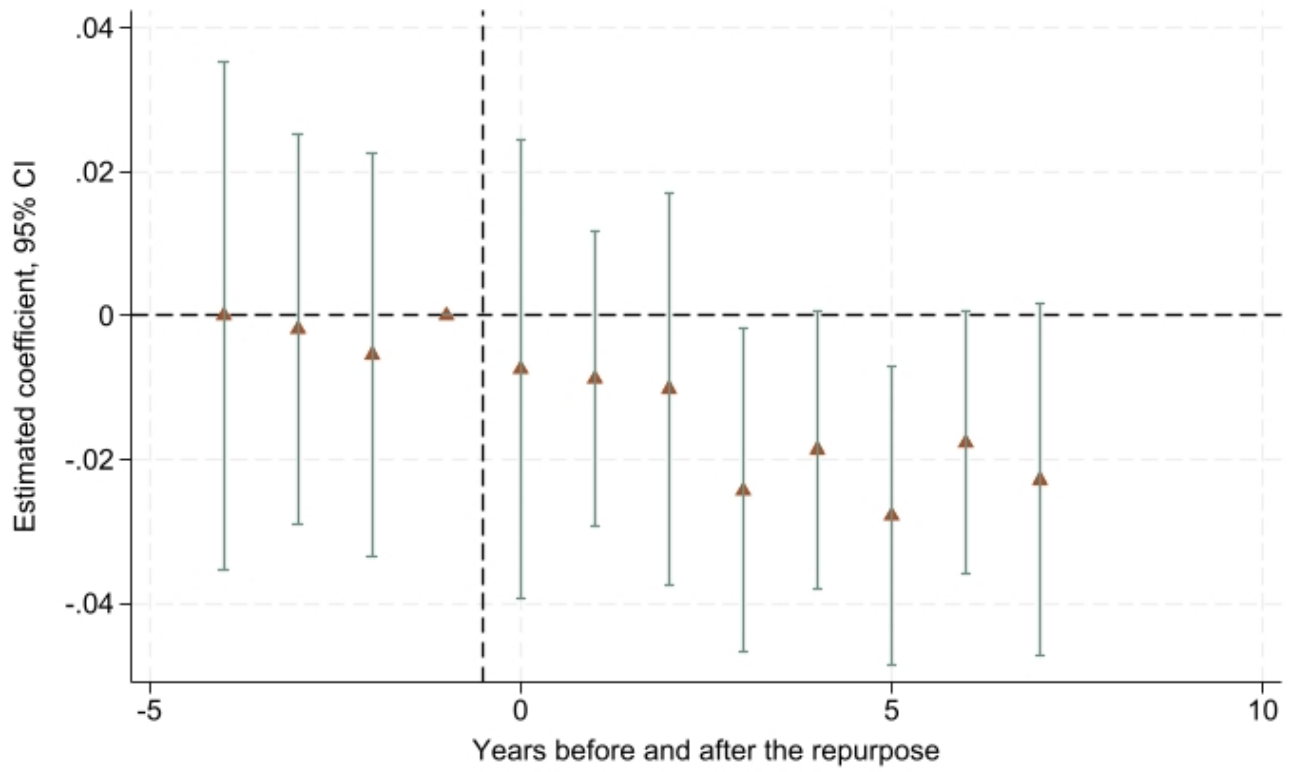


Figure A6 Estimated effects of reusing practices on dropout rate before and after the first reuse starts - event study of marginal effect over reallocations

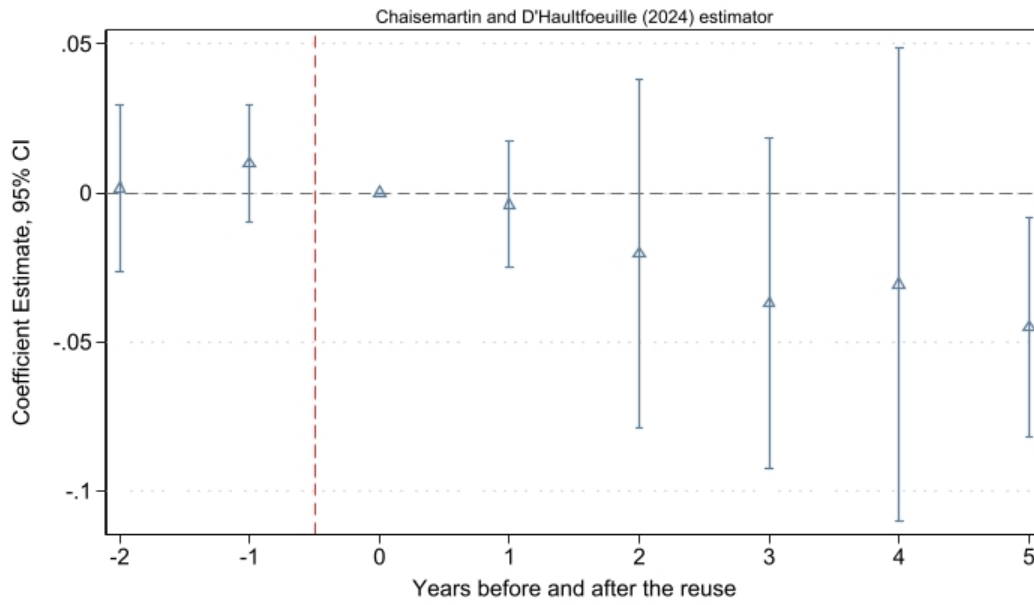


Figure A7 Event study using the count of reused assets weighted by the student population of school catchment areas

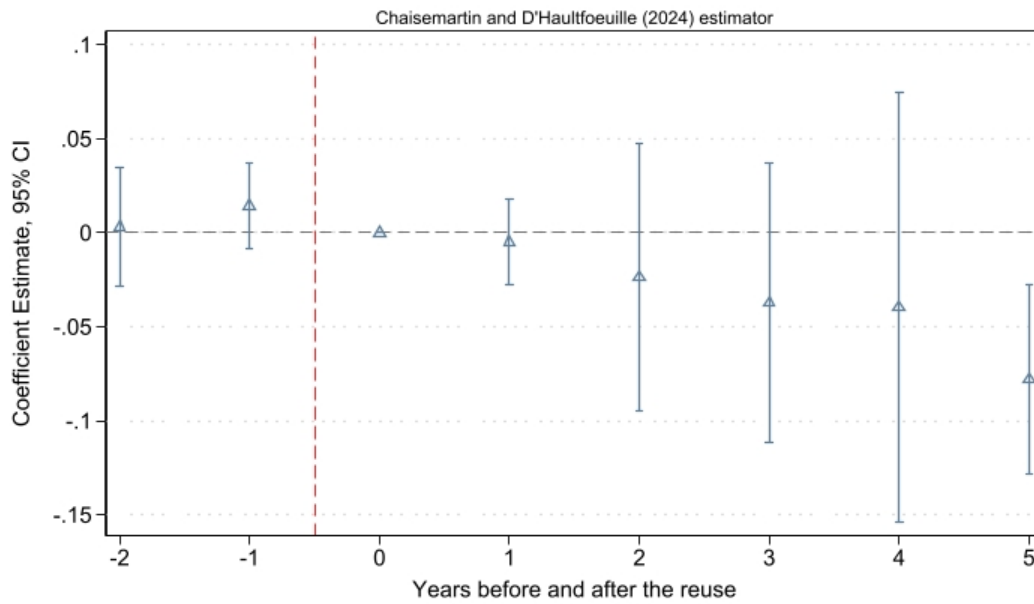


Figure A8 Event study using the count of reused assets weighted by the average distance of properties from the population-weighted centroids of schools' catchment areas

Table A4 Impact of reusing Mafia real estate on students' perceptions of who is stronger between the Mafia and the State

Who is stronger between the Mafia and the State?				
	(1)	(2)	(3)	(4)
	Mafia	State	Equally	Don't Know
Reuse = 1	-0.0312 (0.107)	0.0344 (0.0812)	-0.00151 (0.0698)	-0.00171 (0.0454)
Observations	162	162	162	162
Number of schools	54	54	54	54
clustered SE	yes	yes	yes	yes
time FE	yes	yes	yes	yes
school FE	yes	yes	yes	yes
Mean dep. var.	0.394	0.170	0.296	0.139

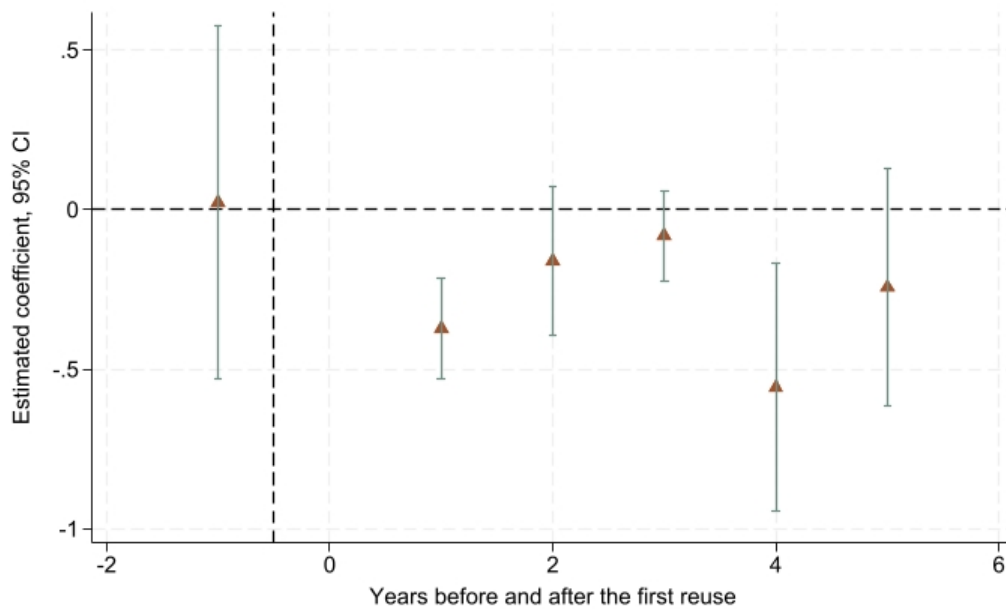


Figure A9 Event study of the Szyuzhet scores

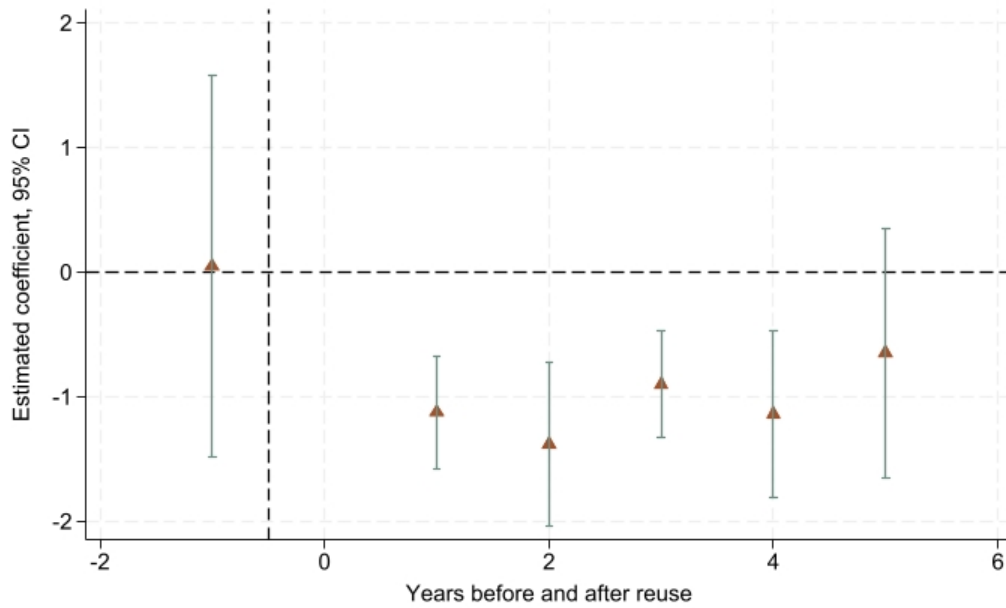


Figure A10 Event study of the AFINN sentiment scores

Table A5 Top 25 terms for positive and negative sentiments

<i>Panel A: top 25% negative words</i>	Anger	Disgust	Fear	Sadness
	Electoral	Ruthless	Forced	Violence
	Laundering	Struggle	Eradicate	Kill
	Murder	Threatening	Hide	Cruel
	Resorting	Inconvenient	Manifests	Unfair
	Conflict	Involve	Struggle	Evil
Observations	638	393	327	274

<i>Panel B: top 25% positive words</i>	Joy	Trust	Surprise	Anticipation
	Money	Money	Money	Public
	Respect	Association	Violent	Respect
	Achieve	Structure	Protection	Protection
	Gain	Respect	Deal	Gain
	Freedom	Achieve	Hope	Poweful
Observations	227	569	740	234

Those words you listed are the most frequent words appearing in sentences that scored high (top 25%) for each specific emotion dummy.

Table A6 Impact of reusing Mafia real estate on the share of students dropping out before the age of 16

Rank	Definition	Italian word count	CSI
0	I don't know	2	-0.35
1	They are organizations that ruin our society	7	-0.22
2	Organizations that follow, therefore adopt, a behavior that may seem beneficial in some aspects such as the economic one and employment	21	0.12
3	Mafia-type organizations are a group of people who act illegally, sometimes hiding behind legal activities. Very often mafia organizations push people towards the wrong path, very often due to people's desperation	40	0.59

Notes:

Appendix B: Attributes of repurposed properties and local context

The repurposed properties in the sample display a fairly homogeneous profile in terms of real estate type. The large majority are residential estates (68%), followed by land (20%), while commercial and industrial properties account for only 10% and a residual share falls into other categories. Consistent with this, the most common prior use before confiscation was villas and houses (45%), followed by other uses (26%) and land (19%), with shops, garages, and commercial deposits representing marginal shares. In terms of reallocation, virtually all properties (99%) were transferred to local authorities, with only one asset sold to a private buyer. Regarding the activities carried out in the repurposed properties, the distribution is relatively balanced between welfare and cultural activities — roughly half of the properties host welfare-oriented activities (50.6%) and a slightly larger share host cultural ones (56.4%) — while employment and other activities remain much less common, at 11.6% and 12.1% respectively. Education activities are present in about one fifth of cases (19.4%).

Table B1 Repurposed properties attributes

Type of real estate	N	%	Reallocation type	N	%
Commercial and industrial estate	35	10	Local authorities	345	99
Residential estate	236	68	Sold to private	1	1
Land	67	20	Total	346	100
Other	8	2			
Total	346	100			

Usage before confiscation	N	%	All types of activities	N	%
Other	92	26	Education	67	19.4
Box, garage	18	5	Welfare	175	50.6
Fabbricate	3	1	Culture	195	56.4
Commercial deposit	3	1	Employment	40	11.6
Shop	11	3	Other	42	12.1
Land	65	19			
Villas and Houses	155	45			
Total	346	100			

Notes:

Turning to the local context, the data paint a picture of small, tight-knit, predominantly native residential communities. With an average of just 361 residents and 136 households per census section, these are not urban neighbourhoods in any dense sense — they are closer to village-scale settlements or peripheral urban pockets, the kind of places where social dynamics

are likely shaped by proximity and long-standing local ties rather than anonymity. The very low share of non-native residents (under 4% on average) reinforces this characterisation of socially homogeneous, relatively closed communities. Household composition skews toward smaller units, with single- and two-person households together accounting for over half the average section, which may reflect an ageing population rather than a young or dynamic one. Educational attainment is modest: high school and secondary diplomas dominate, university graduates make up only 13% of residents, and a non-trivial share holds only a primary diploma or is merely literate. This suggests these are working- and lower-middle-class communities, not areas of high human capital concentration. Labour market conditions are consistent with this reading — while the employment rate averages around 77%, unemployment sits at roughly 11%, pointing to communities that are economically functional but under strain, without the slack of prosperous areas. The local real estate stock is overwhelmingly residential (81%), mostly in good or decent physical condition, with a limited commercial footprint (15%), further reinforcing the image of settled, predominantly domestic environments rather than economically active or commercially vibrant ones. Civic infrastructure is present but uneven: the average of 43 registered NGOs per area suggests some organised social fabric, but participation levels vary enormously across locations, indicating that civil society engagement is far from uniform and likely concentrated in a subset of better-resourced communities.

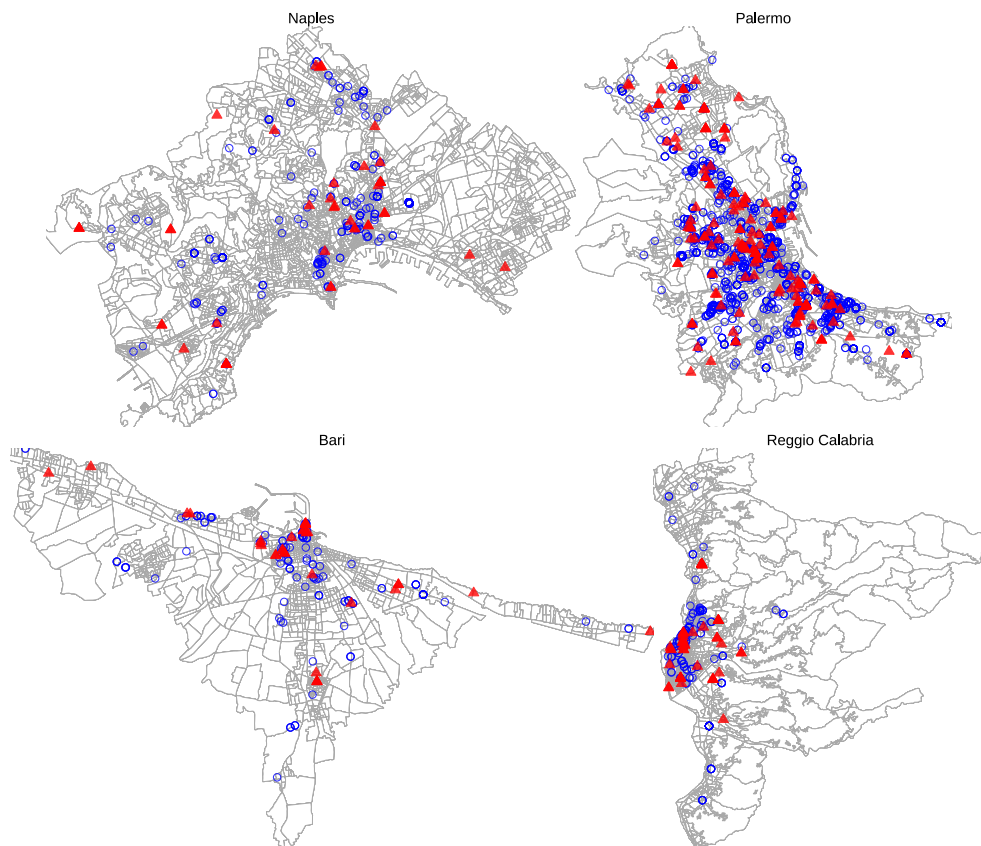
Table B2 Census data

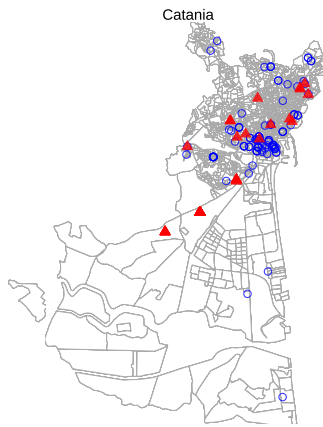
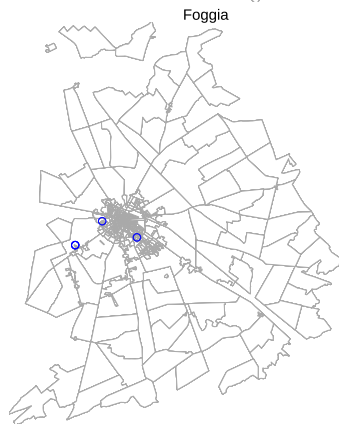
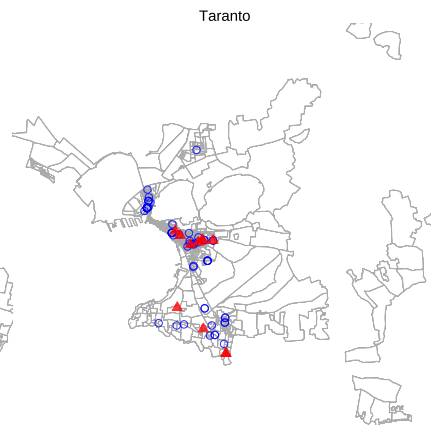
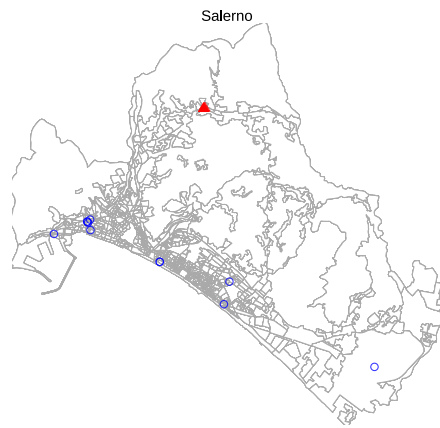
	(1)	(2)	(3)	(4)	(5)
	N	mean	sd	min	max
Population					
Residents	276	360.7	169.8	4	904.7
Residents 15-19 yo	276	0.0568	0.00919	0	0.104
Non-native residents	276	0.0376	0.0434	0	0.438
Number of households	276	136.3	62.78	1	366
Households: 1 component	276	0.264	0.0613	0	0.522
Households: 2 component	276	0.242	0.0297	0	0.341
Households: 3 component	276	0.212	0.0299	0	0.303
Households: 4 component	276	0.203	0.0590	0.0825	1
Households: 5 component	276	0.0589	0.0204	0	0.150
Households: 6 plus component	276	0.0206	0.0160	0	0.146
Education					
University degree	276	0.134	0.0602	0	0.319
High school diploma	276	0.298	0.0668	0.133	0.750
Secondary diploma	276	0.293	0.0586	0	0.461
Primary diploma	276	0.184	0.0383	0	0.289
Literates	276	0.0789	0.0272	0.0263	0.322
Illiterates	276	0.0131	0.00756	0	0.0551
Labour market					
Workforce	276	142.2047	67.46701	2	368.1952
Employed	276	0.7686306	0.0796366	0.4690265	0.9230769
Unemployed	276	0.1073502	0.0214117	0	0.175686
Area characteristics					
Number of reale estate	276	33.63	35.62	1	330
Share of residential real estate	276	0.812	0.101	0.182	1
Share of commercial real estate	276	0.154	0.1000	0	0.776
Real estate: perfect conditions	276	0.153	0.146	0	1
Real estate: good conditions	276	0.416	0.150	0	1
Real estate: decent conditions	276	0.206	0.108	0	0.629
Real estate: bad conditions	276	0.0374	0.0502	0	0.484
Number of NGOs	209	42.80	77.69	0	342
Number of NGOs participants	276	3.848	39.65	0	651

Notes:

Figure B1 provides a comprehensive spatial overview of confiscated Mafia properties across all municipalities part of the sample, distinguishing between reused (red triangles) and not-yet-reused properties (empty blue circles). While confiscated properties are predominantly

located in highly populated areas and regions with greater economic activity, particularly near coastal zones, the maps reveal that reuse patterns do not follow the same geographic clustering. The reused Mafia properties show considerable spatial heterogeneity within these areas, being distributed across diverse urban contexts rather than being concentrated in specific neighbourhoods or zones. This spatial variation is particularly important for the main identification assumptions, as it demonstrates that school catchment areas containing reused Mafia properties are distributed across different geographic and socioeconomic contexts within the broader areas of Mafia presence. Furthermore, the presence of both reused and unreused properties across various municipalities provides a rich spatial framework for comparison, which I exploit for robustness checks in section 6.6.





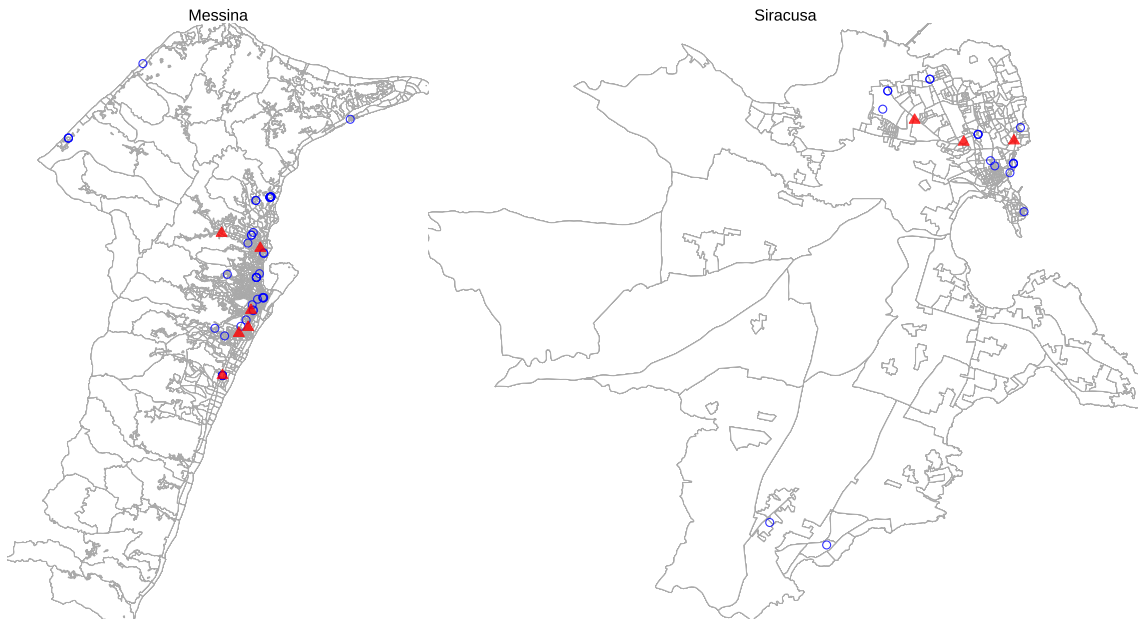


Figure B1 The distribution of Mafia real estate in the 10 metropolitan areas of the historical Mafia-ridden regions. Empty blue circles locate reallocated but not reused real estate, while red triangles indicate the real estate under reusing practices.

Appendix C: Endogeneity Concerns

In this Appendix I investigate the determinants of the reuse of Mafia properties.

It is possible that an endogeneous treatment assignment violates the parallel trends assumption underlying the DiD identification strategy if the decision to reuse confiscated mafia properties is influenced by unobserved factors that also affect educational outcomes over time. While pure selection into treatment does not necessarily bias the results provided parallel trends hold, it is important to investigate the factors driving the reuse of Mafia properties to identify context-specific confounders. According to the CRR policy, local authorities are responsible for identifying local NGOs to manage reallocated Mafia properties and actively pursue their reuse for social activities. Although Table 4 shows no significant differences in street-level characteristics between treated and untreated schools, treated schools might be systematically located in municipalities with stronger institutional capacity, higher civic engagement, or greater commitment to put the policy into practice. Notably, these features can independently influence educational outcomes and create differential trends between treatment and control groups.

To investigate this potential source of endogeneity, I estimate a linear probability model by regressing the probability of mafia property reuse on NGO presence in the year before reuse and several baseline municipality characteristics not controlled for in the main specification. Since reuse is measured in the year when the municipality and local NGO sign a management agreement, the level of NGO presence in the preceding period is crucial because municipalities must identify suitable partner organizations beforehand. I collect several measures of municipal characteristics that could influence both reuse decisions and educational outcomes. First, I obtain information about whether municipalities were ever dissolved for mafia-related activities at baseline from [Avviso Pubblico](#)²⁷. Second, I collect baseline municipal expenditure data from the [Ministry of the Interior](#) for three relevant policy areas: youth policies, urban and territorial planning, and municipal police services. These expenditure categories capture municipal priorities and capacity in areas directly related to property reuse and community development. Finally, I create a transparency indicator equal to 1 for municipalities that failed to regularly publish information about available mafia properties for reuse on their websites before the first treatment occurrence. This measure follows the classification strategy implemented by [Falcone, Illustrazione, Giannone, Mennella, Ferrante and Martone \(2021, 2022\)](#) where municipalities were classified based on the level of transparency shown online in sharing information about the presence of Mafia reallocated properties as inscribed by the law. The model is specified as:

²⁷Avviso Pubblico is an Italian national association created in 1996 to promote transparency in the public administration.

$$P(\textit{Reuse} = 1)_{cm} = \beta_0 + \beta_1 \textit{lag}_{NGO_c} + \beta_2 X'_m + \epsilon_{cm} \quad (5)$$

where $P(\textit{Reuse} = 1)$ is the probability for a Mafia property to get reused in school catchment area c in municipality m . \textit{lag}_{NGO} represents the number of NGOs active at the street-level one year before the reuse in school catchment area c , while X' includes the aforementioned baseline municipalities features.

The results of the LPM are shown in Table B1. Column (3) shows that one additional NGO presence in the year prior to reuse significantly increases the probability of getting a reused Mafia property of 0.11% relative to the mean. Although the magnitude of the effect is very small, this could indicate that areas with stronger organizational capacity are slightly more likely to receive reused properties. Several municipal characteristics also influence reuse decisions: first, municipalities with greater transparency in publishing information about re-allocated Mafia properties seem to be more likely to pursue reuse; second, a doubling of territorial planning expenditure increases the probability of mafia property reuse by 7.79% relative to the mean, while doubling youth policy expenditure increases reuse probability by a relative 6.90%. These substantial effects demonstrate that municipalities with stronger policy commitments and administrative capacity in areas directly relevant to community development and social programming are more likely to pursue reuse initiatives. Notably, Mafia-related municipal dissolution experiences at the baseline do not predict reuse, indicating that treatment assignment is more on current institutional capacity rather than historical Mafia presence.

Table C1 Robustness exercise including time trends and additional controls

	(1)	(2)	(3)
	P(Reuse = 1)		
NGOs t-1	0.000235*		0.000940***
	(0.000133)		(0.000213)
Dissolution = 1		0.0627	-0.0309
		(0.0941)	(0.108)
Transparency = 1		0.228***	0.232***
		(0.0642)	(0.0644)
Exp youth policies		0.0364	0.0594**
		(0.0239)	(0.0258)
Exp education		0.0225	0.000454
		(0.0139)	(0.0152)
Exp urban planning		0.0413***	0.0671***
		(0.0121)	(0.0151)
Exp municipal police		-0.0204	-0.000231
		(0.0148)	(0.0157)
clustered SE	yes	yes	yes
Observations	1,746	2,096	1,746
Mean dep. var.	0.861	0.857	0.861

Notes: LPM model. The outcome variable is equal to 1 whenever there is at least one Mafia property within the school catchment area. Standard errors are clustered at the school level.

To address this endogeneity concerns, I re-estimate the main DiD specification including a control for the lagged presence of NGOs and municipality-specific time trends. This way, I test whether the estimated effect of the reuse of Mafia properties reuse dropout rates are robust after accounting for systematic differences in NGOs and municipal characteristics. Table B2 shows the baseline and the re-estimated results. This exercise demonstrates that the negative effect of reuse activities on dropout rates persists even after controlling for the systematic factors that drive treatment assignment. Comparing the baseline specifications presented in Columns (1) and (2) with the specification accounting for both NGOs and municipalities characteristics in Column (4), the estimated treatment effect remains statistically significant and economically meaningful, declining only by 5.3% relative to the mean. This represents a reduction to the mean from 36.2% to 31.4%, so there is still a substantial 31% decrease in dropout rates. Column (5) replaces municipality-specific time trends with municipality \times year

fixed effects, the most saturated specification. The point estimate remains stable at -0.0159 but falls just short of conventional significance levels ($t = 1.56$, $p = 0.120$). The identification employed in this specification relies exclusively on within-municipality, across-school variation in treatment status in a given year. However, the share of treated schools within municipality-year cells is very close to 0 or 1 in for roughly half of the sample, presenting no within-year variation. This indicates that most treatment variation is between rather than within municipalities, and that municipality X year FEs absorb the bulk of the identifying variation, mechanically reducing statistical power. The persistence of a large negative coefficient across all specifications provides clear evidence that the relationship between reuse activities and improved educational outcomes is robust to concerns about systematic treatment assignment based on local organisational capacity.

Table C2 Estimating reuse predictors

	(1)	(2)	(3)	(4)	(5)
	Dropout rate G11-G13				
Reuse = 1	-0.0192** (0.00934)	-0.0196** (0.00943)	-0.0168* (0.00981)	-0.0166* (0.00979)	-0.0159 (0.01017)
Clustered SE	yes	yes	yes	yes	yes
Student migration	no	yes	no	yes	yes
Grade retention	no	yes	no	yes	yes
NGO lags	no	no	yes	yes	yes
Municipality time trends	no	no	yes	yes	no
Municipality \times year FE	no	no	no	no	yes
Observations	1,296	1,272	1,284	1,262	1,262
Number of schools	235	234	234	233	233
Mean dep. var.	0.0537	0.0531	0.0536	0.0529	0.0529

Notes: TWFE model. The treatment variable is equal to 1 whenever there is at least one Mafia property within the school catchment area. Standard errors are clustered at the school level.

Appendix D: Construction of Additional Variables

This appendix provides additional information on the data and variables used in this paper.

Schools' catchment areas. To test whether the treatment allocation and results are sensitive to changes in the construction of school catchment areas, I build an alternative version where I weight the Euclidean distance used to assign census blocks to schools based on schools' capacity. I proceed in three steps: first, I aggregate census blocks to their closest school based on simple Euclidean distance. Second, I multiply the distance by the average enrollment rate of each school and divide the result by each school's enrollment rate at the baseline as follows:

$$d_{ic}^* = d_{ic} \times \frac{\bar{E}}{E_i}$$

This way, schools with higher capacity, which show an above-average enrollment, will display larger catchment areas, accounting for supply-side factors in the allocation of census blocks. Third, I repeat this process for each of the 14 schools' specialisations to consistently align with a location-allocation approach. Only 17 of the sample schools change their treatment status under these new assumptions, relaxing the concern about artificial treatment allocation. Figure A1 compares schools' catchment areas obtained using Euclidean and weighted-Euclidean distances for language academic high schools in Naples.

As expected, capacity-weighted catchment areas show slightly different boundaries. I employ this alternative specification solely for robustness testing in Section 6.1, where I examine treatment effects only in areas with unchanged boundaries to assess whether the main results are driven by schools with ambiguous treatment allocation across the two construction methods.

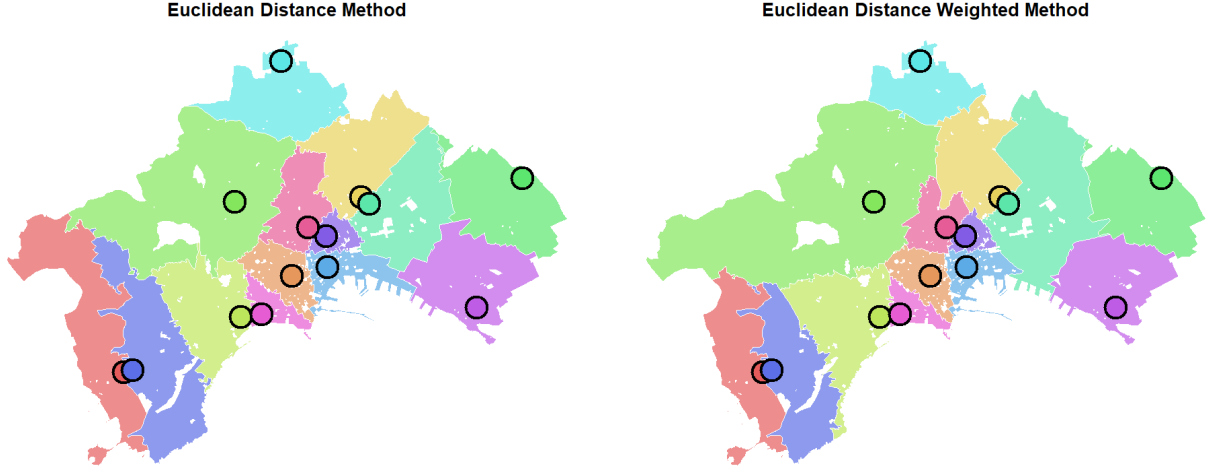


Figure D1 Schools' catchment areas measured with Euclidean distance (left) and capacity-weighted distance (right)

Students' migration. I report below the measure I compute to control for school-specific students' migration patterns, as explained in Section 4.4. I rely on the assumption that students who disappear from enrollment registries before turning 16 are more likely to be transferring to other schools rather than genuinely dropping out, given that education is compulsory until the age of 16. I build this measure following the same construction methodology as the main outcome variable, but capturing the share of students who do not complete grades 9 and 10 as their first and second years of high school. The measure is reported in Equation 6. Starting from the cohort of students who completed grades from 9 to 11 in year t_1 , I subtract those who progressed to complete grade 12 in year t , and those who completed grades 10 and 11 in year t , expressing this as a share of the initial cohort who completed grades from 9 to 11 in year $t - 1$.

$$Dropout_{G9-11_t} = \frac{Completed_{G9-11_{t-1}} - Completed_{G12_t} - Completed_{G10-11_t}}{Completed_{G9-11_{t-1}}} \quad (6)$$

Grade retention rate. It is possible that students repeating years due to inadequate academic performance will confound my measure of dropout by appearing enrolled in the same grade for both time t_1 and time t . To address this, I construct a proxy for grade retention rates for students enrolled on grades 11, 12, and 13. Table 2 in Section 4.1 shows

that students following the standard educational timeline are expected to be 16 or 17 years old in grade 11, and 17 or 18 years old in grade 12.

I calculate the share of students repeating grade 11 as the number of students aged 18 or older as a share of all students completing grade 11 in time t . Similarly, the share of students repeating grade 12 is calculated as the number of students aged 19 or older as a share of all students completing grade 12 in time t . Equations 7 and 8 show the respective grade retention rates. Due to data limitations, I cannot compute the retention rate for grade 13, as I cannot observe whether students are older than 19 in grade 13. However, since the average retention rate declines from 1.2% in grade 11 to zero in grade 12, the grade 13 retention rate would likely be negligible.

$$Retention_{G11t} = \frac{aged18_{G11t}}{Completed_{G11t}} \quad (7)$$

$$Retention_{G12t} = \frac{aged19+_{G12t}}{Completed_{G12t}} \quad (8)$$

Schools' quality index. I construct a composite baseline indicator of school quality, drawing on two dimensions evaluated through a structured assessment framework used by the Italian schools, namely the annual Self-Evaluation Report (RAV). The first dimension, focusing on the school-level learning outcomes, encompasses four criteria: school grades, standardised test scores, civic competences, and long-term outcomes. The second dimension, which focuses on learning process, covers seven criteria related to the organisational and pedagogical functioning of the school: module planning, learning environment, inclusion and diversity, student guidance, school organisation, human resources development, and integration with the local community. For each dimension, I construct a sub-index by taking the row mean of the standardised scores assigned to each criterion of learning outcomes performance and learning process performance, respectively. The overall school performance indicator is then computed as the simple average of these two sub-indices, giving equal weight to outcomes and processes. This produces a composite score at the school level that captures both what students achieve and how the school operates to support that achievement, and serves as the baseline measure of school quality in the analysis.

Table D1 Survey Questions from the Survey of the Perception of the Mafia

Learning Outcomes		Learning Process	
ID criteria	Description	ID criteria	Description
21	School grades	31	Modules planning
22	Standardised test scores	32	Learning environment
23	Civic competences	33	Inclusion and diversity
24	Long-term outcomes	34	Student guidance
		35	School organisation
		36	HR development
		37	Integration with the local community

References

- Acemoglu, Daron, Giuseppe De Feo, and Giacomo Davide De Luca (2020) “Weak States: Causes and Consequences of the Sicilian Mafia,” *The Review of Economic Studies*, 87 (2), 537–581, [10.1093/restud/rdz009](https://doi.org/10.1093/restud/rdz009).
- ANBSC (2019) “Linee guida per l’amministrazione finalizzata alla destinazione degli immobili sequestrati e confiscati,” <https://www.benisequestraticonfiscati.it/linee-guida-per-lamministrazione-finalizzata-alla-destinazione-degli-immobili-sequestrati>
- (2023) “Beni in amministrazione / destinati,” <https://benidestinati.anbsc.it/infoweb>.
- Angrist, Joshua D. and Alan B. Krueger (1991) “Does Compulsory School Attendance Affect Schooling and Earnings?” *The Quarterly Journal of Economics*, 106 (4), 979–1014, [10.2307/2937954](https://doi.org/10.2307/2937954).
- Arlacchi, Pino and Nando Dalla Chiesa (1987) *La palude e la città: si può sconfiggere la mafia*: Mondadori, Google-Books-ID: NR8vAAAACAAJ.
- Baldascino, Mauro and Michele Mosca (2012) “La gestione dei beni confiscati: un’occasione perduta per le imprese sociali?” *Venturi P., Zandonai F. (a cura di), L’impresa sociale in Italia. Pluralità dei modelli e contributo alla ripresa, Altreconomia*, 213–236.
- Balestrini, Nanni (2004) *Sandokan: storia di camorra*, 580: Einaudi.
- Becker, Gary S. (1968) “Crime and Punishment: An Economic Approach,” *Journal of Political Economy*, 76 (2), 169–217, [10.1086/259394](https://doi.org/10.1086/259394).
- Bergman, Peter, Raj Chetty, Stefanie DeLuca, Nathaniel Hendren, Lawrence F. Katz, and Christopher Palmer (2024) “Creating Moves to Opportunity: Experimental Evidence on Barriers to Neighborhood Choice,” *American Economic Review*, 114 (5), 1281–1337, [10.1257/aer.20200407](https://doi.org/10.1257/aer.20200407).
- Boeri, Filippo, Marco Di Cataldo, and Elisabetta Pietrostefani (2023) “Localized effects of confiscated and re-allocated real estate mafia assets,” *Journal of economic geography*, [10.1093/jeg/lbad035](https://doi.org/10.1093/jeg/lbad035).
- Butts, Kyle (2023) “Difference-in-Differences Estimation with Spatial Spillovers,” June, [10.48550/arXiv.2105.03737](https://doi.org/10.48550/arXiv.2105.03737), arXiv:2105.03737 [econ].

- Caglayan, Mustafa, Alessandro Flamini, and Babak Jahanshahi (2017) “Organized Crime and Human Capital,” October, Working paper.
- (2021) “Hindering human capital accumulation: A hidden cost of the silent mafia?” *Journal of Economic Behavior & Organization*, 188, 828–845, [10.1016/j.jebo.2021.05.029](https://doi.org/10.1016/j.jebo.2021.05.029).
- Calamunci, Francesca and Francesco Drago (2020) “The Economic Impact of Organized Crime Infiltration in the Legal Economy: Evidence from the Judicial Administration of Organized Crime Firms,” January, <https://papers.ssrn.com/abstract=3526051>.
- Calamunci, Francesca M., Livio Ferrante, and Rossana Scebba (2022) “Closed for mafia: Evidence from the removal of mafia firms on commercial property values,” *Journal of Regional Science*, 62 (5), 1487–1511, [10.1111/jors.12612](https://doi.org/10.1111/jors.12612), eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/jors.12612>.
- Callaway, Brantly and Pedro H. C. Sant’Anna (2021) “Difference-in-Differences with multiple time periods,” *Journal of Econometrics*, 225 (2), 200–230, [10.1016/j.jeconom.2020.12.001](https://doi.org/10.1016/j.jeconom.2020.12.001).
- Catozzella, Giuseppe (2011) *Alveare. Il dominio invisibile e spietato della ‘ndrangheta del Nord*, Milan: Rizzoli.
- Centro Studi Pio La Torre (2025) “Survey on the Perception of the Mafia 2011-2022.”
- de Chaisemartin, Clément and Xavier D’Haultfoeuille (2020) “Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects,” *American Economic Review*, 110 (9), 2964–2996, [10.1257/aer.20181169](https://doi.org/10.1257/aer.20181169).
- (2024) “Difference-in-Differences Estimators of Intertemporal Treatment Effects,” *The Review of Economics and Statistics*, 1–45, [10.1162/rest_a.01414](https://doi.org/10.1162/rest_a.01414).
- Chetty, Raj and Nathaniel Hendren (2018) “The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects*,” *The Quarterly Journal of Economics*, 133 (3), 1107–1162, [10.1093/qje/qjy007](https://doi.org/10.1093/qje/qjy007).
- Chiodo, Emanuela (2021) “Community work practices against children poverty in Southern Italy. Exploring experiences and perspectives in local welfare,” *International Journal of Sociology and Social Policy*, 42 (9/10), 877–889, [10.1108/IJSSP-04-2021-0077](https://doi.org/10.1108/IJSSP-04-2021-0077).
- Coniglio, Nicola, Giuseppe Celi, and Cosimo Scagliusi (2010) “Organized Crime, Migration and Human Capital Formation: Evidence from the South of Italy,” January.

- Contini, Dalit and Guido Salza (2020) “Too few university graduates. Inclusiveness and effectiveness of the Italian higher education system,” *Socio-Economic Planning Sciences*, 71, 100803, [10.1016/j.seps.2020.100803](https://doi.org/10.1016/j.seps.2020.100803).
- Cunningham, Scott (2021) *Causal Inference: The Mixtape*: Yale University Press, Google-Books-ID: PSEMEAAAQBAJ.
- Damm, Anna Piil and Christian Dustmann (2014) “Does Growing Up in a High Crime Neighborhood Affect Youth Criminal Behavior?” *American Economic Review*, 104 (6), 1806–1832, [10.1257/aer.104.6.1806](https://doi.org/10.1257/aer.104.6.1806).
- Datcher, Linda (1982) “Effects of Community and Family Background on Achievement,” *The Review of Economics and Statistics*, 64 (1), 32–41, [10.2307/1937940](https://doi.org/10.2307/1937940).
- DIA (2015a) “Relazione del Ministero dell’interno al Parlamento Gennaio-Giugno 2015,” Technical report.
- (2015b) “Relazione del Ministero dell’interno al Parlamento Luglio-Dicembre 2015,” Technical report.
- van Dijk, Meintje, Edward Kleemans, and Veroni Eichelsheim (2019) “Children of Organized Crime Offenders: Like Father, Like Child? An Explorative and Qualitative Study Into Mechanisms of Intergenerational (Dis)Continuity in Organized Crime Families,” *European Journal on Criminal Policy and Research*, 25 (4), 345–363, [10.1007/s10610-018-9381-6](https://doi.org/10.1007/s10610-018-9381-6).
- of Education, Ministry (2024) “Scuola secondaria di secondo grado.”
- Falcone, Riccardo Christian, Tatiana Giannone, and Francesco Iandolo (2016) “BeneItalia. Economia, welfare, cultura, etica: la generazione di valori nell’uso sociale dei beni confiscati alle mafie,” research Report, Libera. Associazioni, Nomi e Numeri contro le Mafie, Torino, <https://www.libera.it/documenti/schede/beneitalia.pdf>.
- Falcone, Riccardo Christian, Gerardo Illustrazione, Tatiana Giannone, Luca Mennella, Leonardo Ferrante, and Vittorio Martone (2021) “RimanDATI, i comuni sulla trasparenza dei beni confiscati alle mafie,” Technical report, Libera. Associazioni, Nomi e Numeri contro le Mafie, <https://www.libera.it/schede-1571-rimandati>.
- (2022) “RimanDATI, i comuni sulla trasparenza dei beni confiscati alle mafie II edizione,” Technical report, Libera. Associazioni, Nomi e Numeri contro le Mafie, https://www.libera.it/schede-2086-rimandati_ii_edizione.

- Ferrante, Livio, Stefania Fontana, and Francesco Reito (2021a) “Mafia and bricks: unfair competition in local markets and policy interventions,” *Small Business Economics*, 56 (4), 1461–1484, [10.1007/s11187-019-00250-w](https://doi.org/10.1007/s11187-019-00250-w).
- Ferrante, Livio, Francesco Reito, Salvatore Spagano, and Gianpiero Torrìsi (2021b) “Shall we follow the money? Anti-mafia policies and electoral competition,” *Journal of Policy Modeling*, 43 (5), 1110–1130, [10.1016/j.jpolmod.2021.03.010](https://doi.org/10.1016/j.jpolmod.2021.03.010).
- Gambetta, Diego (1993) *The Sicilian Mafia: The Business of Private Protection*: Harvard University Press, Google-Books-ID: y3bv3tqWftYC.
- García, Jorge Luis, James J. Heckman, and Anna L. Ziff (2019) “Early childhood education and crime,” *Infant Mental Health Journal*, 40 (1), 141–151, [10.1002/imhj.21759](https://doi.org/10.1002/imhj.21759), eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/imhj.21759>.
- Goodman-Bacon, Andrew (2021) “Difference-in-differences with variation in treatment timing,” *Journal of Econometrics*, 225 (2), 254–277, [10.1016/j.jeconom.2021.03.014](https://doi.org/10.1016/j.jeconom.2021.03.014).
- Heller, Sara B. (2014) “Summer jobs reduce violence among disadvantaged youth,” *Science*, 346 (6214), 1219–1223, [10.1126/science.1257809](https://doi.org/10.1126/science.1257809).
- Heller, Sara B., Anuj K. Shah, Jonathan Guryan, Jens Ludwig, Sendhil Mullainathan, and Harold A. Pollack (2017) “Thinking, Fast and Slow? Some Field Experiments to Reduce Crime and Dropout in Chicago*,” *The Quarterly Journal of Economics*, 132 (1), 1–54, [10.1093/qje/qjw033](https://doi.org/10.1093/qje/qjw033).
- Hirsch, Fred (1976) *Social Limits to Growth*., Cambridge, MA: Harvard University Press.
- Huttenlocher, Janellen, Heidi Waterfall, Marina Vasilyeva, Jack Vevea, and Larry V. Hedges (2010) “Sources of variability in children’s language growth,” *Cognitive Psychology*, 61 (4), 343–365, [10.1016/j.cogpsych.2010.08.002](https://doi.org/10.1016/j.cogpsych.2010.08.002).
- Isasi, Jennifer (2021) “Sentiment Analysis with ‘syuzhet’ using R,” *Programming Historian*, <https://programminghistorian.org/en/lessons/sentiment-analysis-syuzhet>.
- ISTAT (2011) “Censimento della popolazione 2011,” <https://www.istat.it/notizia/dati-per-sezioni-di-censimento/>.
- (2021) “Istruzione e Formazione - Scuole Secondarie II grado - indicatori scolastici,” https://esploradati.istat.it/databrowser/#/it/dw/categories/IT1,Z0820EDU,1.0/DCIS_SCUOLE.

- (2023) “La dispersione scolastica aa.ss. 2019/2020 - 2020/2021 aa.ss. 2020/2021 - 2021/2022,” Technical report, https://www.foe.it/files/2024/01/Focus-La-Dispersione-scolastica-aa.ss_.1920_2021-2021_2122.pdf.
- Italian Ministry of Justice (2018) “La Carta di Milano. Dieci tesi per la lotta alle mafie del XXI secolo,” Technical report, Rome, <https://www.giustizia.it/resources/cms/documents/CartadiMilano.pdf>.
- Kenney, Dennis Jay and Roy Godson (2002) “Countering crime and corruption: A school-based program on the US—Mexico border,” *Criminal justice*, 2 (4), 439–470, Publisher: Sage Publications Sage UK: London, England.
- Kim, Hoyeol (2022) “Sentiment Analysis: Limits and Progress of the Syuzhet Package and Its Lexicons,” *Digital Humanities Quarterly*, 016 (2).
- Kleemans, Edward R. and Christianne J. de Poot (2008) “Criminal Careers in Organized Crime and Social Opportunity Structure,” *European Journal of Criminology*, 5 (1), 69–98, [10.1177/1477370807084225](https://doi.org/10.1177/1477370807084225).
- Kline, Patrick and Enrico Moretti (2014) “Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority *,” *The Quarterly Journal of Economics*, 129 (1), 275–331, [10.1093/qje/qjt034](https://doi.org/10.1093/qje/qjt034).
- Lochner, Lance (2004) “Education, Work, and Crime: A Human Capital Approach,” *International Economic Review*, 45 (3), 811–843, [10.1111/j.0020-6598.2004.00288.x](https://doi.org/10.1111/j.0020-6598.2004.00288.x), eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.0020-6598.2004.00288.x>.
- (2011) “Non-Production Benefits of Education: Crime, Health, and Good Citizenship,” January, [10.3386/w16722](https://doi.org/10.3386/w16722).
- Lochner, Lance and Enrico Moretti (2004) “The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-Reports,” *American Economic Review*, 94 (1), 155–189, [10.1257/000282804322970751](https://doi.org/10.1257/000282804322970751).
- Ludwig, Jens, Greg J Duncan, Lisa A Gennetian, Lawrence F Katz, Ronald C Kessler, Jeffrey R Kling, and Lisa Sanbonmatsu (2013) “Long-term neighborhood effects on low-income families: Evidence from Moving to Opportunity,” *American economic review*, 103 (3), 226–231.
- Machin, Stephen and Costas Meghir (2004) “Crime and Economic Incentives,” *The Journal of Human Resources*, 39 (4), 958–979, [10.2307/3559034](https://doi.org/10.2307/3559034).

Mandic, Sandra, Susan Sandretto, Enrique García Bengoechea, Debbie Hopkins, Antoni Moore, Judith Rodda, and Gordon Wilson (2017) “Enrolling in the Closest School or Not? Implications of school choice decisions for active transport to school,” *Journal of Transport & Health*, 6, 347–357, [10.1016/j.jth.2017.05.006](https://doi.org/10.1016/j.jth.2017.05.006).

Martone, Vittorio (2020) *Politiche integrate di sicurezza: tutela delle vittime e gestione dei beni confiscati in Campania*: Carocci editore, Google-Books-ID: XKR9zQEACAAJ.

Menditto, Francesco (2013) “Quale futuro per i beni immobili sequestrati e confiscati? Proposte essenziali per ridurre le criticità esistenti,” *Rivista Diritto penale contemporaneo*, Diritto Penale Contemporaneo, <https://www.penalecontemporaneo.it/d/2510-qual-e-futuro-per-i-beni-immobili-sequestrati-e-confiscati-proposte-essenziali-pe>

Mohammad, Saif M. and Peter D. Turney (2013) “Crowdsourcing a Word-Emotion Association Lexicon,” August, [10.48550/arXiv.1308.6297](https://arxiv.org/abs/10.48550/arXiv.1308.6297), arXiv:1308.6297 [cs].

Mosca, Michele (2017) “The Social Regeneration of Mafia Assets in the Land of Gomorrah: The Role of Social Cooperatives,” in *Social Regeneration and Local Development*: Routledge, Num Pages: 18.

Nazzaro, Sara (2021) “Il valore educativo dei beni confiscati alla mafia,” *Rivista Diritto Penale della globalizzazione - Pacini Giuridica*, <https://www.dirittopenaleglobalizzazione.it/collana-quaderni-crst-centro-ricerca-sicurezza-terrorismo/>, Pacini Editore.

Operti, Elisa (2018) “Tough on criminal wealth? Exploring the link between organized crime’s asset confiscation and regional entrepreneurship,” *Small Business Economics*, 51 (2), 321–335, <http://www.jstor.org/stable/45107020>.

Oreopoulos, Philip (2006) “The Compelling Effects of Compulsory Schooling: Evidence from Canada,” *The Canadian Journal of Economics / Revue canadienne d’Economie*, 39 (1), 22–52, <https://www.jstor.org/stable/3696130>.

Pearce, J. (2000) “Techniques for defining school catchment areas for comparison with census data,” *Computers, Environment and Urban Systems*, 24 (4), 283–303, [10.1016/S0198-9715\(99\)00045-9](https://doi.org/10.1016/S0198-9715(99)00045-9).

Save The Children (2022) “Alla ricerca del tempo perduto,” Technical report, Save the Children Italia Onlus.

- Sciarrone, Rocco (1998) “Il capitale sociale della mafia. Relazioni esterne e controllo del territorio,” *Quaderni di Sociologia* (18), 51–72, [10.4000/qds.1476](#), Number: 18.
- Silge, Julia and David Robinson (2017) *Text Mining with R: A Tidy Approach*: ”O’Reilly Media, Inc.”, Google-Books-ID: qNcnDwAAQBAJ.
- Singleton, Alex D., Paul A. Longley, Rebecca Allen, and Oliver O’Brien (2011) “Estimating secondary school catchment areas and the spatial equity of access,” *Computers, Environment and Urban Systems*, 35 (3), 241–249, [10.1016/j.compenvurbsys.2010.09.006](#).
- Spencer, Sarah, Judy Clegg, and Joy Stackhouse (2012) “Language and disadvantage: a comparison of the language abilities of adolescents from two different socioeconomic areas,” *International Journal of Language & Communication Disorders*, 47 (3), 274–284, [10.1111/j.1460-6984.2011.00104.x](#), eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1460-6984.2011.00104.x>.
- Sun, Liyang and Sarah Abraham (2021) “Estimating dynamic treatment effects in event studies with heterogeneous treatment effects,” *Journal of Econometrics*, 225 (2), 175–199, [10.1016/j.jeconom.2020.09.006](#).
- Sviatschi, Maria Micaela (2022a) “Making a narco: Childhood exposure to illegal labor markets and criminal life paths,” *Econometrica*, 90 (4), 1835–1878.
- (2022b) “Spreading Gangs: Exporting US Criminal Capital to El Salvador,” *American Economic Review*, 112 (6), 1985–2024, [10.1257/aer.20201540](#).
- Villa, Carmen (2025) “The effect of youth clubs on education and crime.”