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

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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 estimation of 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 reuse, I investigate changes in local dropout rates. Results reveal a significant reduction in dropout rates of approximately 36% relative to the mean for students near repurposed properties. I show that these facilities reshape 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.

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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 argue about positive community effects (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 reuse 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 properties[1]. 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. Youth-tailored activities are particularly relevant given that dropout rates in these historically Mafia-affected regions reach concerning levels: 14.6% in Campania and Apulia, and 18.8% in Sicily against a national average of 12.7% (Save The Children, 2022). This setting allows me to exploit the staggered reuse of Mafia properties, conditioning on neighbourhood and

[1]The 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 reusing practices.

municipality-level attributes[2].

I create a novel dataset on the number of reused Mafia properties, the nature and duration of social activities by combining information scraped from the website *Confiscatibene*, several internal surveys from the association Libera, which nationally coordinates anti-Mafia CSOs activities, and information published by the municipalities. I leverage administrative data from the National Agency for the Management of Confiscated Mafia Properties to collect the precise locations of the Mafia properties, and I digitise the Antimafia Investigative Directory maps to measure baseline Mafia presence. I collect the locations of all Italian NGOs from the Ministry of Labour database and use educational records from the Ministry of Education covering high school student enrollment, graduation rates, and students' ages for each academic year and grade. Finally, I employ the Survey of the Perception of the Mafia collected by the Sicilian NGO Centro Studi Pio La Torre to examine students' attitudes toward educational and criminal pathways, supplemented by 2011 census data for baseline socio-economic characteristics.

I employ two-way fixed effects (TWFE) models using 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 the last two years of high school. This approach specifically captures students older than 16—the end of compulsory education age in Italy—allowing me to measure dropout decisions when continued schooling becomes voluntary. Given the absence of official high school districts in Italy, I construct school catchment areas loosely following a location-allocation approach based on distances between high schools and census blocks[3]. Catchment areas are defined as treated when they contain at least one repurposed Mafia property, while control areas have no repurposed properties. In this setting, I estimate the average treatment effect on the treated (ATT) and complement my analysis with several event study specifications robust to heterogeneous treatment effects following Sun and Abraham (2021).

The implementation of social activities in repurposed 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 proportionally 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

[2] I discuss potential endogeneity of the reused properties' location and timing in Section 5 and Appendix B.

[3] Census blocks defined by the Italian Institute of Statistics typically contain on average 200-400 inhabitants.

Italy. I estimate a slightly larger improvement in educational outcomes, which is expected given that I examine historically Mafia-ridden municipalities located in the South, where both the baseline negative effects of the Mafia and the concentration of confiscated properties available for repurposing are substantially greater. The effects 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. The estimated effects are also particularly pronounced in areas deprived at baseline, measured by lower rental prices.

The heterogeneity analysis at the school tracks level unveils important patterns. Indeed, technical high schools emerge as the primary beneficiaries of the properties reuse interventions, exhibiting sustained reductions in dropout rates that become statistically significant between years 2-4 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, making them more susceptible to dropping out before graduation. This indicates that the enhanced community environment resulting from property reuse is key to supporting technical students throughout their educational journey. I test the intensive margin of the treatment, finding that the results are particularly strong where more than 1 property has been reused in the area. I use the count of reused properties rather than the binary treatment indicator and I employ the de Chaisemartin and D'Haultfœuille (2024) estimator to account for dynamic treatment effects; I find for each additional confiscated property reused is associated a 12% decrease relative to the mean[4]. The consistency across binary and continuous treatment specifications reinforces confidence in the robustness of the intensive margin findings.

I conduct several robustness and placebo exercises to test the validity of the results. Since the CRR policy implements a multi-stage process of confiscation, reallocation to local authorities and then reuse of Mafia properties, one might wonder what policy stage drives my effect. First, I show that the estimated effects are not driven by the reallocation of confiscated prop-

[4]Given that treated municipalities have an average of 2.22 confiscated assets, these estimates are remarkably 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.

erties to local authorities before their reuse. Second, it is unlikely that the results simply reflect mean reversion following confiscation, which could have temporarily depressed educational outcomes. The event study specifications reveal no significant differences in pre-trends between treated and control schools. Additionally, I discuss how the estimated results are robust to changes in the assumptions underlying the construction of schools' catchment areas. I rule out that the treatment is endogenous to the presence of NGOs and rental prices up to 3 years before the reuse, finding a zero effect. The main estimates also remain robust to the inclusion of municipality-level time trends, while spillover effects analysis reveals that they capture merely residual variation from the main effect. Importantly, the main effect retains its robustness and statistical significance even after accounting for these spillover effects. As sanity checks, I also test the effect of reuse in the following year on current outcomes and the effect of reuse on dropout rates before students turn 16, finding null effects in both cases.

My empirical analysis suggests that the key mechanism is that the reuse 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 of how students define 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 findings complement anecdotal evidence gathered through interviews about the potential effects of the reuse for social purposes on young people (Nazzaro, 2021; Falcone et al., 2016). 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 reused 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 reuse of Mafia properties on local education and students' attitudes. 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' perception of the Mafia, 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 affecting students' attitudes in areas where the Mafia has long-standing social influence. By fostering cultural capital, the policy shapes youth decisions regarding career advancement in areas where simple educational support may not be effective. While leaving school does not necessarily lead students to join the Mafia, this policy proves particularly significant in such contexts. Second, the paper underscores the importance of supporting the implementation of reuse activities in properties confiscated from the Mafia. Increased governmental funding for these initiatives, along with greater recognition of the local NGOs working to renovate Mafia-ridden areas, would contribute substantially to improving educational outcomes and opportunities for the local youth.

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 Reuse Policy (CRR) in Italy; second, I provide an overview of the current reuse practices of Mafia properties in Italy, their scope, and their beneficiaries.

2.1 The Mafia Confiscated and Reallocated Assets Reuse 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 accumulating both economic resources and social consensus (Sciarrone, 1998). The economic sources of Mafia power were historically neglected [5] until 1982, when the politician Pio La Torre and the Ministry of the Interior Virginio Rognoni drafted a bill

[5] Some preventive measures against people connected to Mafia groups have been previously introduced in 1965 through bill n. 575: *Provisions against mafia-type criminal organisations, including foreign ones.* These measures did not target the Mafia's economic assets.

to target Mafia assets. In 1976 Pio La Torre, to describe the purpose of their effort, stated 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 proposed bill passed and became the main turning point in the Italian fight against the Mafia. The law introduced two key innovations: first, it established the crime of Mafia association under the article 416-bis, making Mafia groups directly liable for specific criminal activities[6]; second, since Mafia families' 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 confiscate 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 a new legislation - the Law 109 of 1996 - to allow confiscated Mafia properties to be reused for urban and social recovery, specifically targeting the most infiltrated areas by the Mafia (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 compromise, indifference, contiguity and therefore complicity.

Following the enactment of Law 109/1996, a standardized procedure for repurposing confiscated Mafia properties was established under the CRR policy. As shown in Figure 1, the Italian CRR policy consists of three main phases: first, Mafia families are arrested and their properties confiscated upon conviction; second, the ANBSC[7] determines how confiscated

[6] The 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 of three to six years. Those who promote, direct or organise the association are punished with imprisonment of four to nine years."*

[7] The National Agency for the Administration and Destination of Properties Seized and Confiscated from

properties are repurposed, allocating them either for institutional use (retained by the state or assigned to law enforcement agencies) or for social purposes (transferred to local authorities). Properties designated for social purposes are then used by local NGOs to carry out community and social activities.

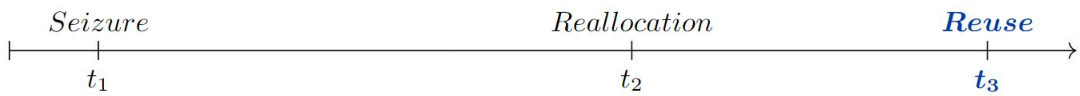


Figure 1 The CRR policy timeline

Figure 2 shows the number of confiscated, reallocated, and reused properties in the historically Mafia-ridden municipalities which are part of my sample. Confiscations and reallocations increased from the 1990s, while the reuse practices, first established in the late 1990s, seem to increase dramatically in the late 2010s. My data shows that on average it takes 14 years for Mafia properties to be effectively reallocated from the confiscation time, while it takes on average 3 years to be reused from the reallocation date. This variation in the timing of reuse allows me to exploit the staggered introduction of repurposed properties to examine whether their reuse drives the observed effects.

Organised Crime (ANBSC) is an executive body which determines how to repurpose confiscated assets, with decisions aimed at compensating local communities (ANBSC, 2019).

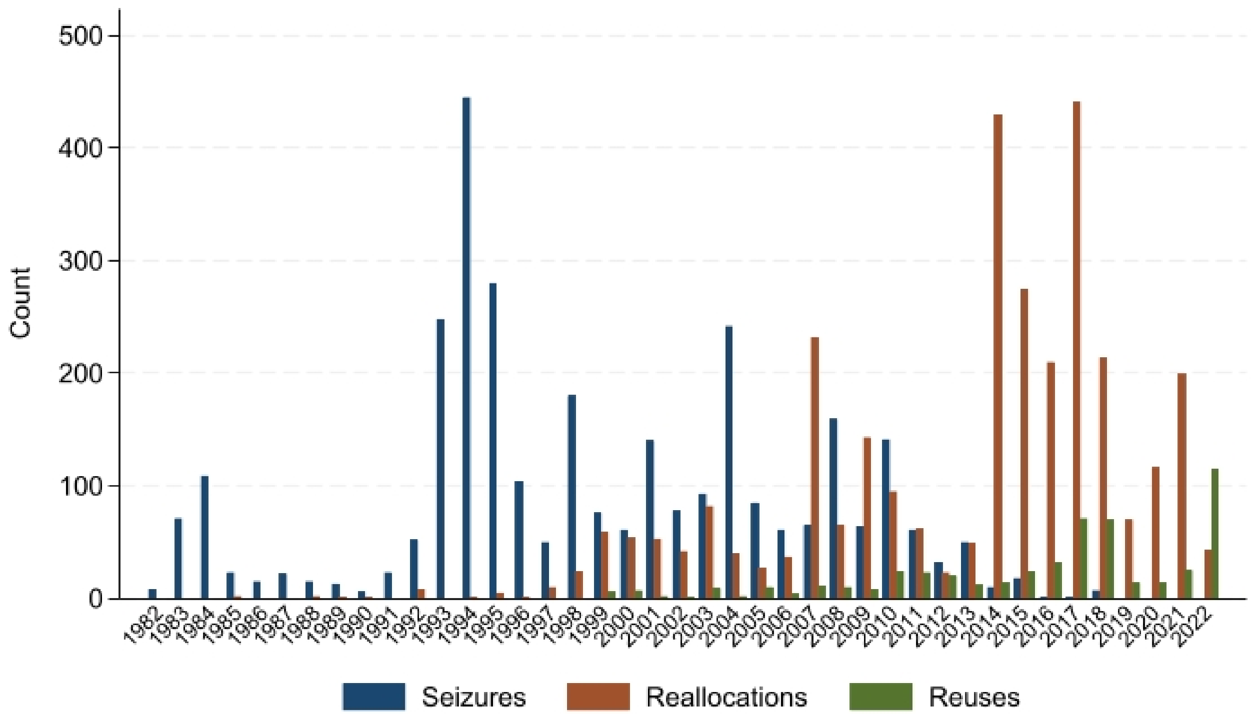


Figure 2 Number of confiscations, reallocations and reuses from 1982 to 2022

2.2 The importance of reuse practices

In this paper, I focus on the final step of the CRR policy: the effect of reusing confiscated Mafia properties for social activities. While existing literature demonstrates that the reallocation of Mafia properties affects housing prices, market concentration, and electoral competition (Boeri et al., 2023; Ferrante et al., 2021a,b), a critical gap remains in evaluating the effective social reuse of these properties (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 absence or removal of Mafia control, it does not constitute tangible social renewal of the local social fabric (Falcone et al., 2016).

Yet, the distinction between the reallocation and the reuse 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 that promotes trust, social cohesion, and sustainable local development (Nazzaro, 2021;

Falcone et al., 2016). Local 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 youth centres that provide 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 reuse activities is perhaps most strikingly demonstrated by the Mafia affiliates, as they frequently attempt to occupy or vandalise their former properties, revealing their deep concerns about the potential for these spaces to be successfully repurposed for community benefit (Italian Ministry of Justice, 2018).

3 Conceptual framework

In this section, I justify why and how the reuse of Mafia-confiscated properties can, in practice, renew the existing juveniles' educational incentives, especially in Mafia-ridden neighbourhoods. I draw on the opportunity cost framework from the economics of crime and education literature, then I review the existing evidence on how Mafia groups use their properties to influence juvenile recruitment, creating alternative authority structures. Second, I examine qualitative evidence from the NGOs operating in repurposed Mafia properties on how their activities influence juveniles' beliefs towards the returns of education. This Section aims to motivate the economic mechanisms behind the estimated treatment effects rather than presenting formal model predictions.

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 pathways available when individuals face such a choice relative to the perceived benefits and social status offered by Mafia affiliation. I argue that the reuse 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). Individuals choose to join the Mafia activities when the total expected benefits exceed the expected costs.

On the other, 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 this appeal, making Mafia affiliation appear as the primary avenue 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 counter this accumulated power (Arlacchi and Chiesa, 1987). The fact of repurposing Mafia properties for the social good directly targets their Mafia-related function as *positional goods*, which are luxury symbols to demonstrate territorial control and legitimacy (Hirsch, 1976; Baldascino and Mosca, 2012). Indeed, these properties serve as visible manifestations of power, helping Mafia families maintain their role model status in local communities (Mosca, 2017). While the reuse activities might not affect the monetary gains of joining the Mafia, which are mostly affected by the confiscation of 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 mechanisms the repurpose of such properties weakens the social influence of Mafia networks? The effect might operate through several channels which will be discussed in Section 7. First, the repurpose of several properties in specific urban areas might improve the overall neighbourhoods conditions as well as local economies (Datcher, 1982; Ludwig et al., 2013); second, the activities offered by local NGOs which provide additional educational support such after-school programs and weekend support programs might simply drive the effect (Heller, 2014; García et al., 2019); third, repurposing previously Mafia-owned properties might demonstrate that former symbols of Mafia power can be transformed into sources of renewed social capital, potentially shifting public perceptions about the Mafia's actual strength and legitimacy (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 provide 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 enroll in university, *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 Education[8]. 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 block[9]. 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).

Table 1 The types of high school tracks

HS Tracks	Description	Specialisations	Sample %
Academic	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
Technical	Provide practical and technical skills related to key sectors such as administration, marketing, and industrial development.	2	0.371
Vocational	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. Table 2 illustrates the expected age of enrolled students measured at

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

[9]As 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 insignificant.

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 at the time of graduation.

Table 2 Students attending HS academic year by age

End of the academic year (May)	Older Born (Jan-May)	Younger Born (Jun-Dec)	Grade
1st year	15 years	14 years	9
2nd year	16 years	15 years	10
3rd year	**17 years**	**16 years**	**11**
4th year	**18 years**	**17 years**	**12**
5th year	**19 years**	**18 years**	**13**

Notes: 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. The Table 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 in school attendance. Before the age of 16, students have limited discretion over school attendance, making dropouts very rare[10]. However, once students turn 16, they gain legal freedom to discontinue their studies. This legal framework leads to specific dropout patterns, which typically worsen 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 Table 2, after completing grade 11, all students are at least 16 years old. The exhisting empirical evidence support this pattern: in 2015, the 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, gaining legal autonomy to discontinue their education[11]. Educational decisions at this juncture are particularly sensitive to contextual influences, as students weigh the costs and benefits of continued schooling against immediate

[10] In 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.

[11] It is possible that students born between January and May will drop out before completing grade 11. Section 6 shows that I don't find any effect on students dropping out between grade 10 and grade 11.

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 shape 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 the transition between grades 11 and 13, since this is when students typically turn 16 or older — the legal minimum dropout age in Italy. The dropout measurement 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 students who completed grades 11, 12 and 13 in year $t-1$. This share tells me how many students from the same cohorts successfully continue in school into the following years after turning 16. The cumulative dropout measure is defined as follows:

$$DropoutG11-13_{ct} = \frac{CompletedG11-13_{ct-1} - GraduatedG13_{ct} - CompletedG12-13_{ct}}{CompletedG11-13_{ct-1}} \tag{1}$$

where $DropoutG11-13$ represents the cumulative dropout rate for students aged 16 or above in year t for school catchment area c, $CompletedG11-13$ represents the number of students enrolled in grades from 11 to 13 in year $t-1$, $GraduatedG13$ is the number of students who completed grade 13 and therefore graduated in year t, and $CompletedG12-13$ 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.

4.2 Mafia properties data

I create a novel dataset of reused Mafia properties by scraping various institutional sources and collaborating with the Italian Antimafia Association *Libera*. 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 [12], with 42% and 41% of them reallocated for social and institutional purposes, respectively. Crucially for this analysis, 66% of the properties have been reallocated under the jurisdiction of the nearest municipality, as only these properties can undergo the complete transformation process from confiscated Mafia properties to community resources. Finally, 83% of 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.

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 the platform 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 crossed my data with the information shared by each single municipality about the current status of Mafia properties under their jurisdiction. [13]. Figure A2 in Appendix A shows the spatial distribution of Mafia real estate in the ten urban areas which I investigate in this paper. Between 2015 and 2022, 397 of the 3199 Mafia properties have been reused for social purposes by the municipalities and local NGOs, with the majority of them being reused in the biggest municipalities, such as Palermo and Naples.

To identify and analyse the types of social activities organised at each site, I manually categorise the reuse activities matching the main keywords of the activities' descriptions and

[12] The majority of the properties which I fail to geocode due to incomplete information represents lands in rural areas, which will less likely affect the dropout of urban areas.

[13] According to the Art. 48 of the Antimafia Code (2011), municipalities are obliged to address trasparency 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.

the categorisations used in previous reports published by *Libera* (Falcone et al., 2016). I identify five main types of activities: educational, welfare, cultural, employment-related, and other. Figure 3 shows the word cloud of the 100 most frequent words in the description of the activities, while Table 1 presents the number of confiscated Mafia properties reused for each activity type, along with a detailed description of the categories.

This research provides the first comprehensive database on the current state of Mafia properties reused for social purposes. 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.

Figure 3 Word cloud of the descriptions of activities in reused Mafia properties illustrating the 100 most common terms used.

Table 3 The types of reuse activities described

Activity	Description	Reused Mafia properties %
Welfare	Places for housing emergency, activities to assist the homeless and people in need, social activities targeting vulnerable groups	0.483
Education	After-school activities and schooling support, socio-educational activities for at-risk juveniles	0.235
Culture	Cultural activities to raise awareness about organised crime, the rule of law and self-responsibility	0.126
Employment	Support and training activities for unemployed people or fragile groups	0.083
Other	Activities in the agricultural industries aiming to sell organic products and other	0.074

4.3 Treatment allocation

Given the localised nature of the treatment effect, it is necessary to identify which students attend which school by linking their residential origin 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 in the use of school-level 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 weighted-Voronoi polygons to address this issue from a geometric perspective, or the location-allocation method, which frames the problem in terms of student demand, based on their residential distribution, and school supply, based on schools' locations. Pearce (2000) shows that while the former offers computational simplicity, the latter is better in predicting the dimensions of schools' catchment areas in real-world applications.

I construct school catchment areas accordingly with the location-allocation method, following 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 the census blocks is obtained from the 2011 Italian census data (ISTAT, 2011). Second, I differentiate catchment areas by educational track, acknowledging that families' and students' choices also depend on the type of track offered. I ultimately created catchment areas for 14 distinct specialisations that map onto the three main tracks described in Table 1. Rather than imposing arbitrary distance constraints, the track-specific assignment approach naturally determines appropriate catchment boundaries by ensuring each census block is matched to its nearest school within each educational track specialisation. This method avoids the problem of unassigned blocks while recognising that students' spatial choices are defined by program availability rather than arbitrary distance thresholds. The original census blocks from my sample total 10556, 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 [14]. Each created catchment area has an average population of around ten thousand individuals, with 570 individuals aged between 14 and 19 years old. As a robustness check, I construct a second set of school catchment areas where I account for the baseline number of students 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 A provides the details of this procedure, while Section 6 presents the results of this additional specification.

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. Those 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 variable 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 roubstness check, I weight each catchment by the average distance of repurposed properties from the population-weighted centroids of each school catchment area [15]. These weighted measures capture both the localized nature of property

[14] Because catchment areas are calculated for each school track, the census blocks sum up only within each track and not across the entire dataset

[15] Population-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

reuse and the expected decay in its effect with distance from the treated sites (Boeri et al., 2023; Damm and Dustmann, 2014).

Figure 4 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 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 help visualising the distance-based assignments. Figure 4 also shows the presence of reused 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.

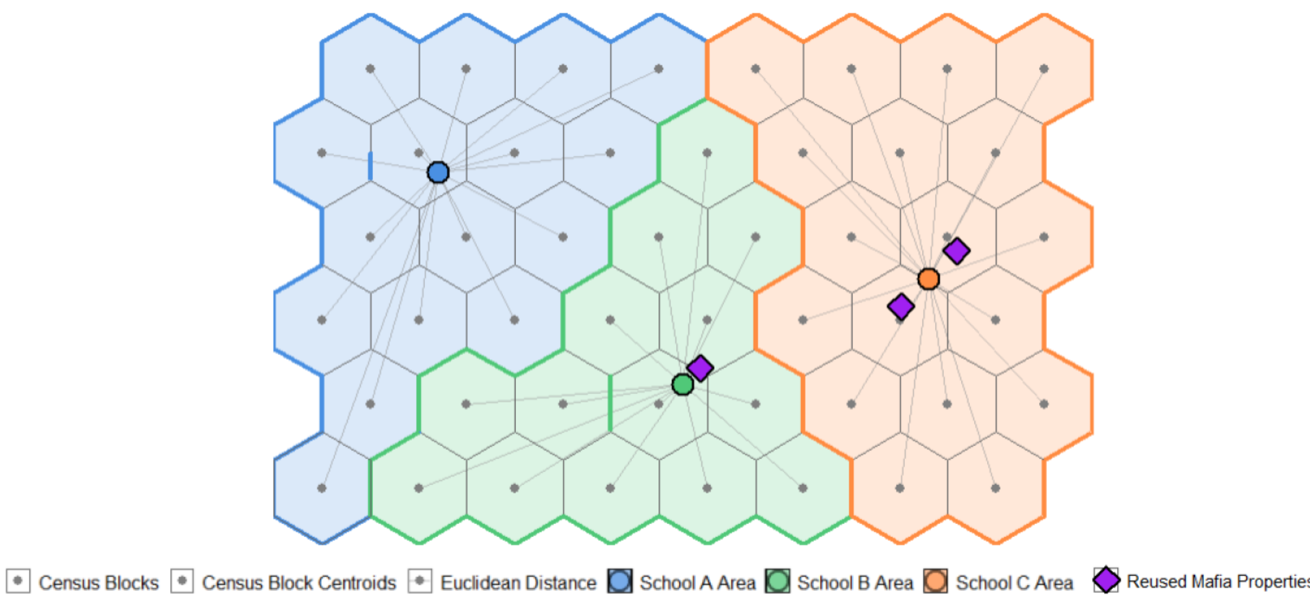


Figure 4 Ad-hoc example of schools' catchment areas construction

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 effect. 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 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. I use these indicators to assess whether the reuse of Mafia properties leads students to change their perception and sentiments towards the Mafia.

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 digitalise on GIS the historical maps about the street-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

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

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 education system entirely 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 level, 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 A presents how these measures are built in more detail.

Table 4 shows descriptive statistics of the observable socioeconomic attributes for both treated and control areas measured at baseline, before the reuse of any Mafia property occurs. First, treated and control areas exhibit virtually identical baseline educational outcomes, 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 NGOs activity and marginally lower rental prices, suggesting they 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 examine whether pre-existing NGOs presence is associated with future dropout patterns. Section 7 reports 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, baseline differences lose statistical significance, indicating that treated and control areas are virtually comparable across all the observed dimensions.

Table 4 Descriptive statistics

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

[17]It 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.

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 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 not. The sample comprises a total of 1487 observations with 293 unique school catchment areas for which the dropout information is not missing[18]; of those, 52 were never treated, while 282 have been treated at some point in the sample. The first model is specified as:

$$DropoutG11-13_{cnmt} = \beta_1 Reuse_{ct} + \beta_2 X^{'}_{ct} + \delta_c + \eta_t + \epsilon_{cnmt} \tag{2}$$

where $DropoutG11-13$ is the share of students dropping out after completing the third year of high school in schools catchment area c, neighbourhood n, and municipality m measured in time t; *Reuse* is a binary indicator equal to 1 if there is at least one Mafia property reused within the school catchment area in time $t+n$ after the reuse. Since schools are treated at different points in time, the coefficient of interest β_1 captures the average treatment effect

[18] The 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.

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 among students and grade retention rates for grades 12 and 13, which account for additional educational disruptions that could be captured by the dropout measure [19]. 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. 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-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 times[20].

5.2 DiD dynamic model

The 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 reuse activities - as reused properties accumulate over time - as well as the location of the reused 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'Haultfœuille (2020). This estimator extends the traditional two-way fixed effects frame-

[19] I 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 C1.

[20] I employ specifically this estimator to properly manage the large amount of time trends and fixed effects that I include in the exercises reported in Table B2.

work 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 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 to 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 reused 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 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 5 Impact of reusing Mafia real estate on the share of students dropping out from grades 11 to 13

	(1)	(2)	(3)	(4)
	Dropout rates G11-G13			
Reuse = 1	-0.0192**	-0.0200**	-0.0191**	-0.0201**
	(0.00934)	(0.00943)	(0.00905)	(0.00910)
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 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 5 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 evident violation of the PTA; additionally, 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 shows that the estimated effects are mostly developing in the long-term: the dropout rate becomes significantly lower between the second and the third year of implementation, while we see lower trends up to 6 years following the start of the first reusing activities. The timing of the treatment variable does not account for the implementation delays inherent in reusing such properties, as the dummy switch to 1 whenever the local NGOs and the municipalities sign a collaboration agreement to reuse the property; it is reasonable that some time is needed to develop impactful activities for the local communities. 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).

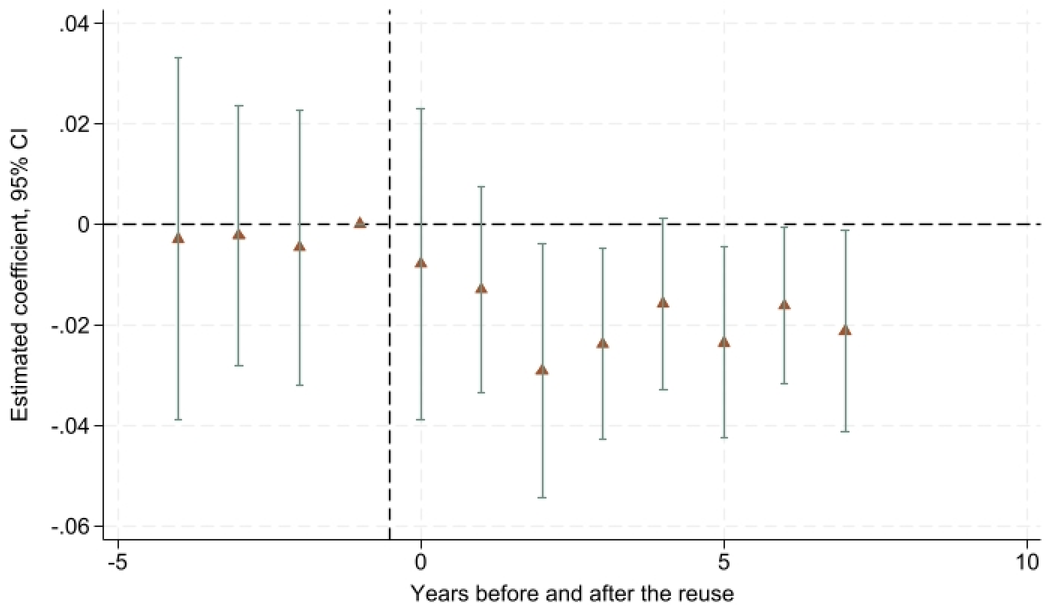
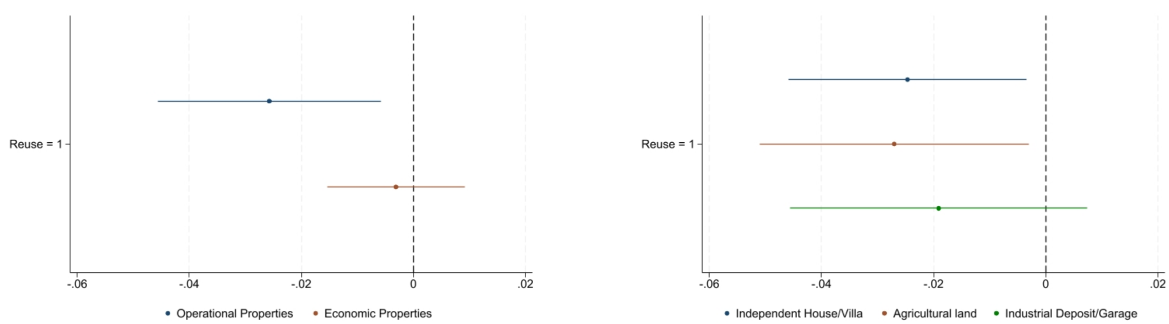


Figure 5 Estimated effects of reusing practices on dropout rate before and after the first reuse starts

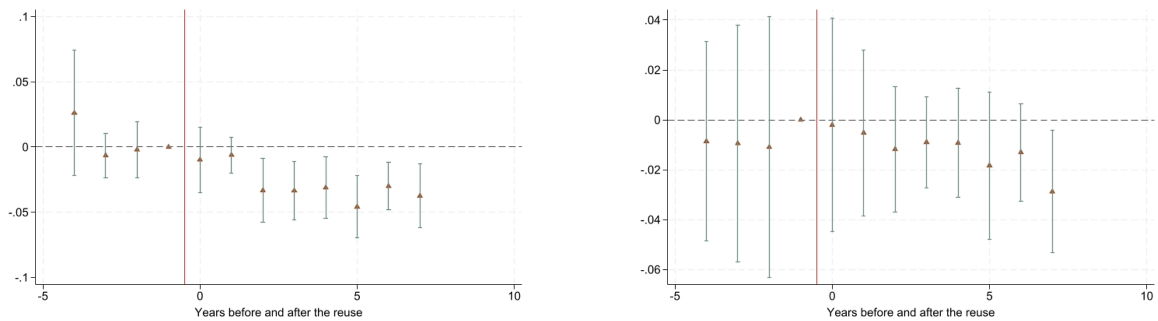


(a) Property use before confiscation

(b) Property type

Figure 6 Estimated effects of reusing practices on dropout rates before and after the first reuse starts by properties' features

Figure 6 presents the ATE of reusing practices on the treated school catchment areas by the level of school quality, which is measured at the baseline as the schools' institutional effectiveness across the academic, organizational, and social dimensions. Figure 6a shows the effect of the first reused Mafia property on dropout rates for schools where the school quality indicator falls below the median, while Figure 6b shows the same effect for high-performing schools, namely where the indicator falls above the median. Both F-tests suggest the absence of differential pre-trends, with p-values of 0.143 for low-performing schools, and 0.941 for high-performing schools. Low-performing schools benefit more from the treatment, showing larger magnitude effects and stronger statistical significance from 2 years after the reuse onwards. This heterogeneous response suggests that the intervention operates through mechanisms that are particularly effective in resource-constrained environments, where marginal improvements in the educational environment generate larger returns on educational outcomes.

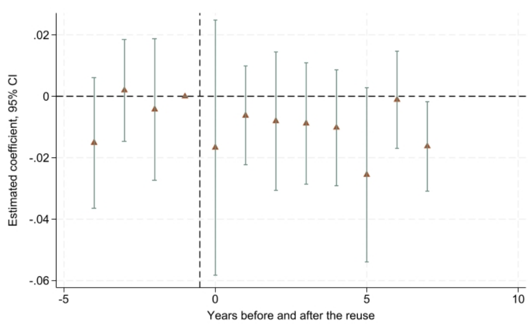


(a) Low Performing Schools **(b)** High Performing Schools

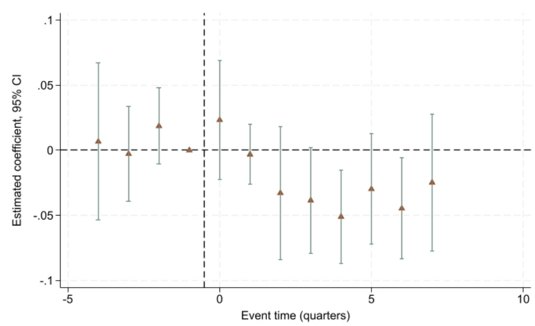
Figure 7 Estimated effects of reusing practices on dropout rates before and after the first reuse starts by the baseline quality of schooling

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.

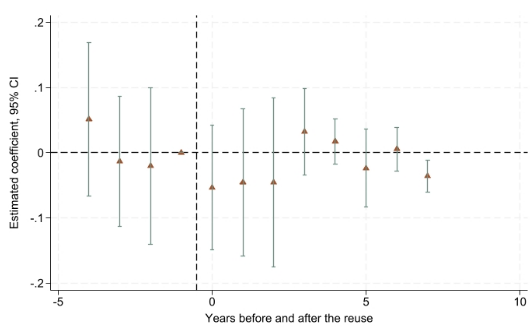
The results reveal substantial heterogeneity in how different educational tracks respond to the reuse intervention. First, academic high schools shown in Figure 7a exhibit coefficients that are relatively small and mostly insignificant throughout the observation period. Second, vocational high schools shown in Figure 7c display a mixed pattern with mostly insignificant effects, which is consistent with their specific institutional structure where students obtain a professional certificate after completing grade 11. Last, Figure 7b shows that technical high schools exhibit a more pronounced and sustained response, with clear negative effects on dropout rates that become statistically significant between year 2 and year 4 after reuse. This heterogeneous response likely reflects the different student populations and institutional contexts of each track. Technical schools, which occupy a middle ground between academic preparation and vocational training, appear to benefit more substantially from the reuse intervention. Research on the Italian education system shows that technical schools have experienced significant declines in their transition rates to tertiary education, falling more sharply than other school types (Contini and Salza, 2020), suggesting these students face particular challenges in their educational trajectories. Technical education students often come from backgrounds that value practical skills alongside academic preparation, making them particularly sensitive to the incentives in continuing education. While vocational students get qualified for jobs with a three-year certificate, technical students need a complete five-year diploma, making dropping out especially detrimental to their employment prospects. For these reasons, the improved educational incentives from reuse practices may be especially valuable for technical programs. Importantly, this differential improvement in dropout rates is not driven by changes in enrollment composition. Table C2 shoes that enrollment patterns for technical schools do not significant change after the first property's reuse, suggesting that the effect operates through reduced dropout rather than student selection into different high school tracks.



(a) Academic High Schools



(b) Technical High Schools



(c) Vocational High Schools

Figure 8 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 depend on the number of Mafia properties reused and their actual distribution within the school catchment area. I therefore explore the dynamic evolution of the treatment effect generated by the reuse of confiscated Mafia properties, examining whether the observed patterns are driven solely by the first reuse activities implemented or by the cumulative exposure to multiple reused properties over time. The underlying hypothesis is that the effects of reuse activities on student outcomes may not materialise immediately after the first reuse. Instead, they are expected to unfold dynamically, depending on both the timing of the reuse and the intensity of exposure within specific catchment areas. In particular, treatment effects may become stronger as the count of reused properties increases and as their location overlaps more closely with the distribution of the student population. I first split the sample between schools wher only at most one Mafia property has been reused across the entire period and schools that experienced multiple reuse practices. Table 6 reports the results, revealing a potential dose-response relationship between reusing practices and dropout reduction. Columns (1) and (2) report that schools exposed to only one reused property show small and non-significant effects on dropout rates. In contrast, schools with multiple reused properties reported in Columns (3) and (4) exhibit substantially larger and statistically significant reductions in dropout rates, respectively, with 51% and 48% reductions relative to the mean. This pattern suggests that the cumulative exposure to multiple reused properties may amplify the treatment effect.

Table 6 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**	
Reuse = 1	-0.00284	-0.00466	-0.0293**	-0.0277**
	(0.0133)	(0.0139)	(0.0123)	(0.0119)
Observations	541	522	755	750
Number of codd	101	101	134	133
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	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 reuse 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 reuse 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'Haultfœuille (2024), which computes the cumulative effect of each treatment dose across all time periods and determines how long these effects persist on average. Figure 8 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 an F-test on the pre-treatment coefficients with a p-value of 0.330. To estimate the event study, I also include a time trend capturing the number of reuses at the baseline.[21]. Figure 8 shows the average cumulative effect per dose of reusing Mafia properties on dropout rates, where each coefficient represents the total impact of adding one more reused property that will accumulate over all future periods. The overall average total effect is negative and equal to 0.64 percentage points, indicating that each additional reused property on average reduces dropout rates by around 12% relative to the mean across all time periods. Additionally, Mafia properties reused in the first and second year of treatment generate a reduction of 0.04 and 1.9 percentage points respectively, while properties reused four and five years after the first time of treatment reduce dropout rates by 3.8 and 5.2 percentage points respectively. This pattern suggests that sustained, long-term programs hosted in reused Mafia properties generate substantially larger benefits than isolated activities.

[21] In the baseline estimator, I account for reusing practices that started before the beginning of the sample by replacing the dummy indicator with a value of 1 whenever at least one Mafia property had already been reused. In this case, the time trend controls for the prior exposure to reuse activities, ensuring that the estimated effects are not driven by pre-sample reuse.

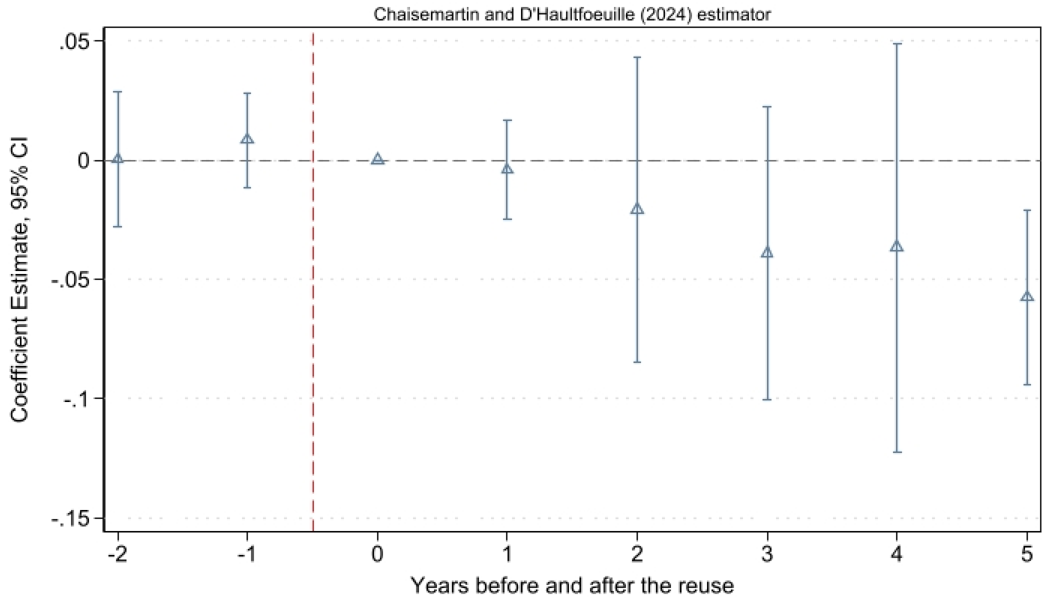


Figure 9 Estimated effects of reusing practices on dropout rate before and after the first reuse starts - intensity treatment effect

I then re-estimate the event study by weighting the count of reused assets by the student population in each school catchment area. While the count-based measure captures the intensity of reuse activities within each catchment area, it does not account for the varying size of the student population that could potentially benefit from these interventions. This population-weighted specification allows me to employ a measure that reflects the concentration of reuse activities relative to the number of potential beneficiaries. I report the results in Appendix C. Figure C1 shows that the results from the population-weighted specification are remarkably similar to those obtained using the simple count measure and if anything stronger, with a reduction of 4.5 percentage points in the dropout rate. This suggests that treatment intensity matters: reuse activities are more effective when concentrated relative to the student population rather than spread thin across larger catchment areas. Finally, I run a distance-weighted specification, where I weigh the treatment measure by the average distance of reused Mafia properties from the population-weighted centroids. Figure C2 confirms the previous results by showing a reduction in the dropout rate of 5 percentage points.

6.1 Robustness and Falsification Checks

The estimated effects of the reuse activities on dropout rates are robust to several tests and changes in the treatment assumptions. This section is structured as follows: first, I test the results' sensitivity to different school catchment area constructions, and I examine whether the results are driven by the presence of reallocations before the time of the reuse. Second, I test for spatial spillover effects to neighbouring schools. Finally, I conduct falsification tests to rule out any anticipation effect and other alternative explanations.

6.1.1 Schools' catchment areas construction

As introduced in Section 4.3, I re-estimate the main results by changing the a underlying the construction of schools' catchment areas. If the effect is artificially driven by how I recode the treatment allocation, I would expect different effects once those assumptions are changed. 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).[22] I find that 18 schools of my sample switch treatment status under these new assumptions. To ensure that my main results are not driven by schools with ambiguous treatment assignment, I re-estimate the main specification excluding these 18 ”switching” schools from the sample. Table 7 shows that the results remain robust when excluding schools whose treatment status is sensitive to a specific distance measurement method. The coefficients of interest of the models estimated on the full sample and on the restricted sample excluding switching schools are virtually unchanged across all specifications. This consistency suggests that the treatment effect is not a result of the catchment area construction method, even though the presence of less precise estimates highlights the importance of sample size for detecting these effects.

[22] Appendix A explains in detail how the areas have been computed.

Table 7 Impact of reusing Mafia real estate on the share of students dropping out at the age of 16 - different catchment areas assumptions

Dep Var: Dropout rate G11-13	(3) **All sample**	(4) **Non-switchers only**	(7) **All sample**	(8) **Non-switchers only**
Reuse = 1	-0.0192**	-0.0206*	-0.0196**	-0.0207*
	(0.00934)	(0.0122)	(0.00943)	(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:

6.1.2 Policy Effects before the Reuse

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 the Mafia properties under the jurisdiction of the local authorities. Boeri et al. (2023) demonstrate that the confiscation of nearby Mafia properties leads to decreased housing prices by signalling the local presence of the Mafia. Conversely, they show that reallocation sends the opposite signal, increasing the level of housing prices. A potential concern is that my estimated effects capture a recovery process following multiple confiscations that negatively impacted neighbourhoods, reduced local economic activity, and contributed to higher dropout rates. None of the event studies I estimate shows any evidence of pre-trends, which alleviates worries that the results are driven by a natural recovery process following confiscations.

Another explanation would be that the reuse treatment is merely capturing the reduction in dropout rates which is driven by the reallocation treatment. I argue that this is implausible for two main reasons: first, reallocation represents a purely administrative process whereby confiscated Mafia properties are formally transferred to local authorities. While this might signal municipalities' intentions to repurpose former Mafia properties, it generates no tangible changes at the community level, nor any social activity that could alter youth perspectives or educational decisions. Second, in Table 8, I employ the timing of reallocations to provide direct empirical evidence: Columns (3) and (4) show no independent effect of reallocations on the dropout rates, with coefficients close to zero and consistently insignificant across specifications. In contrast, Columns (5) and (6) show that the reuse coefficient remains stable in magnitude and statistically significant at the 5% level even when controlling for the effect of reallocations. This evidence supports the argument that meaningful educational impacts might emerge when properties get actively repurposed for community benefit rather than simply transferred to public ownership.

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**	-0.0196**			-0.0193**	-0.0199**
	(0.00934)	(0.00943)			(0.00936)	(0.00948)
Reallocation = 1			0.00477	-0.000235	0.00290	-0.00238
			(0.00653)	(0.0101)	(0.00653)	(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 Spillover effects

In the main results, I compare treated schools to 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 the 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 9 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**	-0.0177**	-0.0201**	-0.0184**
	(0.00934)	(0.00892)	(0.00910)	(0.00874)
Spillover = 1		-0.0116		-0.0132
		(0.0136)		(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.

6.1.4 Anticipation Effects

As a placebo exercise, I test whether the reuse of confiscated Mafia properties in time $t+1$ affects dropout rates measured in time t. A significant coefficient would indicate the presence of anticipation effects, suggesting that families and students might adjust their behaviour in advance as information about the future reuse of Mafia properties spreads through informal or institutional channels. Table 10 shows that the estimated coefficients for the placebo treatment are consistently small in magnitude and not statistically significant across any specification. This suggests that dropout rates do not respond before the actual reuse takes place. In other words, there is no evidence of anticipation effects, reinforcing the credibility of the main identification strategy: the decline in dropout rates occurs only after the Mafia properties are reused and local NGOs start offering social activities in the treated area.

Table 10 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	-0.0137	-0.00994	-0.0116
	(0.00884)	(0.00866)	(0.00880)	(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.

Moreover, Table 11 presents a placebo test designed to validate the key assumption underlying my identification strategy, that students under the compulsory schooling age of 16 cannot legally drop out of education. I estimate the effect of the reuse intervention on the share of students leaving school between grades 9 and 11, which is the same measure used to control for student migration in the main specification. If my assumption holds, the treatment should not affect these younger cohorts, as these students are legally required to remain in education regardless of school quality improvements. The results confirm this expectation, showing a coefficient very close to zero with no statistical significance. This provides reassurance that the main findings for students who drop out between grades 11 and 13 reflect genuine improvements in educational retention rather than spurious effects driven by changes in student mobility.

Table 11 Impact of reusing Mafia real estate on the share of students dropping out before the age of 16

	(1)	(2)
	Dropout rate G11-G13	
Reuse = 1	0.0016	0.0014
	(0.00182)	(0.00182)
clustered SE	yes	yes
catchment school FE	yes	yes
time FE	yes	yes
retention	no	yes
Observations	1,294	1,274
Number of schools	234	234
Mean dep. var.	0.349	0.349

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 them. Standard errors are clustered at the school level.

6.1.5 Alternative explanations

It is still possible that the reuse of confiscated properties is part of broader policy packages or coincides with other educational or social cohesion programs implemented at the municipality level during the same timeframe. To rule out the possibility that the observed effects are driven by such concurrent interventions rather than the reuse itself, I collect data on the number of educational and social cohesion projects implemented in each municipality for each year from the Italian Department for Cohesion Policy (opencoesione.gov.it). The data cover the implementation of projects aimed at addressing several goals of local administrations from 2007 to 2022. I focus specifically on projects regarding education and social inclusion to test whether the current implementation of these programs absorbs the effect captured by the reuse variable. Table 12 presents results controlling for the presence of educational and social inclusion initiatives implemented at the municipal level during the same period as the reuse practices. The coefficient on the reuse treatment remains statistically significant and substantively unchanged across all specifications, ranging from 1.9 to 2.1 percentage points. Crucially, neither educational nor social inclusion projects show any significant association with dropout rates, with coefficients close to zero and large standard errors. This suggests that the dropout reduction effect is specifically attributable to the reuse intervention rather than being part of broader municipal development strategies or coincidental policy implementations targeting education and social outcomes.

Table 12 Alternative explanations: controlling for concurrent municipal programs

	(1)	(2)	(3)	(4)
	Dropout rate G11-G13			
Reuse = 1	-0.0193**	-0.0203**	-0.0198**	-0.0210**
	(0.00903)	(0.00918)	(0.00867)	(0.00876)
Educational programmes	-0.000777	-0.00533	0.00289	-0.00136
	(0.0146)	(0.0139)	(0.0151)	(0.0144)
Social cohesion programmes	-0.000929	-0.00334	-0.00755	-0.00869
	(0.0157)	(0.0153)	(0.0185)	(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.

7 Mechanisms

The activities provided by repurposing Mafia properties contribute to reducing dropout rates in areas where at least one of these properties has been reused for social purposes. The estimated effects are stronger for technical high schools and academically underperforming schools. Additionally, the results show a dose-response relationship where each additional repurposed Mafia property generates incrementally larger effects on dropout reduction in treated areas. In this section, I discuss the mechanisms underlying the treatment effect raising four key arguments: first, I reject gentrification as a primary channel; second, I demonstrate that activities provided in repurposed Mafia properties cannot be easily substituted by other NGO activities; third, I show that results are not solely driven by increased educational support that merely improves academic performance; finally, I argue that repurposed Mafia properties can play a transformative role by directly influencing students' perceptions of education's importance and reducing the Mafia's attractiveness by providing alternative role models. To discuss this, I combine both empirical and anecdotal evidence.

First, I rule out gentrification as the main channel driving the estimated effects by employing 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, specified as:

$$DropoutG11 - G13_{cnmt} = \beta_1 Reuse_{ct} \times Prices_{nt} + \beta_2 Reuse_c + \beta_3 Prices_n + \beta_4 X'_{ct} + \delta_c + \eta_t + \epsilon_{cnmt} \tag{3}$$

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			
Reuse = 1	-0.0144	-0.0208	-0.0137	-0.0213
	(0.0375)	(0.0383)	(0.0372)	(0.0380)
Rental Prices	-0.000801	-0.00469	-0.00128	-0.00475
	(0.00709)	(0.00695)	(0.00691)	(0.00681)
Reuse =1 × Rental Prices	-0.000566	0.000127	-0.000626	0.000191
	(0.00382)	(0.00390)	(0.00375)	(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.

Second, since the local NGOs are in charge of organising the reuse activities, it is essential to test whether the main results are purely driven by the overall presence of local NGOs, which I measure as the number of NGOs at the street level. This way, I can test whether the impact of Mafia property reuse is complementary to or substitutable with other civil society activities.

$$DropoutG11 - G13_{cnmt} = \beta_1 Reuse_{ct} + \beta_2 NGOs_{ct} + \beta_3 X'_{ct} + \delta_c + \eta_t + \epsilon_{cnmt} \tag{4}$$

where β_2 is the coefficient measuring the effect of the street-level presence of NGOs on dropout rates in the school catchment area c in time t, and the rest of the notation is reported as before.

Is there something uniquely valuable about conducting activities in former Mafia properties, or would any NGO activity in the area produce similar dropout reductions? If the observed effects were merely due to the presence of social services in the area, regardless of their location in repurposed Mafia properties, we would expect β_1 to diminish substantially when controlling for the presence of other NGOs. However, if β_1 remains stable while β_2 shows little effect, this would demonstrate that the symbolic and contextual significance of operating within former Mafia properties creates unique and valuable activities which cannot be substituted by other conventional NGO activities. Table 14 shows that activities offered in repurposed Mafia properties cannot be easily substituted by other conventional NGO services. First, Columns (2) and (5) reveal that the presence of other NGOs in school catchment areas has negligible and statistically insignificant effects on dropout rates, suggesting that general NGOs' activities do not meaningfully reduce educational dropout. Second, the repurposing effect remains remarkably stable when controlling for other NGO presence. Comparing the baseline specifications in columns (1) and (4) with the full specifications in columns (3) and (6), the reuse coefficients show virtually no change in magnitude and maintain statistical significance at the 5% level across all specifications. This exercise provides compelling evidence that the observed effects are not driven by general social services provision in the area, but rather by the contextual significance of conducting activities within former Mafia properties.

Table 14 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**		-0.0191**	-0.0196**		-0.0194**
	(0.00934)		(0.00960)	(0.00945)		(0.00963)
NGOs presence		-0.000590	-0.000626		-0.000542	-0.000583
		(0.000392)	(0.000389)		(0.000351)	(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.

Last, having established that repurposed Mafia properties offer non-substitutable services, it is worth examining whether these effects operate primarily by improving educational support. If the reuse activities were simply providing additional educational resources, we would expect stronger effects from properties dedicated to educational activities compared to those reused for social and cultural services. To test this, I interact the treatment binary indicator with a time-invariant indicator which equals to 1 whenever the house has been reused for activities related to education and job training. I define the specification as follows:

$$DropoutG11 - G13_{cnmt} = \beta_1 Reuse_{ct} \times Education_c + \beta_2 Reuse_c + \beta_3 X'_{ct} + \delta_c + \eta_t + \epsilon_{cnmt} \quad (5)$$

where β_1 is the coefficient of interest capturing how the impact of repurposed Mafia properties on dropout rates varies if the purpose of the reuse activities is or is not educationally related. The rest of the equation is reported as before.

The results, presented in Table 15, reveal several important findings. First in Columns (3) and (4), the baseline effect of reusing Mafia properties remains negative and statistically significant at the 10% level; crucially, the interaction coefficient is less than half in magnitude and statistically insignificant across all specifications. This lack of differential effects suggests that properties dedicated to educational activities do not generate stronger impacts on dropout reduction compared to those providing social and cultural services.

Table 15 Impact of reusing Mafia real estate on dropout rates for G11-G13

	(1)	(2)	(3)	(4)
	Dropout rate G11-G13			
Reuse = 1	-0.0173	-0.0173	-0.0189*	-0.0191*
	(0.0106)	(0.0106)	(0.0106)	(0.0105)
Reuse = 1 × Edu	-0.00618	-0.00632	-0.000690	-0.00103
	(0.00934)	(0.00928)	(0.0101)	(0.0100)
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	1,296	1,294	1,274	1,274
Number of schools	235	234	234	234
Mean dep. var.	0.0537	0.0534	0.0530	0.0530

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

These findings have important implications for understanding the main underlying mechanism. The absence of enhanced effects from education-specific repurposing indicates that the dropout reduction benefits do not operate primarily through direct educational resource provision. Instead, the results suggest that repurposed Mafia properties might generate broader community-level benefits by fostering cultural change and reshaping social norms within affected communities. Recent conversations with *Libera*'s Mafia real estate managers and social workers from the NGOs managing the reused Mafia real estate, as well as the interviews conducted by Nazzaro (2021) and Falcone et al. (2016), support this interpretation. The social workers and volunteers from the NGOs describe the reused Mafia real estate 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

The CRR 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 empirical evidence of this cultural shift and changing perspective among young people, 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 strengthens 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 perceptions[23] 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 C4 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.

[23] I 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 ot 7.

Table 16 Impact of reusing Mafia properties on students' perceptions of what is useful for career development

	What do you think will be more useful to find a job in your town?						
	(1) Education	(2) Job centre	(3) Civil service	(4) Ask the Mafia	(5) Ask a politician	(6) Ask family	(7) Ask a friend
Panel A: Very useless							
Reuse = 1	-0.0516	-0.00243	-0.0772	0.136*	0.117*	-0.0788	-0.0575
	(0.0597)	(0.0612)	(0.0469)	(0.0780)	(0.0663)	(0.0614)	(0.0385)
Observations	161	161	161	161	161	161	161
Number of schools	56	56	56	56	56	56	56
clustered SE	yes	yes	yes	yes	yes	yes	yes
time FE	yes	yes	yes	yes	yes	yes	yes
school FE	yes	yes	yes	yes	yes	yes	yes
Mean dep. var.	0.159	0.196	0.163	0.564	0.453	0.197	0.208
Panel B: Very useful							
Reuse = 1	0.161**	0.0143	0.136	-0.110	-0.0755	0.0371	0.0492
	(0.0804)	(0.0719)	(0.0827)	(0.0793)	(0.0863)	(0.0405)	(0.0308)
Observations	161	161	161	161	161	161	161
Number of schools	56	56	56	56	56	56	56
clustered SE	yes	yes	yes	yes	yes	yes	yes
time FE	yes	yes	yes	yes	yes	yes	yes
school FE	yes	yes	yes	yes	yes	yes	yes
Mean dep. var.	0.480	0.400	0.426	0.280	0.280	0.303	0.273

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

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 C3 and C4 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 17 Impact of reusing Mafia properties on students' sentiment scores

Sentiment analysis outcomes

	(1) Syuzhet Score	(2) AFINN Score
Reuse = 1	-0.266**	-0.417**
	(0.112)	(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 perception of the Mafia across eight distinct emotional categories: anger, disgust, fear, sadness, joy, trust, surprise, and anticipation. Table C5 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 18 Impact of reusing Mafia properties on students' emotional sentiments towards the Mafia

Sentiment analysis outcomes

	(1) Anger	(2) Disgust	(3) Fear	(4) Sadness
Panel A: Negative sentiments				
Reuse = 1	-0.0151	-0.0637	0.254**	0.0764
	(0.140)	(0.0705)	(0.125)	(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) Joy	(2) Trust	(3) Surprise	(4) Anticipation
Panel B: Positive sentiments				
Reuse = 1	-0.136*	-0.0221	-0.0180	-0.0153
	(0.0694)	(0.104)	(0.0777)	(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.

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 reused Mafia properties within those areas. School catchment areas are defined as treated whenever there is at least one Mafia real estate reuse within the area boundaries. I compare school catchment areas affected by the reuse of Mafia properties to those unaffected before and after the first experience of reuse.

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 margin effect decreases as the distance to the student population-weighted centroid increases, and is stronger when weighted by the average catchment area student population. The estimates are not driven by gentrification patterns, nor do the reuse activities seem to be easily substitutable by other general NGOs' activities. Triple difference-in-differences estimates interacting the treatment indicator with neighbourhood rental prices show virtually zero and statistically insignificant coefficients, indicating that the dropout reduction effects do not operate through neighbourhood upgrading. Furthermore, controlling for the presence of other NGOs in school catchment areas leaves the reuse coefficient stable while the NGOs presence variable itself has negligible and insignificant effects, demonstrating that the contextual significance of operating within former Mafia properties creates unique additional value to the conventional NGO services delivered elsewhere in the area.

The key mechanism mediating the effect likely involves how the symbolic reclamation of Mafia properties alters students' perceptions of legitimate and illegitimate pathways to success. Students exposed to repurposed properties increasingly define the Mafia with greater fear and diminished positive emotions, while simultaneously viewing educational achievement and meritocratic pathways as more viable routes to employment. This shift in perception, rather than gentrification or mere provision of tutoring services, appears central to the policy's success. The presence of cultural and welfare activities, as opposed to purely educational support, drives the strongest effects, underscoring that what matters is the provision of alternative social frameworks and role models rather than simply supplementing academic instruction.

These results carry substantial implications for designing and implementing anti-Mafia policy in Italy and internationally. Most fundamentally, they demonstrate that successful crime prevention requires moving beyond confiscation alone to actively constructing legitimate alternatives. The challenge lies not in seizing criminal assets but in rapidly and effectively deploying them as community resources. Currently, more than half of the reallocated properties remain unused, representing missed opportunities to disrupt Mafia recruitment pipelines. This paper supports the need to accelerate the bureaucratic transition from reallocation to actively reused former Mafia properties. Moreover, local NGOs operating these spaces require sustained financial support. Enhanced funding mechanisms, streamlined administrative procedures, and stronger partnerships between the local authorities and CSOs could amplify the policy's impact.

SUPPLEMENTARY APPENDICES

Appendix A: Data and Variable Definitions

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.

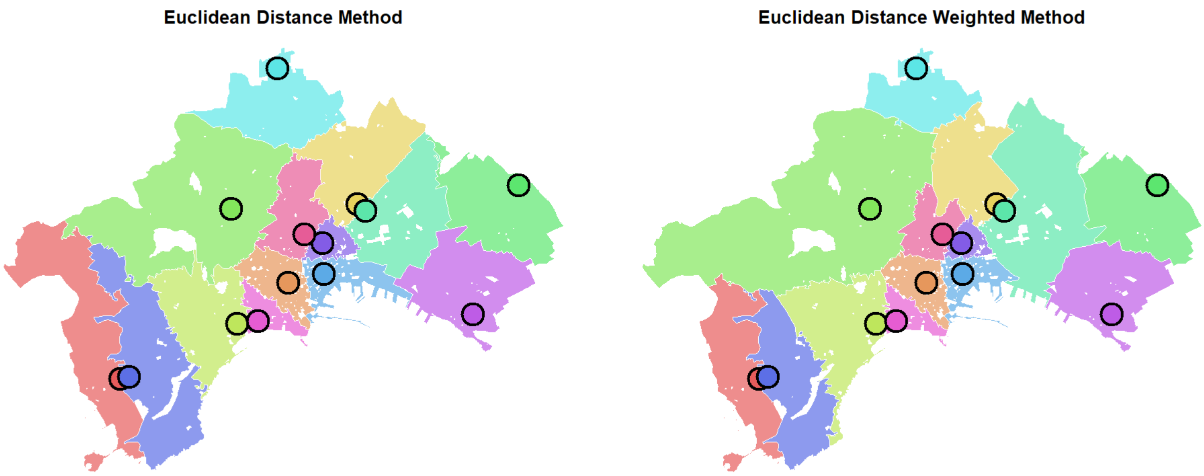


Figure A1 Schools' catchment areas measured with Euclidean distance (left) and capacity-weighted distance (right)

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 $t1$, 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 $t-1$.

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

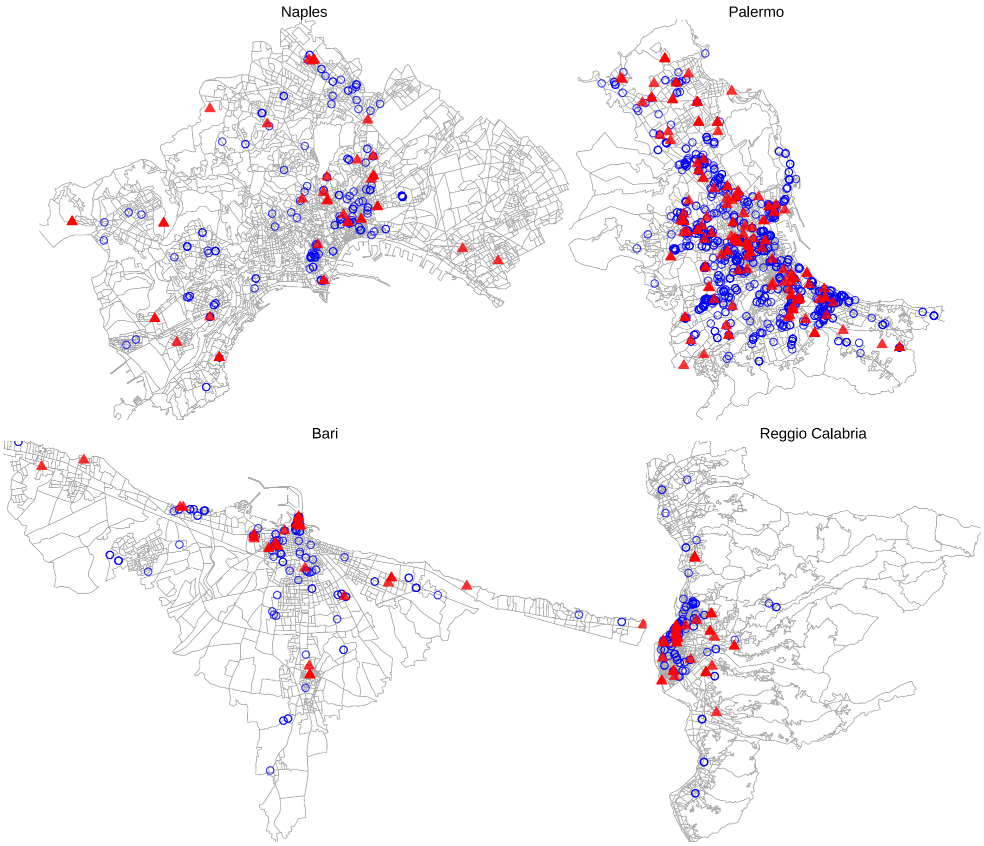
Grade retention rate. It is possible that students repeating years due to inadequate academic performance will confound my measure of dropout by appearing enrolled in the same grade for both time $t1$ and time t. To address this, I construct a proxy for grade retention rates for students enrolled on 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.

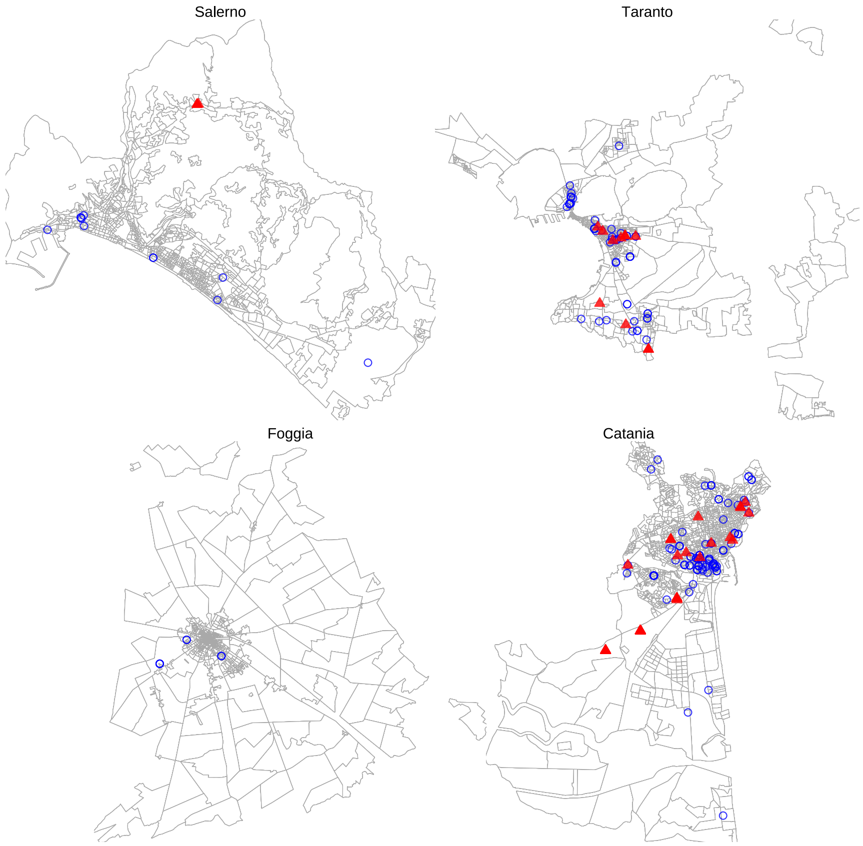
I calculate the share of students repeating grade 11 as the number of students aged 18 or older as a share of all students completing grade 11 in time t. Similarly, the share of students repeating grade 12 is calculated as the number of students aged 19 or older as a share of all students completing 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.

$$Retention_{G11_t} = \frac{aged18_{G11_t}}{Completed_{G11_t}} \tag{7}$$

$$Retention_{G12_t} = \frac{aged19+_{G12_t}}{Completed_{G12_t}} \tag{8}$$

Reused Mafia properties. Figure A2 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.


Naples
Palermo
Bari
Reggio Calabria


Salerno
Taranto
Foggia
Catania

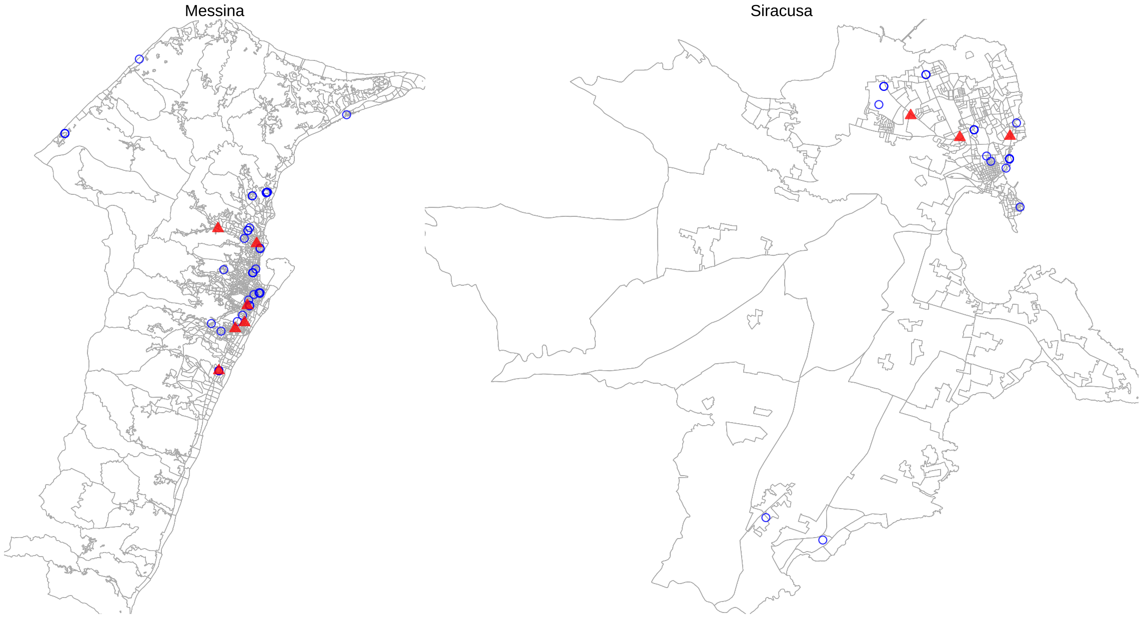


Figure A2 The distribution of Mafia real estate in the 10 metropolitan areas of the historical Mafia-ridden regions. Empty blue circles locate reallocated but not reused real estate, while red triangles indicate the real estate under reusing practices.

Survey Data. As discussed in Section 4.4, Table A1 reports the full questions I employ to investigate mechanisms from the *Survey on the Perception of the Mafia* (Centro Studi Pio La Torre, 2025).

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	**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 usless (7)**		
	Invest in education	Index 1-7	School
	Participate in a publci competition	Index 1-7	School
	Turn to job centre	Index 1-7	School
	Turn to the Mafia	Index 1-7	School
	Turn to a politician	Index 1-7	School
	Ask family	Index 1-7	School
	Ask a friend	Index 1-7	School
V32	**In your opinion, who is stronger between the State and the Mafia? Choose an option**		
	The Mafia	Multiple choice	School
	The State	Multiple choice	School
	Equally	Multiple choice	School
	I don't know	Multiple choice	School

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

Table A2 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 giudance
		35	School organisation
		36	HR development
		37	Integration with the local community

Appendix B: 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[24]. 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 where classified based on the level of trasparency shown online in sharing information about the presence of Mafia reallocated properties as inscribed by the law. The model is specified as:

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

$$P(Reuse = 1)_{cm} = \beta_0 + \beta_1 lag_{NGO_c} + \beta_2 X'_m + \epsilon_{cm} \tag{9}$$

where $P(Reuse = 1)$ is the probability for a Mafia property to get reused in school catchment are c in municipality m. 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 mangitude 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 reallocated 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 B1 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. 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 B2 Estimating reuse predictors

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

8.1 Appendix C: Additional Results and Robustness

Table C1 Testing the effect of the treatment on the main controls

	(1)	(2)	(3)	(4)
	Student migration		**Grade retention**	
Reuse = 1	0.00160	0.00159	-0.000460	0.000469
	(0.00182)	(0.00182)	(0.00120)	(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 C2 Effect of the treatment on selection in enrollment preferences

	(1)	(2)	(3)	(4)
	Enrollment Share			
Reuse = 1 X Technical	-0.00723	-0.0117	-0.00778	-0.0116
	(0.0127)	(0.0121)	(0.0125)	(0.0115)
Reuse = 1 X Academic	0.0120	0.0240	0.0121	0.0235*
	(0.0148)	(0.0145)	(0.0147)	(0.0140)
Reuse = 1 X Vocational	-0.0638**	-0.0647**	-0.0637**	-0.0645**
	(0.0250)	(0.0266)	(0.0246)	(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.

Table C3 Dropout rates by single grade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dropout G9		**Dropout G10**		**Dropout G11**		**Dropout G12**		**Dropout G13**	
Reuse = 1	-0.0195	-0.0205	-0.00535	-0.0110	-0.0334**	-0.0342**	-0.0123	-0.0217	-0.000674	0.00328
	(0.0240)	(0.0237)	(0.0455)	(0.0462)	(0.0139)	(0.0140)	(0.0146)	(0.0153)	(0.00572)	(0.00447)
clustered SE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
school FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
time FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
migration	no	yes	no	yes	no	yes	no	yes	no	yes
retention	no	yes	no	yes	no	yes	no	yes	no	yes
Observations	1,259	1,236	1,263	1,240	1,295	1,273	1,301	1,273	1,312	1,274
Number of schools	228	228	229	229	234	234	236	234	240	234
Mean dep. var.	0.0998	0.100	0.000936	0.000659	0.0689	0.0687	0.0433	0.0422	0.0289	0.0275

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.

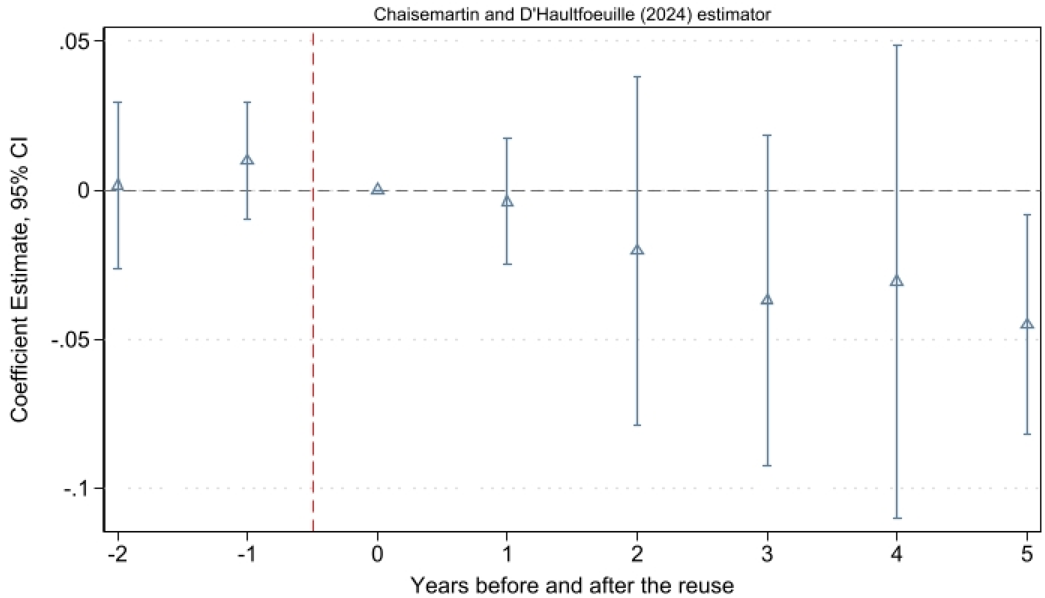


Figure C1 Event study using the count of reused assets weighted by the student population of school catchment areas

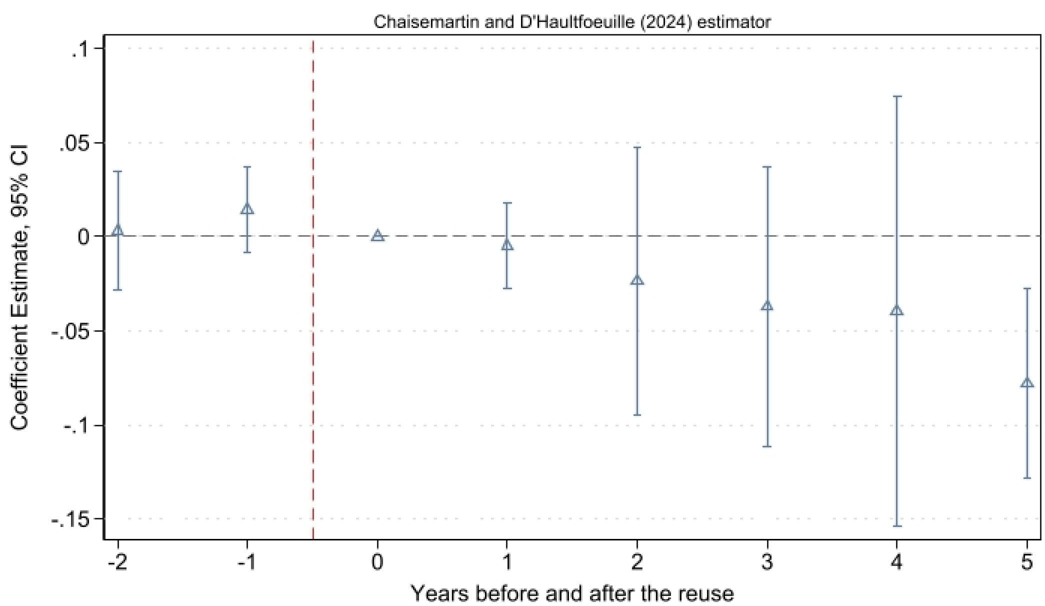


Figure C2 Event study using the count of reused assets weighted by the average distance of properties from the population-weighted centroids of schools' catchment areas

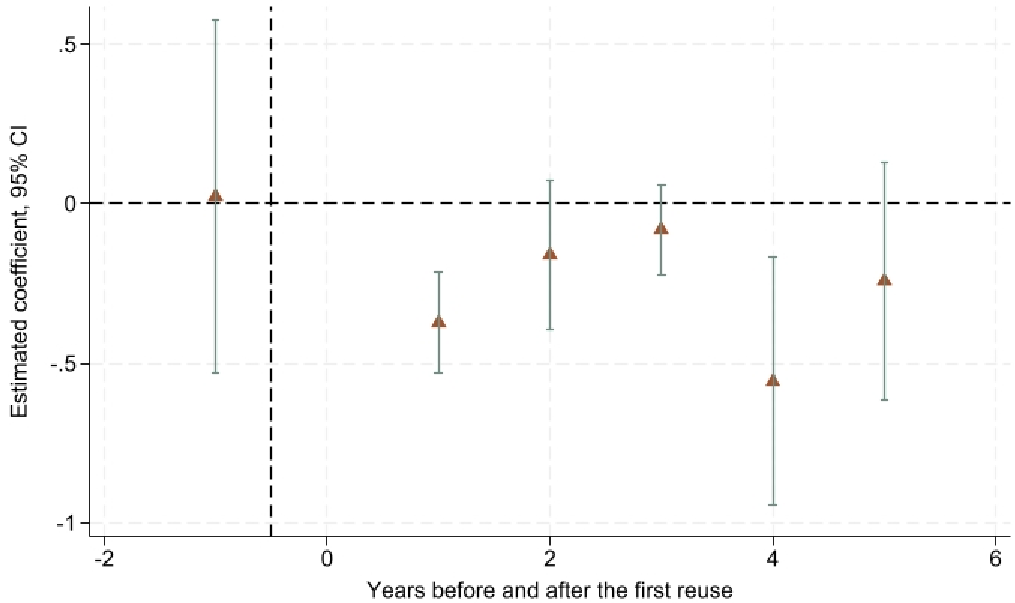


Figure C3 Event study of the Szyuzhet scores

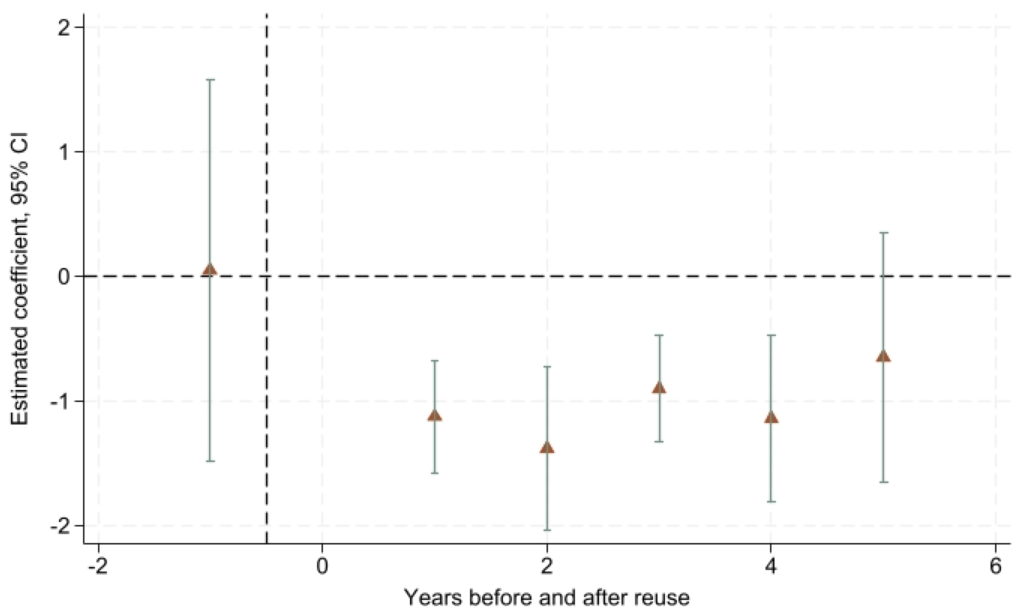


Figure C4 Event study of the AFINN sentiment scores

Table C4 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	0.0344	-0.00151	-0.00171
	(0.107)	(0.0812)	(0.0698)	(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

Table C5 Top 25 terms for positive and negative sentiments

Panel A: top 25% negative words	**Anger**	**Disgust**	**Fear**	**Sadness**
	Electoral	Ruthless	Forced	Violence
	Laundering	Struggle	Eradicate	Kill
	Murder	Threathening	Hide	Cruel
	Resorting	Inconvenient	Manifests	Unfair
	Conflict	Involve	Struggle	Evil
Observations	638	393	327	274
Panel B: top 25% positive words	**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.

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