Out of the darkness: Re-allocation of confiscated real estate mafia assets *

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Abstract

In an effort to tackle criminal groups, the Italian State allows the confiscation of properties belonging to individuals convicted for mafia-related crimes, and their re-allocation to a new use. This policy is considered both as an anti-mafia measure and as a way to partially compensate the society for the harm made by the criminal organisations. Whether and how this measure have had an impact on the local areas where it is implemented, however, has not yet been investigated. We test the hypothesis that the policy contributes to the regeneration of urban spaces by assessing its impact on the value of buildings in the vicinity of confiscated/re-allocated properties. To this aim, we perform difference-in-differences analyses, both at the level of local housing markets and at the level of individual buildings, investigating the externalities of the policy across the whole Italian territory. The results unveil a positive and significant effect of re-allocations of confiscated real estate assets on house prices, declining with distance from the re-allocation site. The impact is larger in cities with stronger mafia presence and driven by the conversion of confiscated assets into public amenities. This suggests that the policy contributes to add value to the territory where it is applied and favours processes of urban revitalisation. These findings have important implications for the territorial development of deprived urban areas characterised by a strong presence of criminal organisations.

Keywords: Organised crime, real estate confiscation, hedonic analysis, urban renewal policy, Italy.

JEL classification: K42, H23, R32, I24.

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1 Introduction

Urban areas are often characterised by pockets of poverty, crime, and marginalisation (Rosenthal & Ross, 2015). In light of that, addressing urban deprivation by means of effective regeneration measures represents a key challenge for policymakers (Bailey & Robertson, 1997). In particular, crucial objectives for interventions aimed at fostering the overall quality of cities - especially in underprivileged neighbourhoods - include tackling criminal activities and improving public spaces and housing (Atkinson & Helms, 2007; Koster & Ommeren, 2019). Yet, evidence on the effectiveness of urban renewal policies of this kind is very limited.

This paper focuses on a large-scale, nationwide policy intended to reach the double goal of contrasting organised crime and contribute to the territorial development of local urban areas. The Italian law allowing the confiscation and re-allocation of properties of individuals convicted for mafia-related crimes allows to seize any real estate asset previously owned by organised crime members or affiliates and, through re-allocations, re-assign these assets to local communities by converting them into public housing amenities. The intention of re-allocations, as conceived by the Italian legislator, is to contribute to the revitalisation of local areas in which they are made. As such, this measure not only acts as a crucial device allowing the appropriation of relevant resources from criminal activities, but also allows its redistribution to local communities. In this way, it contributes to eradicate criminal organisations in the areas where they are most rooted, preventing their spreading in territories selected by criminal groups for investment and money laundering, while also providing new opportunities to the residents of neighbourhoods plagued by the mafia. The buildings re-assigned to the citizenry, in their new role, should stimulate the creation of a 'culture of legality', favour local entrepreneurship, and help recovering disadvantaged people from their conditions. Ultimately, re-allocations are aiming to promote the development of local territories and increase their economic value (Falcone et al., 2016; dalla Chiesa, 2016).

While some descriptive and anecdotal evidence exists on the use and application of the policy (Camera dei Deputati, 2009; 2018; Transcrime, 2013; Falcone et al., 2016), this evidence tells little on its actual effectiveness. When confiscated assets are discussed in the media, the monetary value of the assets is systematically presented (e.g. Repubblica 2019), but other local effects, let alone overall capitalisation effects, are seldom discussed. In spite of the fact that policies to recover organised crime assets are widely diffused in several countries across the world[1], the re-allocation measure adopted by the Italian State has thus far been ignored by the academic literature. Whether and how real estate asset confiscations and re-allocations have had an impact on the wider society has not yet been investigated.

In this paper, we aim to fill this gap and investigate whether the re-allocation of confiscated mafia real estate assets produces any external effects on the local territory where such initiative takes place. Following the literature evaluating the impact of urban renewal policies, we capture the spillover effects of the intervention by looking at how the monetary value of buildings in the surrounding of confiscated and re-allocated buildings responds to the increase in public housing resulting from the application of the law. The evidence produced by previous studies assessing the external effects of regeneration policy measures is mixed. While some works reveal that localised investments to revitalise urban areas have converted into higher house prices of neighbouring buildings (Santiago et al., 2001; Schwartz et al., 2006; Rossi-Hansberg et al., 2010; Ooi and Le, 2013; Koster & Ommeren, 2019), others find that they have no effect on the property value of surrounding areas (De Souza, 1999; Lee et al., 1999; Ahlfeldt et al., 2016). Almost all these studies focus on specific neighbourhoods of single cities where the regeneration programme has been implemented, producing hardly generalisable findings[2]. Different from that approach, we perform our analysis on the entire Italian territory, thus focusing on a very large and highly heterogeneous context.

Hence, the main contribution of our work relates to the peculiarity of the intervention we examine, aiming to improve neighbourhoods by both increasing the stock of amenities and by tackling organised crime, as well as to the size and the spatial scale of the policy initiative.

Furthermore, our analysis is based on a unique database which allows to better identify the policy's impact. We exploit detailed information on the exact location and timing of almost 10,000 confiscated and re-allocated properties in Italy, and investigate their spillover effect in two ways adopting difference-in-differences empirical settings. First, we develop a panel model estimating how micro-aggregated local housing markets across the entire Italian territory respond to real estate asset confiscation and re-allocation. Second, exploiting information on over 60,000

[1] According to the Asset Recovery Office of the European Commission, organised crime assets worth over 4 billion euros have been recovered in Europe alone in 2014 (the last year for which data is available) (ARO, 2014). Of this amount, over €1.6 billion was recovered in Italy.

[2] The only exception is the recent contribution by Koster and Ommeren (2019), estimating the external benefits of a programme improving the quality of public housing in 83 impoverished neighborhoods throughout the Netherlands.

geo-localised house sale points in the 55 major Italian cities, we provide a close examination of the impact of re-allocations on the housing value of neighbouring buildings, as well as a detailed investigation of the spatial decay of the estimated effect. These two empirical strategies complement each other. The first analysis covers the whole of the Italian territory, focuses on a longer time period (2005-2016) but it is relatively less geographically accurate, given that it is based on local area data. The second presents a more limited temporal span (2011-2017) but the precision and accuracy of the analysis are higher due to the use of georeferenced real estate data as units of observation, and to the possibility of accounting for a very large set of building characteristics as controls. This setting allows to minimise any issue of selection and to control for any potentially confounding housing market dynamics. In addition, detailed information on confiscated/re-allocated assets allows to separately identify the two aspects of the policy (i.e. the confiscation and the re-allocation).

The results reveal strong and robust evidence of an external effect of re-allocations on neighbouring properties, significantly increasing their value following the conversion of confiscated buildings into new amenities. This finding, consistent across estimation methodologies, reveals that for every re-allocated building, surrounding properties increase their monetary value between 0.6% and 1%, after the re-allocations. Examining the temporal dynamics of the effect by means of an event study, we show that the impact materialises the year following the re-allocation. Additionally, we show that this effect decays with distance and becomes insignificant 350m from the re-allocated building. When sub-dividing our sample into mafia and non-mafia regions, we show that the effect is driven by mafia-rigged areas, where the majority of confiscations and re-allocations have been. This suggests that the legislator's intent to improve the quality of neighbourhoods where the mafia presence is more pronounced through the policy has been effective.

A number of channels may be driving the uncovered effect. On the one hand, property values are directly influenced by the stock of amenities of the kind of those chosen for the re-allocations. A higher provision of green spaces, cultural facilities, social engagement centres, and similar buildings are expected to positively affect the monetary value of the neighbourhood they are in (Gibbons & Machin, 2008; Gibbons et al., 2014). Moreover, the presence of amenities may attract talented people (Storper & Venables, 2004; Florida, 2005; Scott, 2008; Storper, 2013) whose presence may also contribute to raise the value of the urban space where they move. In line with these views, we show that the results are mainly driven by re-allocations of buildings to a new 'social use'. On the other hand, the confiscation/re-allocation policy can influence disamenities such as the level of violence and crime, whose reduction also increases property prices (Gibbons, 2004, Linden & Rockoff, 2008, Ihlanfeldt & Mayock, 2010) [3]. Coherent with the explanation, we do find a negative association between the number of re-allocations and the intensity of violent mafia crimes in Southern Italian cities, a result which suggests that the re-allocation policy - through the conversion of real estate into buildings for 'institutional use' such as police stations - may limit the violent activity of criminal organisations and reduce their control of the territory.

Our research, besides contributing to the above-mentioned literature on urban renewal policy evaluation, adds up to the growing studies on organised crime (e.g. Acemoglu et al., 2013; Barone & Narciso, 2015; Pinotti, 2015; Alesina et al., 2018; Di Cataldo & Mastrorocco, 2018; Pinotti & Stanig, 2018) and, more specifically, to the recently developing literature studying the societal implications of public initiatives against criminal organisations. While a number of recent works have investigated the effectiveness of some anti-mafia measures[4], no study has yet looked at the policy of confiscation and re-allocation of mafia real estate assets which we evaluate in our paper.

The remainder of the paper is organised as follows. Section 2 describes the legislative measures we aim to evaluate, providing some key descriptive statistics. Section 3 presents our data. Section 4 introduces our empirical strategy at local housing market (OMI zone) and sale-point (micro) levels. Section 5 presents our findings. Section 6 concludes.

[3] Other mechanisms which may be triggered by the policy have to do with housing market dynamics, i.e. variations in the supply of real estate properties. An increase (decrease) in housing supply would reduce (increase) house prices (Glaeser et al., 2008; Caldera & Johansson, 2013).

[4] The most widely analysed policy is the Italian law allowing the dissolution of local governments upon clear evidence of links between mafia clans and local public officials. Acconcia et al. (2014) exploit the temporary contraction in public investment occurring in post-dissolution periods to obtain estimates of the fiscal multiplier for Italian provinces. Daniele and Geys (2015) and Galletta (2017) demonstrate that the dissolutions affect the quality of elected politicians and proportion of public investments in neighbouring municipalities. Another examined policy is the accomplice-witnesses regulation. Acconcia et al. (2009) show the policy to be more effective the less efficient the prosecution system and the higher the internal cohesion of mafia organisations, while Garoupa (2006) analyse the policy within a principal-agent theoretical environment.

2 Institutional background: confiscation and re-allocation of mafia assets

The rise in mafia activities throughout the 1980s and a series of violent attacks led the Italian central government to introduce a set of tougher anti-mafia measures. On 13 September 1982, in the aftermath of the murders of politician Pio La Torre and anti-mafia prefect Carlo Alberto Dalla Chiesa in Palermo, the national Parliament approved the ″Rognoni-La Torre″ law (646/82), which represents a turning point in the fight against organised crime. This bill introduces two key measures contrasting mafia activities, namely the inclusion in the Penal Code of membership of a mafia-type criminal organisation as a crime independent of other criminal acts (so-called 416-bis article), and the possibility for the courts to confiscate any assets of the persons belonging to the criminal associations, as well as of relatives, partners and relatives who in the past five years played a cover-up role for criminal organisations. Any individual condemned with article 416-bis would immediately get their assets seized. The seizure may be converted into confiscation by the judges. To make law enforcement quick and effective, the law granted the judiciary full access to bank records in order to follow money trails.

The ″Rognoni-La Torre″ law (646/1982) prescribes four steps to obtain the final confiscation:

1. The properties of suspects of belonging to mafia groups are scrutinised by the competent tribunal;
2. The seizure is decided upon by a panel of 3 judges. The asset goes under judiciary administration;
3. The judges provide a motivation for confiscation. The asset goes under first degree confiscation;
4. If appealed, the confiscation decision is reviewed by the Court of Appeal. The order can be ′revocation′ [5] or confirmation (second degree confiscation).

The possibility of confiscating mafia-related goods and properties represents an extremely powerful tool in the hands of the Italian State in its fight against criminal organisations. Real estate asset confiscation is nowadays recognised as a funda-

[5]Of all the confiscated buildings, only 14 have been ′revoked′. This suggests that judge bribing, even if taking place, is ineffective and plays little role as a confounder of our analysis

mental instrument contributing to eradicate the pervasive presence of the mafia in the areas where it is most deeply rooted (Falcone et al., 2016). This is because real estate properties have a strong symbolic meaning for criminal groups. They are a physical representation of their power on the local territory, and are often chosen by mafia families for their meetings. In addition, considering the large share of liquidity laundered by mafia groups into real estate properties - more than 50% of illegal mafia profits are reinvested into the legal economy, with real estate as one of the preferred sectors of investment (Transcrime, 2015) - the confiscation policy is a way to harm their business model and earnings.

A fundamental step in the management procedure of seized assets is their re-allocation to a new use by "returning them to the citizenry" (Frigerio & Pati, 2007). This is operated by the Italian State, after the confiscation has been completed. The procedure of re-allocation, already introduced in the 646/82 law, has been regulated more clearly in 1996, when law 109/96 has been promulgated. As can be seen in Figure 1, the number of re-allocations has increased drastically in the aftermath of the approval of the 1996 law, and the large majority of re-allocations have occurred in the last few years.

Figure 1: Re-allocated real estate assets by year

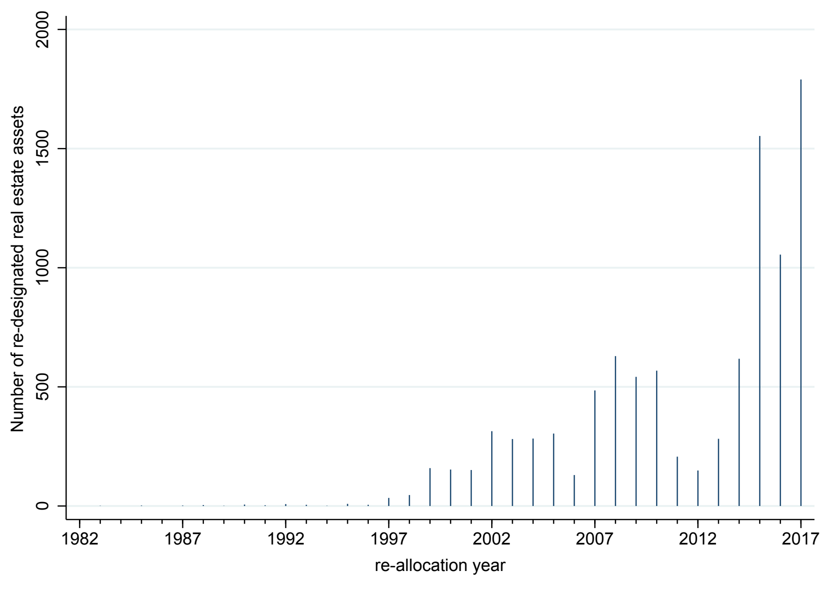
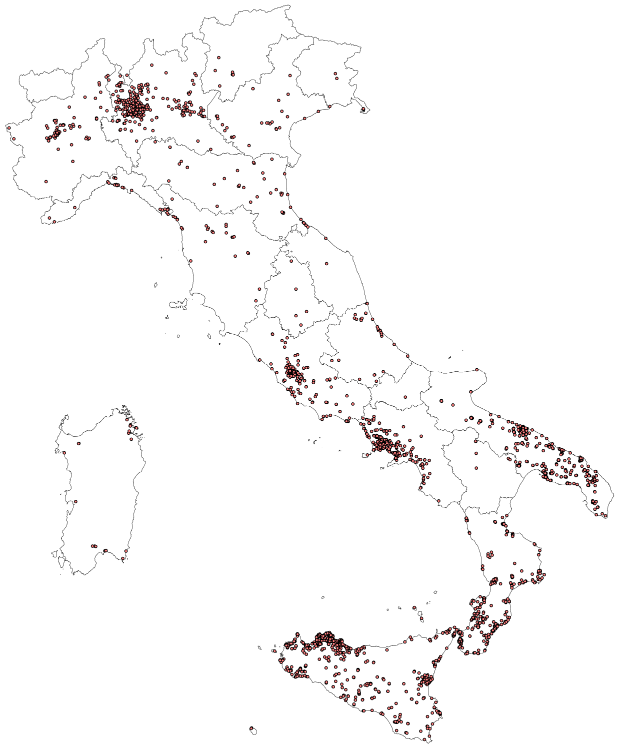


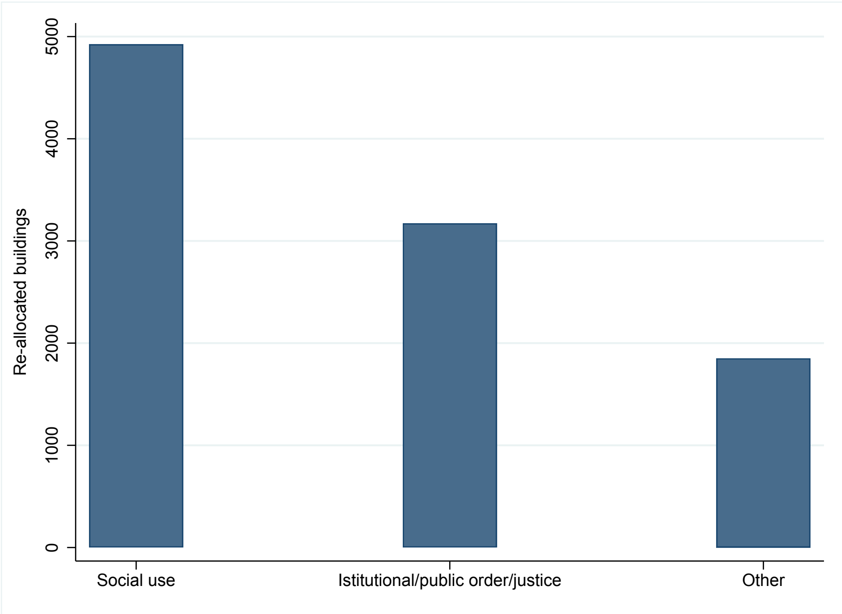
Figure 2 shows the geographical location of re-allocated properties across the Italian national territory. The confiscated and re-allocated mafia assets seem to be concentrated in metropolitan urban areas. Clusters can be observed in cities such as Milan, Rome, Naples, Bari and Palermo. A concentration of assets also seems to emerge in Southern Italian cities, with fewer clusters in Northern cities and even less in the central regions of Italy. The regions of Sicily, Puglia, Calabria and Campania also present higher concentrations of confiscated assets, which comes as no surprise given the publicised presence of mafia in these regions.

Figure 2: Re-allocations in Italy



The approval of the 1996 law on re-allocation was the result of lobbying activity from the anti-mafia association *Libera*, asking for a faster management of confiscated assets and the possibility to use re-allocated goods for social purposes. As a result of that, the law lists a whole set of different uses for the re-allocated assets. The two broader categories are: "social use" and "institutional, justice and public order" (Figure 3). The former category include conversions of buildings into: anti-mafia/non-for-profit associations, senior centres, under18 centres, disable centres, health care centres, sport centres, green spaces. The latter includes: tribunal, police station, centre for migrants, archive, council houses. The logic of the policy is to use re-allocated assets to establish the principle of legality precisely where the control of the mafia is most entrenched, for example with the creation of police stations. Alternatively, buildings re-allocated for social use (e.g. by creating centres for employment-seekers) may contribute to provide concrete alternatives for individuals potentially attracted by organised crime. In all cases, the main principle behind this measure is the possibility for re-allocated assets to contribute to the regeneration of a local area and/or to become a fundamental resource in the fight against criminal organisations.

Figure 3: Re-allocation type



2.1 Local areas of confiscation/re-allocation

By exploiting 2011 Census data, it is possible to descriptively examine the characteristics of the areas where confiscated and re-allocated buildings are located. In order to do that, we construct a dataset at the level of Census areas for the entire Italian territory and focus on micro-areas with 100 or more inhabitants. For each of them, we are able to say whether there have been confiscations/re-allocations. We then test for the correlation between a treatment dummy (taking value 1 if in a given Census area there has been at least one episode of confiscation and re-allocation, and 0 otherwise) and a number of Census characteristics. The results of this test are reported in Table A1 in the Appendix. As visible in the table, territories where the policy has been applied are relatively smaller in size, as shown by the negative association between the treatment dummy and the log population variable, and they have a higher proportion of unemployed people, of families renting their house, and buildings in bad conditions. All in all, this evidence seems to suggest that, as hypothesised, the policy is most often being implemented in underprivileged territories[6]. Crucially, when we replicate the empirical test with the inclusion of

[6]In Italy, around 72% of the houses are owned by residents. As a result, being rented is often a condition of more disadvantaged families

local housing market fixed effects (OMI FE), it can be noted that none of the Census variables returns a significant coefficient, indicating that area characteristics are balanced in this case.

2.2 Re-allocation timing

The implementation of law 109/96 and the creation in 2010 of a National Authority for Mafia-Confiscated Assets (hereafter ANBSC) has contributed to speed up the application of the law, progressively increasing the number of confiscated real estate assets being re-allocated. Yet, the average time between confiscation and re-allocation has been of over 8 years even after 1996, with only 31 properties in total being re-allocated in the same or the following year of the confiscation, as visible in Table 1. The average length of the re-allocation procedure is sharply varying across the national territory, as illustrated in Figure A1 in the Appendix, with no clear identifiable geographical pattern.

Table 1: Timing of re-allocations

	Years between confiscation and re-allocation					
	0-1	2-3	4-5	6-7	8-9	10+
Number of re-allocated real estate properties	31	325	564	1069	851	4641

Source: own elaboration with ANBSC data.

Table A2, reporting the count and share of re-allocations by political colour of local governments over the 1998-2017 period, suggests that the length of the re-allocation procedures is unrelated with the political colour of the municipal government where the asset is located. The proportion of buildings taking either less than 10 years or 10 years or more to re-allocate is almost the same for each government type[7].

Next, we examine how the length of re-allocation procedure correlates with the characteristics of local areas and the type of building being assigned to a new use. Table A3 reports the results of an exercise testing for the correlation between the re-allocation procedure duration, computed as the difference between the year of re-

[7]Comparing column (4) with column (2) of Table A2, it also appears that re-allocations occur less than proportionally under governments run by civic lists - i.e. politicians with no clear ideological affiliation - than in governments ruled by left-wing, right-wing, or centre governments. As a consequence, it appears important to account for the political colour of the local governments in our analysis, which we do as we control for any municipality time-varying characteristics by means of municipality-year fixed effects.

allocation and the year of confiscation, and a number of variables measured either at the Census level or at the level of re-allocated building. The correlation between these variables and the length of re-allocations is estimated first by accounting for re-allocation year fixed effects, then including local housing market (OMI) fixed effects. Table A3 shows that re-allocations tend to take longer in territories with higher unemployment, i.e. in more deprived territories where it may be presumed that courts are relatively less efficient. However, as fixed effects are included in the model, none of the local characteristics emerges as significantly associated with the policy implementation timing. Furthermore, re-allocations take generally longer for buildings assigned to institutional use, while they take less time for buildings assigned to social use. Again, this correlation disappears with the the inclusion of fixed effects in the model[8].

2.3 Heterogeneity of re-allocated assets and policy impact

Mafia organisations generally own both operational and economic assets. The former are critical resources to exercise sovereignty over their market, whereas the latter are investments and money laundering machines. Operational assets such as real estate properties serve both as inputs for the illicit activities, insurance system against detection for the family of the members of the organisation and institutional signals for the entire community. The different role played by these assets suggest to distinguish between different regions where they are located. Another important source of heterogeneity is linked to the different types of re-allocation.

The policy's impact can materialise in different ways. First, the confiscation/re-allocation may be weakening criminal organisations. Asset seizure and confiscation might have a direct effect on the mafia's economic power, and act as a deterrent reducing *ex ante* its size[9]. In addition, the policy might be particularly effective when complemented with plea-bargaining and other forms of amnesty, since it counterbalances the potential savings in labour cost for the criminal organisation with a higher punishment in case of detection for the employer. Moreover, the simple confiscation could have *per se* an effect on the perception of impunity that often characterise mafia groups. A weaker presence of organised crime is expected to materialise into a higher value of buildings in the area where confiscations take

[8]This exercise has been reproduced also by including fixed effects for local Court instead of OMI fixed effects, obtaining very similar results.

[9]This second dynamic is consistent with the model proposed by Garoupa (2000), where a higher punishment for the employer fosters a decrease in the number of agents and in information diffusion.

place (Gibbons 2004, Linden & Rockoff 2008, Ihlanfeldt & Mayock 2010).

Second, the re-allocation measure could serve as an extraordinary engagement device for the local community (Falcone et al., 2016). Non-profit organisations could use assets located in critical areas to organise bottom-up initiatives and sustain institutional change. This process may contribute to the revitalisation of the targeted areas also through the attraction of competitive firms and skilled workers (Storper & Venables, 2004; Florida, 2005). All this would capitalise into higher house prices in the neighbourhood area .

3 Data

The empirical analysis relies on a novel dataset constructed from a wide-range of sources. First, data on confiscated and re-allocated real estate assets has been extracted from the National Agency for the Administration and Destination of Seized and Confiscated Assets from Organised Crime (ANBSC). This includes detailed information on all the 9947 re-allocated buildings on the whole Italian territory with their full address, the date of confiscation and re-allocation, the type of building and of re-allocation, the date of confiscation and re-allocation, the local court responsible for completing the procedure, the administrative entity responsible to manage the building once re-allocated. Each of them has been correctly geolocalised. Of these buildings, a relatively small portion is sold on the housing market (509) or demolished (2). These buildings are dropped from our sample.

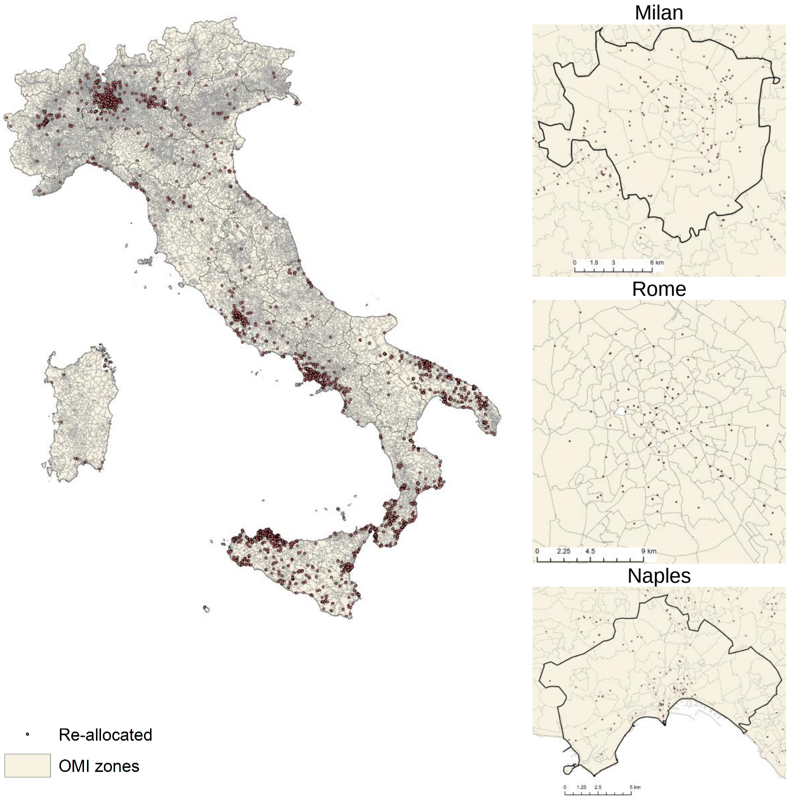
In the first part of our analysis, we use housing transaction data at a micro-aggregated zone level (*Osservatorio del Mercato Immobiliare*, or OMI), a spatial division of the Italian territory proposed by the Italian Revenue Agency. OMI zones are smaller than neighbourhoods and correspond to functional local housing markets, i.e. homogeneous real estate markets for similar property types. The dataset spans from 2006 to 2016. For each OMI zone of Italy (see Figure A1 in the Appendix) and for each real estate asset typology, the dataset includes maximum and minimum selling prices of properties. We compute average selling price over time for each OMI zone. Within each OMI, the square deviation is usually lower than 1.5. Areas are revealed at the infra-district level, sharing similar socio-economic and urban characteristics, building infrastructures and quality. All these features are crucial to determine prices[10]

[10]The prices reported in the OMI dataset are obtained from various sources, principally the analysis of actual prices specified in administrative archives or quoted by market operators. In cases of missing observations, the data is integrated with assessments of local experts aimed at correcting

(Budiakivska & Casolaro, 2018).

We decide not to exploit all the information of the OMI dataset and to consider the value of prices only for the most representative categories, i.e. civil properties in normal state of conservation which are usually private residential buildings (excluding chalet, villas and business buildings). We retain over 38,000 OMI zones per year from 2005 to 2016, 1718 of which have had at least one episode of re-allocation over the analysed period. Figure 4 zooms into three major Italian cities, Milan, Naples, and Rome, to show their OMI zones and re-allocations.

Figure 4: OMI zones (Italy, Milan, Rome, Naples)



The second part of our analysis exploits 53,728 geo-localised house sale points, spanning from 2011 to 2017 and collected from Immobiliare.it, the biggest Italian real estate website. This data is based on real estate properties sold in the 55 major Italian cities[11], , with homogeneous coverage of the website across different cities

imperfections or attributing a reference price whenever the low number of transactions limits the representativeness of the reported values.

[11]These are: Alessandria, Ancona, Aosta, Ascoli Piceno, Bari, Bergamo, Bologna, Bolzano, Brescia, Cagliari, Campobasso, Caserta, Catania, Catanzaro, Cosenza, Firenze, Foggia, Genova, Isernia, La Spezia, L'Aquila, Latina, Livorno, Matera, Messina, Milano, Modena, Monza, Napoli, Novara,

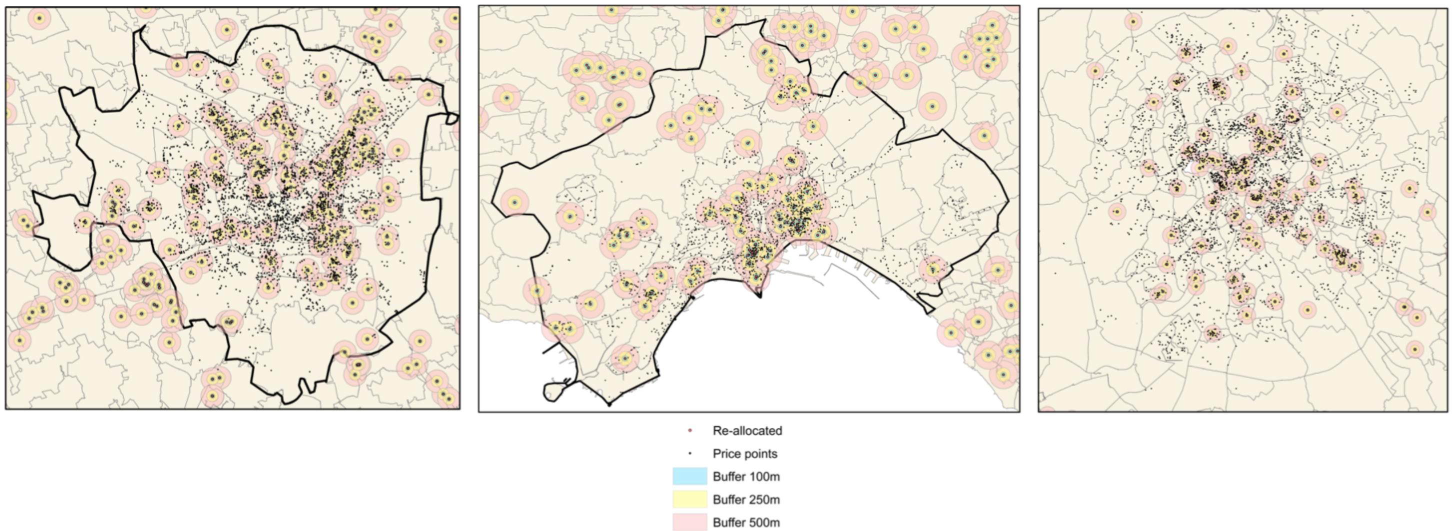
as shown in Figure 5. The dataset is not composed by selling prices but is relative to bids, collected in monthly files. The files have been then compiled, cleaned and checked for duplicates through the website unique identifier for each add [12]. Finally, some of the missing values were filled by using the textual description of the ads. A recent paper by Loberto et al. (2018) which focuses on the comparison between Immobiliare.it data and OMI data provided by the real estate market observatory of the Italian Tax Office, found the Immobiliare.it data provides an appropriate picture of the Italian housing market, consistent with official sources.

Figure 5: Sale points in Italian cities

Nuoro, Padova, Palermo, Parma, Perugia, Pesaro, Pescara, Pordenone, Potenza, Prato, Reggio di Calabria, Roma, Salerno, Sassari, Savona, Taranto, Teramo, Terni, Torino, Trento, Trieste, Udine, Venezia, Verona, Viterbo.

[12]When a change of price was tracked, the final most conservative price was recorded.

Figure 6: Sale points in major cities (Milan, Naples, Rome)



The micro-level dataset includes a wide range of structural attributes including floor space (m2), building height, type of property (studio, apartment, house, villa), the number bedrooms and bathrooms, floor, the date of construction, garage or parking facility and the type of heating an energy consumption.

In addition, a long list of controls are collected from the Italian census (2011), the Italian National Geoportal of the Environment, the Real Estate Observatory of the *Agenzia del Territorio* (AT), the Ministry of Education and Open Street Map. These include a series of controls for pre-existing amenities (i.e. already in place before re-allocations) such as typology of buildings on the street of the asset, distance to a range of natural and commercial amenities, distance to parking and transport controls, as well as the locations of schools. Labour market, education, real estate quality and demographic data collected for the 2011 Italian Census were also obtained from the Italian Institute of Statistics (ISTAT).

Descriptive statistics for treatment and control variables are reported in the Appendix (Tables A5, A6, and A7).

4 Empirical Strategy

In order to correctly estimate the effect of the confiscation and re-allocation of Mafia assets, we develop two complementary empirical strategies. First, we focus on the longitudinal trends of local homogeneous housing markets (OMI), exploiting the 2005-2016 time period and considering the entire Italian territory. This difference-in-differences strategy allows us to first test for a significant policy effect on micro-aggregated local housing markets. Next, we perform our analysis at the level of sale point, further testing for the spillover effect of the policy on house prices, capturing the spatial decay of the estimated effect and investigate the heterogeneous treatment effect. This hedonic pricing model is estimated as a repeated cross-sectional difference-in-differences.

4.1 OMI areas

First, we analyse the effect of confiscation/re-allocation policies on housing prices aggregated at the OMI area level. Average values are computed starting from the minimum and maximum market values per zone to obtain average euro/m2 house prices.

In order to test for the effect of confiscation and re-allocation of real estate assets on house prices, we rely on a differences-in-differences panel model accounting for the timing of confiscation and re-allocation of one or more properties in each OMI zone.

The estimated model is as follows:

$$\ln p_{zt} = \alpha C_{zt} + \beta R_{zt} + \sum_{k=1}^{n-1} \gamma_k X_{zkt} + \delta_z + \lambda_t + e_{zt} \tag{1}$$

Where the natural logarithm of average housing prices per square meter in OMI z and year t is a function of a different set of variables. The two key variables in the model are the treatment variable C_{zt}, switching on for OMI i in the year(s) when confiscation(s) took place in the OMI zone, until the moment of the re-allocation, and the treatment variable R_{zt} switching on from the moment in which a confiscated property has been re-assigned to a new use until the end of the sample period. As per our hypotheses, we expect a general increase in house prices in 'treated' OMI areas during the post-re-allocation period. This model captures the extensive margin effect of confiscations/re-allocations.

To control for different sources of heterogeneity in the sample, we exploit time-variant variables (X_{zkt}) retrieved from the 2011 Italian Census. We control for the number of properties in each areas, the status of the buildings and other socio-economic conditions of the household living there (unemployment, level of education). In all specifications, we include time (λ_t) and OMI (δ_z) fixed effects. Year dummies allow to control for significant sudden generalised shocks in the Italian housing market, while OMI dummies account for any time-invariant factors at the level of local housing markets[13]. Furthermore, we minimise spatial autocorrelation by clustering standard errors at the level of municipality. The model is estimated for the 2005-2016 period.

In order to isolate the effect of confiscations and re-allocations, we focus exclusively on OMI zones having experienced only *one* episode of confiscation(s) or re-allocation(s) in time. That is, we exclude all OMI zones where confiscations and re-allocations have occurred over multiple years. The single episodes of treatment we consider may involve more than one single building confiscated/re-allocated if the confiscations/re-allocations of buildings in that OMI area have been established

[13]Adopting OMI zones as our unit of analysis allows to minimise unobserved heterogeneity potentially confounding our estimates, given that these geographical units correspond to functional local housing markets.

all in the same moment. To minimise the effects of confiscations on re-allocations, we test our findings by excluding all OMI zones where the re-allocation took less than 10 years to be completed.

4.2 Sale-point analysis

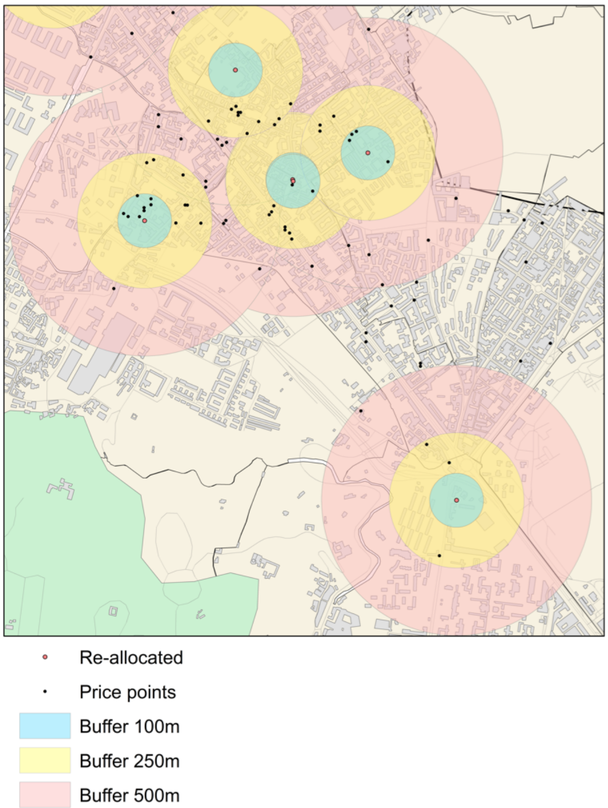
In our main specification, we estimate a hedonic pricing model using micro geo-localised data at the level of sold building. Although this is considered the ideal approach in the hedonic literature, few studies have used this approach to explore the impact of public policies as punctually localised as the one under consideration in this paper. Moreover, our data-set is novel in terms of size and spatial detail for the Italian territory. In line with other policy evaluations (e.g. Ahlfeldt et al., 2017), our first assumption lies in expecting a very localised effect of confiscated assets on surrounding real estates.

Using geographic information system (GIS), we begin by drawing perimeters up to 500m radii around each of the re-allocated assets. These buffers roughly correspond to an average 5 minute walking distance from the real estate asset, spatially translating the expected local effect (EVSTUDIO, 2016; Gibbons & Machin, 2008). The buffers of 500m represent the maximum extent to which we expect to measure a local effect. Given the punctuality of the policy, we in fact expect externalities to be more localised, with radii varying between 100m to 500m from confiscated/re-allocated assets[14].

Figure 7 provides an illustration of our approach. All sale points outside the buffer zone (and within the same OMI areas of re-allocated assets) act as controls, while treated units are located inside the buffer's radius. Exploiting information on each building's sale date, we can exploit the timing of the re-allocation and identify the impact of the policy on the prices of buildings inside the buffer and being sold *after* the re-allocation took place. This method allows us a highly accurate focus on the neighbourhood of the confiscated and re-allocated asset, identifying with precision the treatment area.

[14]In choosing our buffer radii we follow the literature on the evaluation of the spillover effects of urban renewal policies (i.a. Linden & Rockoff 2008; Schwartz et al., 2006; Rossi-Hansberg et al., 2010; Ahlfeldt et al., 2017)

Figure 7: Buffer zones



To compute the external impact of the confiscated and re-allocated real estates we estimate the following hedonic pricing model:

$$\ln p_{izmt} = \alpha C_{i,t-n}(d) + \beta R_{i,t-n}(d) + \rho X_i + \lambda_t + \delta_z + \theta_{mt} + e_{izmt} \quad (2)$$

where $\ln p_{izmt}$ is the natural logarithm of house price per m^2 of real estate property i in OMI zone z, municipality m, sold in year t. $C_{i,t-n}$ is a treatment indicator, defined as number of buildings confiscated within a radius d from building i in year $t-n$ before it was sold. Similarly, $R_{i,t-n}$ is a treatment indicator defined as the number of buildings re-allocated within distance d from building i in year $t-n$. The two treatment variables capture the intensive margin effect of confiscations and re-allocations on house prices of neighbouring buildings.

X_i is a vector of structural and amenity controls of property i, the latter which were constructed from multiple geographical data sets for all the Italian territory. We compute distances to a large range of amenities as specified in the data section (including distance to city CBD) to account for omitted variable bias. We also control for socio-economic conditions by census tract from the 2011 Italian Census. Although our temporal dimension is shorter than for our OMI analysis, we control for local time-invariant factors and for common shocks, adopting time (λ_t), OMI zone (δ_z), and municipality-year (θ_{mt}) fixed effects. The model is estimated for the 2011-2017 period, for every distance $d = \{50, 100, 150, 200, 250, 300, 350, 400, 450, 500\}$. Standard errors are clustered at the OMI zone level.

This research design allows to separate the effect on property values of confiscation or re-assignment of real estate assets from correlated location effects (Koster et al., 2012; Noonan & Krupka, 2011). e_{izmt} is the error term for property i.

4.3 Estimation issues

In order to correctly identify the effect of confiscation/re-allocations on housing prices, a number of estimation issues need to be addressed.

First, we need to consider potential problems of selection. According to Transcrime (2017), mafia organisations tend to invest more often in territories they control. If housing prices in these areas have peculiar trends for reasons not associated with the analysed policy, our results may be biased.

Second, the application of the policy may depend on the quality of public institutions. In areas where public authorities are more likely to be captured by criminal organisations through bribes and/or where the re-allocation procedure takes more time to be completed, we expect a lower density of seized (and re-allocated) assets. Figure A1 in the Appendix shows no clear geographical/regional pattern in relation to the efficiency of local courts responsible for re-allocations, suggesting that court efficiency is semi-random. The Figure shows a high degree of heterogeneity, with no clear differences in the length of the procedure between Northern and Southern Italian regions. However, Table A2 shows some evidence that the duration of the re-allocation procedure may vary depending on the political colour of the local government administrating the municipality where the asset is located.

In order to deal with these issues, we include a number of controls in our models. To start with, we always include OMI zone fixed effects in the estimates. As mentioned above, OMI are micro-geographical areas, smaller than neighbourhoods, characterised by homogeneous real estate markets. Areas are revealed at the infra-municipality level, sharing similar socio-economic and urban characteristics, building infrastructures and quality, namely the features which are crucial to determine house prices (Budiakivska & Casolaro, 2018). In Table A1, we exploit data retrieved from the 2011 Italian Census to test the balancing properties of our setting on a number of local area characteristics, finding no significant difference within OMI areas (when OMI fixed effects are controlled for), confirming the homogeneity of these geographical units.

As a further test for that, we also verify if OMI areas can be considered as homogeneous units for less 'tangible' characteristics such as social capital[15]. To study the endowment of social capital within OMI areas we follow Putnam's (1993) seminal contribution and more recent literature (Peri, 2004; Guiso et al., 2004) and use voter turnout as a proxy for civic engagement. We are able to measure this variable at the level of polling station in the four largest Italian cities: Rome, Milan, Naples, and Palermo, which are also those with most confiscated and re-allocated assets (see Figure A2). To minimise any distortion of electoral competition from organised crime (more common for elections held at the municipal level) we focus on the 2009 European Elections[16]. The results shown in Table A8 report a negative association between voter turnout and re-allocations, which however becomes insignificant when OMI fixed effects are accounted for, thus again confirming the homogeneity of OMI zones.

In addition to OMI fixed effects, our hedonic models control for Census area characteristics, further any minimising potential confounder within OMI areas. Moreover, the specifications account for generalised shocks in housing markets by means of year fixed effects, as well as for any municipality-specific characteristics varying over time with municipality-year fixed effects. The latter control allows to account for any change in the political composition of the local government potentially influencing the timing of the policy and its implementation. To conclude, the very large set of control variables at the level of building - including a number of variables identifying pre-existing amenities - further minimises the possibility that any observed policy effect is due to non-random characteristics of the local area where the policy is put in place.

Finally, another possible issue relates to the fact that our study focuses on a policy being implemented in two steps: first the confiscation, and then the re-allocation. In

[15]Scholars sub-divide social capital into bridging and bonding, the former referring to linkages between different groups in society, while the latter referring to strong ties within the same groups. In Southern Italy, a lower level of bridging and an excess of bonding social capital has been connected with the activity of criminal organisations (Trigilia, 2001; Storper, 2005)

[16]European Elections are known to be hardly influenced by criminal organisations, due to the size of electoral constituencies (the Italian territory is divided in 5 macro-constituency). Moreover, contrary to mayors and Municipality/regional councillors, Members of the European Parliament do not have the power to affect the allocation of funds at the local level.

order to minimise any possible effect of confiscations on re-allocations, our analysis focuses on re-allocations taking ten years or more to be completed. The 'double' treatment may give rise to one additional concern, namely the fact that the confiscation affects other outcomes such as labour mobility. To minimise this issue we test the impact of the policy within a very limited distance from the treatment site, as low as 100m, where the probability of any labour/firm relocation is unlikely to be more concentrated than in the outer ring.

5 Results

5.1 OMI-level analysis

We begin by performing the analysis at the level of OMI areas, focusing on the whole Italian territory and relying on a panel dataset between 2005 and 2016. The OMI dataset includes information on house prices - our dependent variable - for a large variety of real estate properties. In order to obtain comparable observations and minimise heterogeneity, we perform our estimates by focusing on the monetary value of the most common type of property in Italy, i.e. civic houses , further restricting the analysis to civic houses whose quality status is classified as 'normal' by the Italian land registry. While this strategy marginally reduces the number of OMI areas in the sample, it prevents differences in property prices to be driven by the diverse composition of buildings in a given area.

We restrict our analysis to OMI zones having experienced confiscations and/or re-allocation only once over the full period of implementation of the policy (1982 to date). In other words, we exclude from the sample all local areas having experienced multiple confiscation/re-allocations. The results of the difference-in-differences analysis are reported in Table 2.

We begin by testing the relationship between confiscation and house prices. The first specification in column (1) only includes the treatment variable accounting for whether an OMI zone has experienced a confiscation of one or more real estate assets at any point in time during 2005-2016. This variable switches on in the year of confiscation until the moment of the re-allocation. In column (2) we exclude all re-allocation years from the analysis. In both cases, the coefficient is not statistically significant, suggesting that house prices have not varied significantly in the aftermath of a confiscation episode.

Next, we test the effect of re-allocation on OMI zones house prices. In column (3) we include the treatment variable for re-allocation, switching on at the time of the re-allocation episode in the OMI zone. This specification considers all re-allocated buildings, regardless of the time it took to re-allocate them, while in column (4) we focus our attention only on re-allocation that took 10 or more years to be completed. Finally, in column (5) we include both treatment variables at the same time. It can be seen that in all cases the estimates return a positive and strongly significant coefficient, indicating that the selling price of houses within OMI areas in which the re-allocation took place increased in the aftermath of the re-allocation. It must be noted that, as all the sold re-allocated buildings are dropped from our sample, these estimates are testing the effect of real estate assets which are appropriated and managed by public institutions (mainly municipalities). Therefore, the observed increase in value in the OMI zones is due to a higher price of the buildings in the same local housing market of the re-allocated one(s).

Table 2: Baseline DiD estimates (OMI zones)

Log euro per m^2	(1)	(2)	(3)	(4)	(5)
Confiscation	-0.0116	0.0140			0.0101
	(0.0078)	(0.0285)			(0.0195)
Re-allocation			0.0174*	0.0301*	0.0213*
			(0.0104)	(0.160)	(0.0109)
Census controls	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Re-all. time	Any	No re-all. years	Any	10+	10+
Observations	255,125	253,336	253,336	253,298	252,590
R-squared	0.965	0.965	0.965	0.965	0.966

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: log house prices per square metre. Sample: columns (1) and (3): full sample; column (2): re-allocation years excluded from sample; columns (4)-(5): only re-allocations taking 10 or more years from confiscation.

One possible interpretation for the positive coefficient is that the re-allocation has increased the monetary value of a local area because it has contributed to its process of regeneration. This outcome may be more likely if the seized property has been converted into public amenities (Gibbons & Machin, 2008; Gibbons et al., 2014). We test for this in Table 3, where we sub-divide re-allocated buildings into those converted for social use (e.g. anti-mafia associations, non-profit associations, senior centres, under18 centres, disable centres, health care centres, sport centres, green spaces) and for institutional use (e.g. tribunal, police station, centre for migrants, archive, council houses). The coefficients for re-allocations assigned to social use retain significance, while the one related to institutional use loses it. This suggests that the former type of re-allocations are driving our overall results.

Table 3: Heterogeneity analysis (OMI zones)

Log euro per m^2	Social use			Institutional use		
	(1)	(2)	(3)	(4)	(5)	(6)
Confiscation			0.0120			0.0166
			(0.0188)			(0.0192)
Re-allocation	0.0204**	0.0359**	0.0230*	0.0177	0.0179	0.0174
	(0.0097)	(0.0150)	(0.0122)	(0.0161)	(0.0229)	(0.0189)
Census controls	✓	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Re-all. time	Any	10+	10+	Any	10+	10+
Observations	255,125	253,336	253,336	253,298	252,590	252,590
R-squared	0.965	0.965	0.965	0.965	0.966	0.965

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: log house prices per squared meter. Treatment: columns (1)-(3): re-allocated for social use; columns(4)-(6): re-allocated for institutional use.

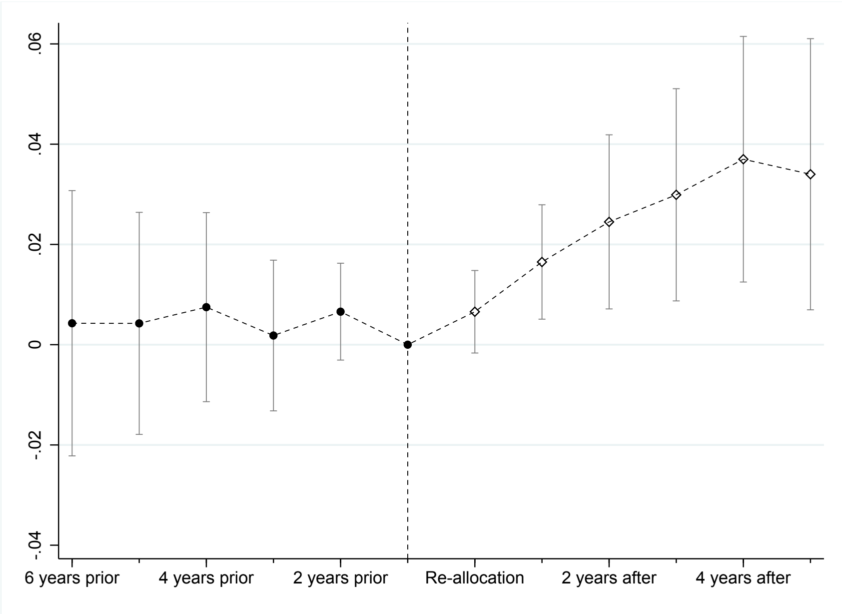
In Figure 8 we examine the timing of the estimated re-allocation effect. We perform an event study (Angrist & Pishke, 2008) by including a full set of leads and lags dummy variables for the entire period before the treatment year and during the treatment, using the year before the re-allocation as reference category [17]. As before, the sample is restricted to OMI zones having experienced only one re-allocation in time.

Figure 8, showing the coefficients for each year pre/during treatment with 90% confidence intervals, provides further evidence on a positive and significant effect of the re-allocation event. In all years before the re-allocation, there is no significant difference in house prices between treated OMI zones (i.e. those in which real estate assets will be re-allocated) and other OMI zones, as all coefficients specifically referring to years prior to the re-allocation are not statistically different from zero. The significant difference in prices emerges in the following years, already visible

[17] While this implies including dummies up to 11 years before and during the treatment, the reliability of estimated coefficients reduces for years far away from the start of the treatment, as the number of observations for each year is inevitably lower.

in the first post-treatment year.

Figure 8: Event study - re-allocation



5.2 Sale-point analysis

Having shown some evidence of a significant re-allocation effect of the value of buildings surrounding those re-allocated, we further examine this relationship with micro-level data. Tables 4 to 6 report the results for the hedonic analysis at the level of sale points, using different radii to define the treatment area.

Results for the model estimated at a distance threshold of 250m are reported in table 4. The first specification in column (1) includes structural controls and OMI/year fixed effects only. It can be seen that the estimate returns a positive and significant coefficient one and three years after the treatment kicks in. Results are consistent in column (2)-(4), where we progressively add building, pre-existing amenity and socio-economic controls. Overall, the regression results suggest positive and lasting effect of the re-allocation policy. It must be noted that, as no information is available on the exact period of the year when each property is re-allocated, re-allocations in t_0 might happen prior to the housing sale event. As a result, it is not surprising to find no significant result at t_0, consistently with the event study in Figure 7. In general, the time trend is characterised by a relatively constant coefficient magnitude in the three years following the policy. The coefficients, although still positive, are no more significant four year after the policy. This result can be interpreted as a new equilibrium following input reallocation in the market.

In column (5) we extend the specification to include municipality-year FE, in order to control for city-level exogenous shocks. Doing that, we implicitly rule out any municipal-level treatment effect. If this hypothesis might be realistic with respect to the largest cities in our sample, medium-size urban areas might still record an overall benefit from the policy. Results appear consistent with these predictions. The coefficient in column (5) is positive and significant in the year following the treatment, but is no more significant in the following years. Once identified the time trend in the event study, we estimate the overall effect of the policy. Column (6) only includes a cumulative treatment proxy, corresponding to the sum of the neighbouring assets re-allocated over the 5-year period. Finally, in column (7) we include in our specification a similar proxy for confiscated assets. Once again, the estimates report a positive and significant coefficient for re-allocations, while insignificant for confiscations. Overall, the results are consistent with the existence of a positive externality arising from the reallocation of confiscated assets.

In table 5 are reported regression results for the hedonic micro-level model estimated within a radius of 100m, that we consider the minimum area of analysis, based on our sample size and the related literature(e.g. Rossi-Hansberg et al., 2010). The basic specification in column (1) reports positive and significant coefficients for the first and third year following the treatment. The results are generally confirmed in magnitude and significance while adding to the specification the full set of housing sale level controls. While estimating the cumulative treatment in column (6) and (7), the treatment coefficient is higher but less significant than the one estimated with a 250m radius. Overall, at 100m distance, we again find evidence of a positive effect of the re-allocation policy.

This result, obtained with such a small distance from the treatment point, allows to further minimise any potential concern of endogeneity due to the presence of time-varying confounding factors at the OMI level. If, for instance, the confiscation has activated some dynamics we are not explicitly accounting for in the model (e.g. related to labour mobility), this may bias our estimates. However, the likelihood that these dynamics are stronger within the 100metres from the treatment sites than in the rest of the OMI area is extremely low.

Table 4: Sale point analysis - d = 250m

Log euro per m^2	Buffer radius: 250m						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Re-allocation year	0.00231	0.00201	0.00206	0.00242	-0.00104		
	(0.00263)	(0.00263)	(0.00262)	(0.00253)	(0.00274)		
1 year after re-allocation	0.00994***	0.00954***	0.00933***	0.0108***	0.00854***		
	(0.00283)	(0.00286)	(0.00300)	(0.00254)	(0.00244)		
2 years after re-allocation	0.00747***	0.00713***	0.00678**	0.00622**	0.00481		
	(0.00277)	(0.00275)	(0.00274)	(0.00257)	(0.00335)		
3 years after re-allocation	0.0119***	0.0108**	0.0107**	0.00879**	0.00777*		
	(0.00417)	(0.00427)	(0.00421)	(0.00409)	(0.00458)		
4 years after re-allocation	-0.00126	-0.000558	-0.00141	-0.00229	-0.00100		
	(0.00651)	(0.00658)	(0.00655)	(0.00658)	(0.00692)		
Re-allocation						0.00418**	0.00422**
						(0.00181)	(0.00186)
Confiscation							0.00059
							(0.00183)
Structural controls	✓	✓	✓	✓	✓	✓	✓
Building controls		✓	✓	✓	✓	✓	✓
Amenity controls			✓	✓	✓	✓	✓
Socio-econ. controls				✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓	✓	✓
Municipality-year FE					✓	✓	✓
Observations	52,526	52,513	52,513	52,513	51,906	51,906	51,906
R-squared	0.768	0.769	0.771	0.777	0.784	0.784	0.784

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Sale point analysis - d = 100m

Log euro per m^2	Buffer radius: 100m						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Re-allocation year	0.00655	0.00654	0.00624	0.00706	0.00346		
	(0.00515)	(0.00493)	(0.00494)	(0.00483)	(0.00439)		
1 year after re-allocation	0.0115**	0.0118**	0.0108*	0.0124**	0.00915*		
	(0.00578)	(0.00563)	(0.00582)	(0.00503)	(0.00603)		
2 years after re-allocation	0.0111	0.0101	0.00924	0.00790	0.00789		
	(0.00694)	(0.00700)	(0.00736)	(0.00723)	(0.00766)		
3 years after re-allocation	0.0189***	0.0164***	0.0164***	0.0119***	0.0145***		
	(0.00291)	(0.00289)	(0.00301)	(0.00313)	(0.00537)		
4 years after re-allocation	-0.0209*	-0.0196	-0.0244*	-0.0246	-0.0223		
	(0.0126)	(0.0129)	(0.0144)	(0.0144)	(0.0148)		
Re-allocation						0.00614*	0.00611*
						(0.00365)	(0.00360)
Confiscation							0.00236
							(0.00310)
Structural controls	✓	✓	✓	✓	✓	✓	✓
Building controls		✓	✓	✓	✓	✓	✓
Amenity controls			✓	✓	✓	✓	✓
Socio-econ. controls				✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓	✓	✓
Municipality-year FE					✓	✓	✓
Observations	52,526	52,513	52,513	52,513	51,906	51,906	51,906
R-squared	0.768	0.769	0.771	0.777	0.784	0.784	0.784

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In table 6 we investigate treatment effects at 500m radius. Columns (1) to (5) report results for our main specification. Overall, the re-allocation is found to have a positive and lasting effect on the neighbouring properties. As in the previous table, we are not able to define a clear cut time trend. Interestingly, the coefficients show a lower magnitude with respects to the the once estimated in the 250m distance specification. Consistently, the coefficient is 60% lower when considering the cumulative treatment and non-significant when controlling for confiscation (respectively column (6) and (7)).

As for the magnitude of the estimated coefficients, our estimates reveal an increase in the value of buildings surrounding re-allocated ones between 0.6% and 1%, for each re-allocated real estate asset.

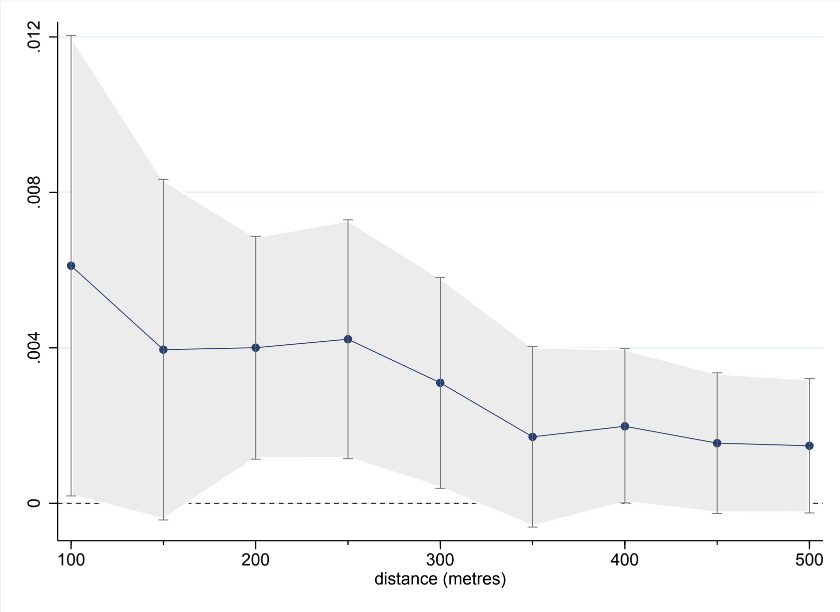
Table 6: Sale point analysis - d = 500m

Log euro per m^2	Buffer radius: 500m						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Re-allocation year	0.00316**	0.00308**	0.00300**	0.00306**	0.00121		
	(0.00127)	(0.00131)	(0.00131)	(0.00131)	(0.00150)		
1 year after re-allocation	0.00390***	0.00350***	0.00349**	0.00371***	0.00253**		
	(0.00137)	(0.00135)	(0.00136)	(0.00133)	(0.00117)		
2 years after re-allocation	0.00331*	0.00312	0.00308	0.00330**	0.00117		
	(0.00184)	(0.00190)	(0.00191)	(0.00167)	(0.00242)		
3 years after re-allocation	0.00637***	0.00640***	0.00614***	0.00536**	0.00808***		
	(0.00216)	(0.00231)	(0.00223)	(0.00216)	(0.00308)		
4 years after re-allocation	-0.00609	-0.00560	-0.00579	-0.00565	-0.00604		
	(0.00448)	(0.00440)	(0.00433)	(0.00448)	(0.00523)		
Re-allocation						0.00176**	0.00148
						(0.00088)	(0.00105)
Confiscation							-0.00207
							(0.00166)
Structural controls	✓	✓	✓	✓	✓	✓	✓
Building controls		✓	✓	✓	✓	✓	✓
Amenity controls			✓	✓	✓	✓	✓
Socio-econ. controls				✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓	✓	✓
Municipality-year FE					✓	✓	✓
Observations	52,526	52,513	52,513	52,513	51,906	51,906	51,906
R-squared	0.768	0.769	0.771	0.777	0.784	0.784	0.784

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

To further characterise the estimated spillover, we investigate the spatial decay of the policy effect. Figure 9 combines together the estimated coefficients from 100 to 500m, with relative confidence intervals, controlling for confiscation and all other set of controls and fixed effects. The Figure allows to appreciate the spatial decay characterising the cumulative treatment. The coefficients are monotonically decreasing, with a larger standard error up to 150m due to the lower sample size. Overall, the policy is found to have a positive and significant effect up to 350m. At a radius of 300m the policy still has a positive effect, but the declining coefficient suggest the transactions localised further than the 300m threshold to be less affected. At 350m distance the coefficient is still positive, but no longer significant.

Figure 9: Sale point analysis - distance decay



In Table A7, we test the robustness of these results by including in the model a control for the buffer zone. If there is any time-invariant characteristics which are specifically located within the 100m to 500m from the re-allocated real estate asset and may have an influence on house prices, it would act as an omitted variable and bias our estimates. The specification including a buffer zone dummy variable is fully controlling for that. As shown in Table A9, the inclusion of this control leaves the main results virtually unaltered, as the re-allocation retains significance and the magnitude of the coefficients is lower as we move away from the treatment point. Interestingly, the buffer zone dummy is statistically insignificant up until 300m from the re-allocated asset, suggesting no generalised difference in house prices in the treatment areas vis-à-vis the untreated area within OMI zones.

To conclude, we exploit the geographical extension of our dataset to test if the re-allocation effect is stronger in areas where the mafia is traditionally more rooted. To do that, we sub-divide our sample into regions of high mafia intensity (Campania, Calabria, Puglia and Sicily) and all remaining regions[18]. The results, shown in Table 7, indicate that the effect we obtain appears to be driven by the regions where

[18]While organised crime is spread across the entire Italian territory (and beyond), it still maintains its strongest presence in the areas where it was formed. According to Transcrime (2013), the Cosa Nostra (Sicily), 'Ndrangheta (Calabria), Camorra (Campania) and Sacra Corona Unita (Puglia) preserve their strongholds in their regions of origin. The cities in our sample belonging to the four regions of high mafia intensity are: Bari, Foggia, Taranto (Puglia); Napoli, Caserta, Salerno (Campania); Catanzaro, Cosenza, Reggio di Calabria (Calabria); Palermo, Messina, Catania (Sicily)

organised crime has a stronger presence. As shown in Figure 2, these regions are also those where the majority of re-allocations have been made.

Table 7: Sale point analysis - regional heterogeneity

	Campania, Calabria, Puglia, Sicily			Other Italian regions		
Dep. variable: Log euro per m^2	100m	250m	500m	100m	250m	500m
	(1)	(2)	(3)	(4)	(5)	(6)
Re-allocation	0.00718**	0.00427**	0.00137	-0.00985	0.00431	-0.00210
	(0.00329)	(0.00190)	(0.00106)	(0.00948)	(0.00776)	(0.00776)
Confiscation	0.00302	0.00155	0.00155	0.00691	-0.00604	-0.00833
	(0.00290)	(0.00185)	(0.00185)	(0.0340)	(0.0115)	(0.0068)
Structural controls	✓	✓	✓	✓	✓	✓
Building controls	✓	✓	✓	✓	✓	✓
Amenity controls	✓	✓	✓	✓	✓	✓
Socio-econ. controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓	✓
Municipality-year FE	✓	✓	✓	✓	✓	✓
Observations	11,891	11,891	11,891	40,015	40,015	40,015
R-squared	0.719	0.719	0.719	0.787	0.787	0.787

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.3 Confiscation, re-allocation, and mafia activity

So far we have provided extensive evidence to demonstrate that re-allocations of confiscated mafia assets adds economic value to the neighbourhood where buildings formerly owned by the mafia are located. This dynamics appears to be driven by the conversion of buildings into amenities, as shown by the fact that re-allocations into buildings for 'social use' are those determining the observed increase in house value, a result consistent with the literature regarding urban amenities as increasing the monetary value of neighbourhoods (Gibbons & Machin, 2008; Gibbons et al., 2014). However, policy-makers have conceived the confiscation/re-allocation measure mainly as a way to tackle organised crime. Therefore, the policy is expected to limit criminal activity, another way through which it would contribute to local regeneration (Linden & Rockoff, 2008).

In this section, we provide a preliminary test in this direction, verifying whether confiscations and re-allocations are in some way associated with variations in criminal activity. We focus specifically on violent crimes committed by mafia organisations. We restrict our attention on the main regions of mafia presence (Calabria, Campania, Sicily, Puglia), those where we have shown that the re-allocation policy produces the strongest effects. For this purpose, we have compiled a database of violent mafia crimes adopting the reports published by *Avviso Pubblico* between 2010 and 2016 and listing all sorts of criminal acts against the the local government and local public administration[19]. This information is only available for municipalities, implying that our entire dataset needs to be collapsed at this level of analysis in order to perform the study. We end up with a longitudinal dataset reporting the cases of mafia violence, the number of confiscated and re-allocated mafia assets per municipality per year for 2010-2016. We then calculate the number of violent mafia attack per thousands inhabitants, to test how this variable correlates with confiscations and re-allocations.

Due to the aggregated level of analysis, the number of municipality-years without cases of confiscation/re-allocations are not many. In particular, if we take cities such as Naples, Reggio Calabria and Palermo, the policy has been applied almost every year. To avoid losing larger cities altogether, we then compute the treatment variables as the number of confiscations/re-allocations per thousand inhabitants in municipality m and year t. We include as controls the same socio-economic variables used above, namely the level of education, unemployment, the proportion of buildings being rented and in bad conditions. Importantly, both treatment variables enter in the model with a one year lag to minimise reverse causality. Standard errors are clustered at the municipality level.

The results of this analysis are reported in Table 8. The coefficient of both confiscation and re-allocation is negative, which in the case of re-allocation is statistically significant. This suggests that the number of episodes of mafia-related violence occurring in municipalities is significantly lower in the aftermath of re-allocations. In addition, when sub-dividing the sample of re-allocated buildings by type of re-allocation (social use vs. institutional use), we note that it is the latter that drives the whole effect. This should not surprise, given that re-allocations for institutional use mainly involve the conversion of buildings into police stations. When distinguishing into different types of crime, we find that the reduction mainly relates to

[19]The set of violent crimes includes arson attacks (cars or other properties set on fire, houses on fire), physical assaults, murders, terrorist attacks (e.g. bombing), shootings, threats (bullets/dead animals sent by post or outside homes, threatening letters/phone calls, killing domestic animals, felling private trees).

arson and physical assaults[20].

These findings, while interesting, should be taken with caution due to the relatively aggregated level of investigation. Omitted variables may bias the estimates and imply that the results cannot be interpreted in a causal way. That said, this study reveals an interesting association between re-allocation and mafia crime. This suggests that the policy may actively contribute to reduce the power and the strength of criminal organisations, favouring the diffusion of a 'culture of legality' in mafia-rigged cities.

Table 8: Confiscation/re-allocation and mafia violence

Dep. variable: mafia violence		Social use	Institutional use
	(1)	(2)	(3)
Confiscation	-0.00106	-0.00111	-0.000409
	(0.000857)	(0.000853)	(0.00514)
Re-allocation	-0.00344**	-0.00263	-0.00201***
	(0.00158)	(0.00386)	(0.000599)
Controls	✓	✓	✓
Municipality FE	✓	✓	✓
Year FE	✓	✓	✓
Re-all. time	Any	Any	Any
Observations	9,856	9,856	9,856
R-squared	0.200	0.200	0.200

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Mafia violent crimes per thousand inhabitants. Treatment: confiscated buildings per thousand inhabitants (lagged); Re-allocated buildings per thousand inhabitants (lagged). Sample: mafia regions (Campania, Calabria, Puglia, Sicily).

6 Conclusions

In an effort to tackle criminal organisations, the Italian State allows for the possibility to confiscate real estate properties previously belonging to mafia groups. Such policy, widely considered as one of the most crucial tools to undermine the power of organised crime in local areas, entails the re-allocation of confiscated assets to a new use, supposedly contributing to the revitalisation of the territory in which this this intervention takes place.

This paper assesses the extent to which re-allocations contribute to such regener-

[20]Regression results available upon request

ation process by testing their external effects on the monetary value of properties in the surrounding areas. Our estimates, performed at different geographical units of analysis and making use of unique micro-level datasets, unveil a robust positive relationship between re-allocation cases and the property price of neighbouring buildings. The increase is equal to 0.6% to 1% per each re-allocated building, lasting a minimum of three years following the re-allocation.

This finding suggests that, as hypothesised (and as expected by the Italian legislator), re-allocations lead to significant spillover effects that add value to the whole territory where they are implemented. Such effect is visible in the range of up to 350m from each episode of re-allocation, and it is mainly driven by the conversion of formerly-owned mafia real estate assets into so-called 'social' buildings, i.e. local amenities mainly conceived for improving the conditions of the most marginalised groups in society.

The channels through which this effect materialises may be many. In part, the capitalisation of re-allocations into higher house prices of surrounding buildings may be due to a safer environment, 'cleaner' from the activity of criminal organisations. This kind of dynamics would be consistent with the fact that a stronger effect is visible in mafia-rigged regions, where the larger proportion of mafia investment into real estate are made (Transcrime, 2013). The effect we obtain may also be the result of the improved view of a previously more deprived and less attractive neighbourhood, thanks to the new amenities. This explanation is linked to the the fact that the majority of re-allocations take place in local areas characterised by a high share of buildings in bad state. Connected to that, another reason for the estimated impact may be the increased attractiveness of urban spaces as a result of the re-allocation(s). This, in turn, may have incentivised the mobility of more skilled labour and businesses towards the area. However, the latter hypothesis contrasts with the finding that the spillover effect declines steeply with distance from the re-allocation point. In all cases, these different explanations are not mutually exclusive. Rather, they may all co-apply. We intend to examine these mechanisms further in future research.

Therefore, the observed increase in house value may be a sign that the re-allocation policy has favoured positive processes of regeneration and territorial development which have then uplifted the economic value of the area. In line with the hypothesis that re-allocations favour the development of local areas by limiting criminal activities, we find a significant and negative association between the application of the policy and the intensity of mafia violent crimes. This result, driven by the conversion of confiscated real estate into new buildings for 'institutional use' (mainly police stations) suggests that re-allocations is effective in contrasting the violence presence of criminal organisations.

In sum, what emerges with clarity from our study is that the policy of re-allocating real estate assets recovered from criminal organisations has the important role of adding value of local neighbourhoods where such buildings are located, an effect that is likely due to the triggering of positive processes of territorial development in mafia-rigged areas. While the policy we have assessed is not explicitly characterised as 'place-based' in nature, in the sense that it is not specifically intended for poor neighbourhoods but can be implemented in more and less developed areas, we have shown that its primary application has been in local areas characterised by high unemployment and more unattractive buildings. Furthermore, its effect is significantly larger in cities where the presence of organised crime is stronger. Hence, this suggest that an effective and rapid implementation of the re-allocation policy may favour the revitalisation of urban areas at higher disadvantage, where criminal groups hold the upper hand.

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Appendix

Figure A1: Re-allocation duration by courts

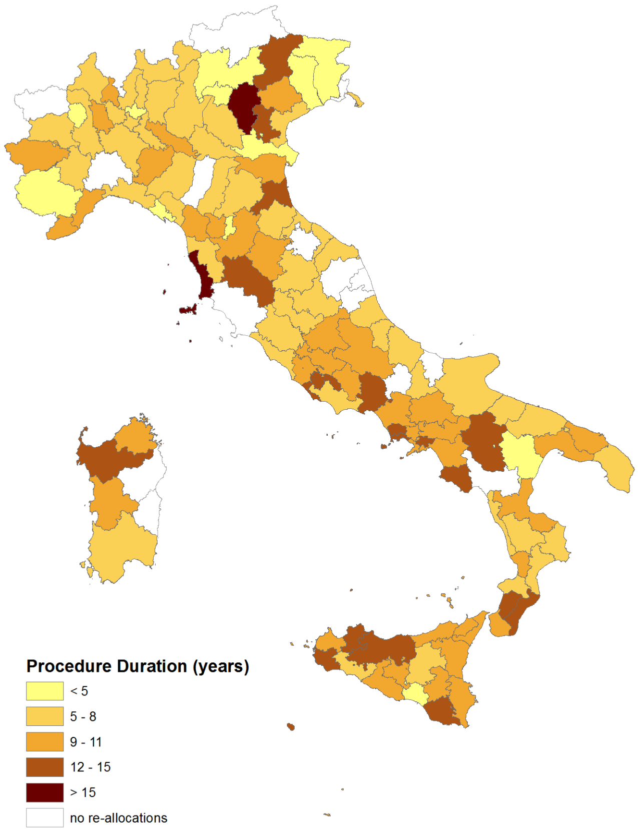
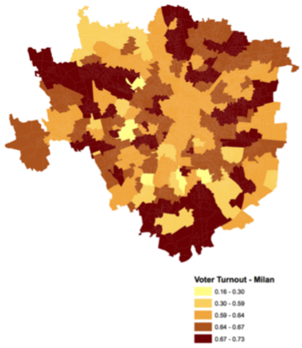
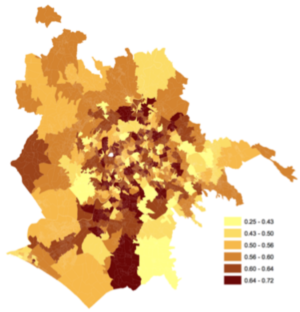


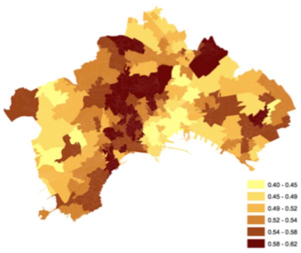
Figure A2: Polling station areas



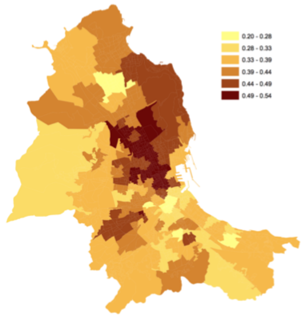
(a) Milan



(b) Rome



(a) Naples



(b) Palermo

Table A1: Re-allocation and local area characteristics

	Local area characteristics:									
Dep. variable: Re-allocation	Ln pop		Illiterate pop		Unemployed		Rented pop		Buildings bad conditions	
	(1)	(2)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	-0.0153*	-0.000189	0.00851	0.000228	0.01758**	0.000092	0.00695***	6.53e-05	0.00441**	-0.00337
	(0.00859)	(0.000682)	(0.00674)	(0.000369)	(0.00710)	(0.000250)	(0.00229)	(6.36e-05)	(0.00182)	(0.00660)
OMI FE		✓		✓		✓		✓		✓
Observations	123,718	121,174	123,718	121,174	123,718	121,174	123,718	121,174	123,648	121,107
R-squared	0.001	0.913	0.001	0.913	0.007	0.913	0.017	0.913	0.002	0.913

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Re-allocation dummy. Local area conditions: Log population, percentage of residents with tertiary education, percentage of illiterate population, percentage of unemployed, percentage of foreigners, Buildings being occupied and used as percentage of total in local area, buildings in excellent conditions as percentage of total in local area, buildings in bad conditions as percentage of total in local area.

Table A2: Local governments and re-allocation duration

	Italy local Governments 1998-2017		Re-allocations 1998-2017		Re-allocations timing: 0-9 years		Re-allocations timing: 10+ years	
	Count	Percentage	Count	Percentage	Count	Percentage	Count	Percentage
Party colour	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Right	5,886	14.3	2,436	26.9	1,256	27.9	1,777	39.2
Centre	5,158	12.6	595	6.6	305	6.8	290	6.4
Left	9,950	24.3	3,359	37.2	1,582	35.2	1,180	26.1
5Star	425	1.1	290	3.2	49	1.1	241	5.3
Civic list	23,664	57.7	2,280	25.3	1,332	29.7	948	20.9
Dissolved	274	0.7	300	3.3	202	4.5	98	2.1

Party colour: ideological leaning/party type of municipal governments during 1998-2017 in Italy. Civic lists: electoral lists/parties different from national parties, often created ad hoc for local elections. Right, Centre and Left include civic lists of that political colour. Civic list includes both ideologically identifiable lists and non-identifiable lists. Dissolved: municipal governments dissolved for any reason, such as collusion/corruption, financial disarray, vote of no confidence.

Table A3: Re-allocation duration procedure and local area/building characteristics

	Local area characteristics					Re-allocated building characteristics			
Dep. variable: Re-allocation timing	Ln pop	Illiterate pop	Unemployed	Rented pop	Buildings bad conditions	Social use	Institutional	Residential buildings	Terrains
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	6.23e-06	0.0274	0.429***	0.0460	0.0746	-1.967***	2.440**	-0.269	-0.386
	(0.306)	(0.102)	(0.105)	(0.0342)	(0.0732)	(0.652)	(1.023)	(0.493)	(0.540)
Re-allocation year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5,999	5,999	5,999	5,999	5,999	8,969	8,969	8,969	8,969
R-squared	0.005	0.005	0.006	0.005	0.006	0.009	0.009	0.007	0.007
	-0.284	0.0915	0.403	-0.0105	-0.0140	-1.862	1.883	-0.202	-2.458
	(0.531)	(0.168)	(0.402)	(0.0647)	(0.120)	(1.669)	(2.211)	(0.318)	(2.630)
Re-allocation year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5,593	5,593	5,593	5,593	5,579	8,438	8,438	8,438	8,438
R-squared	0.078	0.078	0.078	0.078	0.077	0.089	0.089	0.089	0.089

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Length of re-allocation procedure. Independent variable: columns (1)-(5): local area conditions. Log population, percentage of residents with tertiary education, percentage of illiterate population, percentage of unemployed, percentage of families being rented, buildings in bad conditions as percentage of total in local area. Columns (6)-(9): re-allocated building characteristics (dummy variables). Re-allocated for social use, re-allocated for institutional use, residential buildings, terrains.

Table A4: Property characteristics

Type of data	Variables
Identifiers	Unique ad identifier, date in which the ad was created in the database, date in which the ad was removed from the database, date in which one of the characteristics of the ad was modified for the last time
Numerical	Price, floor area, rooms, bathrooms, year built
Categorical	Property type, kitchen type, heating type, maintenance status, floor, air conditioning, energy class
Type of building	Elevator, garage/parking spot, building category
Geographical	Longitude, Latitude, address
Temporal	Ad posted, ad removed, ad modified
Contractual	Foreclosure auction
Textual	Description

Table A5: Descriptive statistics: treatment variables

Variable	Obs	Mean	Std. Dev.
OMI zones:			
Price €/m2	262,740	1188.5	778.9
Re-allocation	388,884	0.0166	0.128
Confiscation	388,884	0.0134	0.115
Sale points:			
Price €/m2	52,651	2415.3	1525.3
Re-allocation	52,651	0.166	1.269
Confiscation	52,651	0.0391	0.721
Re-allocation year	52,651	0.0487	0.608
1 year after re-allocation	52,651	0.0521	0.615
2 years after re-allocation	52,651	0.0339	0.594
3 years after re-allocation	52,651	0.0169	0.286
4 years after re-allocation	52,651	0.0142	0.197

Table A6: Descriptive statistics: sale point characteristics

Variable	Obs	Mean	Std. Dev.
Distance to green area	4,305.6	6,647.6	4,305.6
Distance to beach max 20km	335,000	172,000	335,000
Distance to city viewpoint 1km	10,809.2	19,962.3	10,809.2
Distance to a University	27,780.2	50,317.5	27,780.2
Distance to bus, tram or metro	755.6	3,081.6	755.6
Distance to Intercity transport, railway	1,750.8	6,017.8	1,750.8
Distance to airport	17,172.8	17,593.4	17,172.7
Distance to commercial centre	14,489.2	25,858.5	14,489.2
Distance to church	406.9	729.5	406.9
Distance to state schools	994.2	6,896.7	994.2
Noise - within 500m of a highway	0.06	0.23	0.06
Dummy industrial area	0.03	0.16	0.03
disINDUS	2,665.2	5,859.9	2,665.2
Distance to construction site	9,124.5	19,820.4	9,124.5
Month of offer	5.00	3.51	5.00
Lift dummy	0.41	0.49	0.41
Building height	14.05	8.04	14.05
Typology of building	2.62	1.24	2.62
Area of building	538.4	1,141.1	538.4
Average typology of building in street	2.71	0.66	2.71
Property up for auction	0.02	0.14	0.02
Type of property	4.02	0.71	4.02
Number of rooms	2.80	1.30	2.80
Number of bathrooms	1.51	0.69	1.51
Type of kitchen	1.46	0.70	1.46
Floor number	2.01	2.61	2.01
Parking with property	0.33	0.47	0.33
Periods year built	2.49	2.01	2.49
Property condition	2.19	1.08	2.19
Property heating type	0.93	0.73	0.93
Air conditioning	0.27	0.44	0.27
Energy Efficiency	0.87	0.83	0.87

Table A7: Descriptive statistics: Census area characteristics

Variable	Obs	Mean	Std. Dev.
Population	123,718	341.7	265.8
% Illiterate population	123,718	0.94	1.43
% Unemployed	123,718	3.24	1.82
% Rented families	123,718	8.30	7.20
% Buildings bad conditions	123,648	1.15	4.28

Census areas in the Italian territory with 100 or more inhabitants.

Table A8: Re-allocation and electoral turnout

	Dep. variable: Re-allocation		*Dep. variable:* Re-allocation timing	
	(1)	(2)	(3)	(4)
Turnout	-0.168***	0.0115	-17.46***	-0.984
	(0.00935)	(0.0162)	(1.857)	(5.306)
OMI FE		✓		✓
Observations	26,898	26,898	633	633
R-squared	0.003	0.044	0.123	0.445

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable (columns (1)-(2)): Re-allocation dummy. Dependent variable (columns (3)-(4)): Length of re-allocation procedure.

Table A9: Sale point analysis controlling for buffer zone

Dep. variable: Log euro per m^2	100m	200m	300m	400m	500m
	(1)	(2)	(3)	(4)	(5)
Buffer zone	-0.00762	-0.0188	-0.0192	-0.0301*	-0.0328*
	(0.0112)	(0.0169)	(0.0149)	(0.0172)	(0.0175)
Re-allocation	0.00706**	0.00402**	0.00335**	0.00222**	0.00175*
	(0.00342)	(0.00171)	(0.00153)	(0.00110)	(0.00088)
Structural controls	✓	✓	✓	✓	✓
Building controls	✓	✓	✓	✓	✓
Amenity controls	✓	✓	✓	✓	✓
Socio-econ. controls	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
OMI FE	✓	✓	✓	✓	✓
Municipality-year FE	✓	✓	✓	✓	✓
Observations	51,906	51,906	51,906	51,906	51,906
R-squared	0.784	0.784	0.784	0.784	0.784

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1