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

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Abstract

Can anti-mafia policies contribute to local regeneration? 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. The policy is considered both as a preventive measure and as a way to partially compensate the society for the harm made by the criminal organisations. Whether and how this measure has been beneficial for the wider society, however, has not yet been investigated. We test the hypothesis that the policy is able to produce positive externalities on the local community by influencing property prices in the surroundings of confiscated/re-allocated properties. To this aim, we first conduct an exploratory analysis on the whole Italian territory, implementing a differences-in-differences strategy at the level of local housing markets. Next, we adopt micro geo-localised data on house sales in all major Italian cities to estimate a hedonic pricing model assessing the effect of re-allocations on the value of surrounding buildings, up to a distance between 100m and 500m. The results unveil a positive and significant effect of re-allocations of confiscated properties, declining with distance. Magnitude and spatial decay are found to vary considerably depending on property type and environmental characteristics. Our research sheds new light on the spatial externalities of institutional signals and on the societal implications of initiatives against organised crime.

Keywords: Organised crime, confiscation, hedonic analysis, property prices, Italy.

JEL classification: K42, H23, R32, I24.

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1 Introduction

Mafia-type criminal organisations are are based on a strong territorial control at the local level (Gambetta, 1993; Dalla Chiesa, 2012). This highlights the importance of physical proximity for mafia-controlled activities and firms (Dickie, 2005; Sciarrone, 2011), suggesting that policy strategies undertaken to tackle organised crime should be targeted to relatively small areas. Criminal organisations' control of the territory, maintained through the deployment of a network of clienteles, makes them play a crucial role in local communities and act as a second-best alternative to an efficient state (Falcone & Padovani, 1992; Gambetta, 1993; Lavezzi, 2008). In contexts where individual actors may feel marginalised and lack valuable alternatives to affiliations with criminal groups, in order to eradicate the plague of organised crime policy-makers should try to engage local citizens and encourage bottom-up processes.

In this paper, we evaluate the impact of a local policy introduced by the Italian State and allowing to first confiscate, and then re-allocate, any real estate property previously owned by members of organised crime. Through re-allocations, buildings are re-assigned to the local communities in a new form (e.g. centres for disadvantaged groups, green spaces, police stations). Such policy measure is intended to produce positive consequences for the development of local areas in which such re-allocation is made. In the intention of the Italian legislator, the long-term effect of this policy measure is the regeneration of territories, contributing to eradicate criminal organisations in the areas where they are most rooted or to prevent their spreading in territories selected by the mafia for investments and money laundering. Besides its deterrence effect, the policy may act as a crucial device allowing the reallocation of relevant resources from criminal activities to deprived local communities.

While descriptive evidence exists on the effectiveness of the policy in achieving some of these goals (Camera dei Deputati, 2009; 2018; Libera, 2016), media and activists have often complained that the policy implementation is slow and the coverage too limited. Despite the high media attention devoted to this issue, no empirical study has so far examined the comprehensive role the policy may play in contributing to the welfare and revitalisation of local areas.

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 broader local territory where such initiative takes place. As the policy - by generating new amenities - is expected to contribute to enhance the value of an area, one way to capture its effect may be to look at fluctuations in the local housing market. This may be directly

influenced by the presence of amenities of the kind of those chosen for the re-allocations (Gibbons & Machin, 2008; Gibbons et al, 2014) or it may be indirectly affected through the re-allocations' impact on disamenities such as crime (Gibbons, 2004; Linden & Rockoff, 2008; Ihlanfeldt & Mayock, 2010). Alternatively, an effect may be induced by housing market dynamics, i.e. variations in the supply of real estate properties (Glaeser et al., 2008; Caldera & Johansson, 2013).

This paper exploits detailed information on the location and timing of confiscated and re-allocated properties to assess the spatial spillover effect the policy has on the local real estate market. We address this research topic in two ways. First, we develop a differences-in-differences empirical model estimating how local housing markets across the entire Italian territory respond to real estate asset confiscation and re-allocation. Second, exploiting a unique hedonic micro-level dataset covering over 60,000 geo-localised house sale points in the 55 major Italian cities, we provide further 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 effect.

Results obtained at the level of functional local housing market and on the whole Italian territory provide evidence of a significant increase in house prices in the aftermath of re-allocations. The observed change in price is driven by the buildings in the same neighbourhood of the re-allocated ones, but not by the re-allocated themselves. These findings, obtained for the 2005-2016 period, suggest that the policy has an effect on property prices of neighbouring comparable buildings. As we perform the micro-level hedonic analysis, testing whether the monetary value of buildings in the vicinity of re-allocations changes significant after the buildings are re-allocated, we find confirmation of such effect. For every re-allocated building, we observe a 0.6 % to 1% increase in the value of surrounding properties, after the re-allocations. Additionally, we show that this effect decays with distance and becomes insignificant 350m from the re-allocated building.

Our research contributes to the growing economic 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 literature studying the market and societal implications of public initiatives against criminal organisations. The latter is a growing field of studies. 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. Finally, the only study focusing on the policy we aim to evaluate is by Operti (2018), finding a significant association between building confiscation and entrepreneurial entry in Italian provinces. No study has ever looked at re-allocations specifically, adopted the fine-grade unit of analysis we use in our paper, or attempted to uncover clear causal effects.

We also contribute to a literature that investigates the impact of public policies on house prices. Property prices have been exploited to evaluate a variety of local planning policies, these including density planning, enterprise zones and other areas based initiatives, as well as natural and cultural heritage policies among others (Gibbons, Mourato, & Resende, 2014; Ahlfeldt, Redding, Sturm, & Wolf, 2015; WWC, 2016; Ahlfeldt & Holman, 2017; Ahlfeldt & McMillen 2018). A little number of studies has focused specifically on the spillover effects produced by local regeneration policies. These include Rossi-Hansberg, Sarte, & Owens III (2010), uncovering clear evidence of significant housing externalities, declining steeply with distance, Schwartz et al. (2006) and Ooi and Le (2013), showing positive spillovers of housing subsidies and infill developments, respectively, and Ahlfeldt et al. (2017), finding no external effects from an urban renewal policy. Unlike these studies, we do not focus our attention on a single city but rather we evaluate a policy which has been implemented in a scattered way across an entire national territory.

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 discusses our findings. Section 6 concludes.

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' (only 14 cases) 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 fundamental 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 2 shows the geographical location of re-allocated properties across the Italian national territory.

[Figure 1]

[Figure 2]

The 1996 law lists a whole set of different uses for the re-allocated asset. The two broader categories are: "social use" and "institutional, justice and public order" (Figure 2). 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 re-allocated assets can be used to establish the principle of legality precisely where the control of the mafia is most entrenched, by creating 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]

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.

[Table 1]

2.1 Heterogeneity of confiscated and re-allocated assets

Mafia organisations generally own both operational and economic assets. The former are critical resources to exercise sovereignty over their market, whereas the latter are simply investments and money laundering machines. Even though economic assets might be partially associated with illicit activities, such as unfair competition and abuse of dominant position, they do not constitute the core business of the organisation. On the other hand, operational assets 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 real estate property types (small flats, villas, entire buildings, etc.) and regions where they are located. Another important source of heterogeneity is linked to the different types of re-allocation, as mentioned above. The overall effectiveness of the policy may be influenced by the correct combinations of asset types and re-allocations. Moreover, we expect them to produce different socio-economic outcomes.

First, the policy could be particularly effective in weakening criminal organisations. As a matter of fact, asset seizure might have a direct effect on its economic power, as well as a deterrent effect able to reduce ex ante its size. 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. In addition, this policy might be particularly effective when complemented with plea-bargaining and other forms of amnesty for the agents, since it counterbalances the potential savings in labour cost for the organisation, with a higher punishment in case of detection for the employer. Anecdotal evidence suggests that family might play an important role in mafia bosses' utility function. Decreasing the welfare of individuals linked by strong ties to the mafia could constitute a relevant deterrent even in absence of detection.

Second, the policy 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 the institutional change. Moreover, the simple confiscation could have per se an effect on the perception of impunity that often characterise these organisations. Third, the involvement of local authorities in the decision process regarding the allocation of the real asset could counterbalance the influence exerted by the criminal organisation. A corrupted politician might selfishly decide to support the fight against the organisation, in order to obtain political support thanks to the provision of a new public asset.

3 Data

The empirical analysis relies on a novel data set constructed from a wide-range of sources. We have compiled three distinct data-set for two stages of the empirical analysis. First, the confiscated real estate asset data-set from the National Agency for the Administration and Destination of Seized and Confiscated Assets from Organised Crime (ANBSC). The data includes 9947 re-allocated assets on the whole Italian territory with their full address, and other relevant information such as date of confiscation and re-allocation. Of these, 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 (OMI zone), a spatial division of the territory proposed by the Italian Revenue Agency, the Italian government agency that collects taxes and revenues, roughly equivalent to a neighbourhood. The dataset spans from 2006 to 2016, and for each OMI zones of Italy (see Figure A1 in the Appendix) and for each real estate asset typology includes maximum and minimum selling prices of properties. OMI are geographical areas characterized by a homogeneous real estate market for similar property types. Within each OMI, the square deviation is usually lower than 1.5. Areas are revealed at the infra-district level, sharing in general similar socio-economic and urban characteristics, building infrastructures and quality, namely the features which are crucial to determine prices (Budiakivska & Casolaro, 2018).

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, data is integrated by assessments of local experts aimed at correcting imperfections or attributing a reference price whenever the low number of transactions limits the representativeness of the reported values. We decide not to exploit all the information of the 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 apartments (excluding chalet, villas and business buildings). We retain over 38,000 observations per year from 2005 to 2016. Merging confiscated real estate coordinates with a map of the 38,000 OMI zones, it was possible to determine in which OMI zones properties has been confiscated and re-allocated.

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 (see Figure 4), 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 4]

The second part of our analysis exploits 53,728 geo-localised house sale points, spanning from 2011 to 2017 collected from Immobiliare.it, the biggest Italian real estate website. 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. When a change of price was tracked, the final most conservative price was recorded. Finally, some of the missing values were filled by using the textual description of the ads.

A recent paper by Loberto, Luciani and Pangallo (2018) which focused 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 a picture of the housing market broadly consistent with official sources. The micro data include 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.

A long list of controls are collected, in order to diminish omitted variable bias in the baseline regressions were 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 amenity controls 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). Istat provides detailed geocoded data on the Italian territory, divided into 402,000 areas, hosting on average 142 people each.

Descriptive statistics for treatment and control variables are reported in the Appendix.

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 exploiting a large time period and considering the entire Italian territory. The DID strategy implemented allows us to detect the existence of some significant policy effect. Then, in order to understand the spatial decay of the policy and investigate the heterogenous treatment effect, we estimate a hedonic pricing model, exploiting a large geocoded dataset.

4.1 OMI areas

First, we analyse the effect of confiscation 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 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:

$$\ln p_{zt} = \alpha(C_z * postC_t) + \beta(R_z * postR_t) + \sum_{k=1}^{n-1} \gamma_k X_{ikt} + \delta_i + \lambda_t + e_{it} \tag{1}$$

Where the natural logarithm of average housing prices per square meter in OMI i and year t, is a function of a different set of variables. The two key variables in the model are the treatment variable $Conf_{it}$, 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 $Realloc_{it}$ 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-reallocation period.
To control for different sources of heterogeneity in the sample, we exploit a rich set of time-variant variables (X_{ikt}). We retrieve from the 2011 Italian Census information regarding the number of properties in each areas, divided by age of construction, status of the building and socio-economic conditions of the household living there. In order to control for local time-invariant factors at the level of OMI zones and for common shocks, we adopt time (λ_t) and OMI (δ_i) fixed effects.

Adopting OMI zones corresponding to local housing markets as our unit of analysis allows to minimise unobserved heterogeneity potentially confounding our estimates. 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. Clearly, the single episode of treatment may involve more than one single building confiscated/re-allocated if the confiscation/re-allocation has been established in the same moment. Furthermore, 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. Although this is considered the standard approach adopted in the literature to evaluate policy effects, few studies have explored 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, Moeller, Waights, & Wendland, 2017), our first assumption lies in expecting a very localised effect of confiscated assets on surrounding real-estate.

Using geographic information system (GIS), we begin by drawing perimeters with 500m radii around each of the confiscated assets. This buffer roughly corresponds to an average 5 minute walking distance from the confiscated asset, spatially translating the expected local effect (EVSTUDIO, 2016; Gibbons & Machin, 2008). This buffer represents 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 5000m from confiscated or re-allocated assets. In testing these distances, our assumption is that all property prices within d metres boundaries are treated and those outside are untreated. This method allows us a more accurate focus on the neighbourhood of the confiscated asset, identifying more precisely the area of treatment.

To compute the impact of the facility we estimate a hedonic pricing model:

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

where lnp_{izmt} is the natural logarithm of house price per m^2 of real estate property i in omi zone z, municipality$m$. $C_{i,t-n}$ 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 reallocated within distance d from building i in year $t-n$. While our standard models use a buffer area of 500 metres, we also experiment with various alternative distance specifications. s_i is the size of the sold property in squared meters, 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, we adopt time (λ_t) and neighbourhood (δ_z) and municipality-year (θ_{mt}) fixed effects. The model is estimated for the 2011-2017 period, for every distance $d = \{50, 100, 150, 200, 250, 300, 350, 400, 450, 500\}$. 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.

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 differences-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).

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 amenities, recognised by the literature as having the effect of inflating the prices of real estate properties in the surrounding area (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 sta-

tion, centre for migrants, archive, council houses). The former type of re-allocations are clearly driving our overall results. In Figure 4 and 5 we examine the timing of the re-allocation/confiscation effect. We perform an event study (Angrist and Pishke, 2008) by including a full set of leads and lags dummy variables up to the fifth year before/after the treatment year. As before, the sample is restricted to OMI zones having experienced only one re-allocation in time. Again, confiscation is found to have no significant effect on housing prices. The positive but non-significant coefficients found after the first three years might be associated with the re-allocation of some of the assets. However, as explained before, the heterogeneity in the timing of the procedure does not allow to the policy to have a clear cut effects in the following years. On the other hand, Figure 5 provides further evidence on a positive and significant effect of the re-allocation event. In the five 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 in the first post-treatment year and showing a significant difference in prices from the second year.

[Table 2]

[Table 3]

5.2 Sale-point analysis

In tables 4-7 are reported the results for the hedonic analysis at the level of sale points. 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 FE only. It can be seen that the estimate returns a positive and significant coefficient one and three years after the treatment. Results are consistent in column (2-4), where we progressively add building, amenity and socio-economic controls. Overall, the regression results suggest positive and lasting effect of the re-allocation policy. It must be noted that no information is available on the exact period of the year when each property is re-allocated. Reallocations in t_0 might happen prior to the housing sale event. As a result, it is not surprising to find no significant result t_0. 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. To further characterise the spillover, we investigate the spatial decay of the policy.

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. 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.

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).

Figure 8 allows to better 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 250m. At a radius of 300m the policy still has a positive effect, but the declining coefficient suggest the transactions localised further than the

250m threshold to be less affected. At 350m distance the coefficient is still positive, but no longer significant.

[Table 4]

[Table 5]

[Table 6]

[Figure 6]

6 Conclusions

In an effort to tackle criminal organisations, the Italian State allows for the possibility to seize and 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 policy intervention takes place.

This paper assesses the extent to which re-allocations contribute to such regeneration 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. 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 supposedly contributing to an improvement of the conditions of the most marginalised groups in society.

Hence, an effective and rapid implementation of the re-allocation policy may favour the eradication of criminal activity particularly in areas at high disadvantage where mafia groups hold the upper hand.

References

[1] Acconcia, A., Immordino, G., Piccolo, S., & Rey, P. (2009). Accomplice-witnesses, organized crime and corruption: Theory and evidence from Italy (No. 232). Centre for Studies in Economics and Finance (CSEF), University of Naples, Italy.

[2] Acemoglu, D., Robinson, J. A., & Santos, R. J. (2013). The monopoly of violence: Evidence from Colombia. Journal of the European Economic Association, 11(suppl_1), 5-44

[3] Ahlfeldt, G. M., & Holman, N. (2017). Distinctively Different: A New Approach to Valuing Architectural Amenities. Economic Journal (Fourthcoming).

[4] Ahlfeldt, G. M., Moeller, K., Waights, S., & Wendland, N. (2017). Game of Zones: The Political Economy of Conservation Areas. The Economic Journal, 127(605), F421-F445.

[5] Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., & Wolf, N. (2015). The Economics of Density: Evidence from the Berlin Wall. Econometrica, 83(6), 2127-2189.

[6] Baccara, M., & Bar-Isaac, H. (2008). How to organize crime. The Review of Economic Studies, 75(4), 1039-1067

[7] Barone, G., & Narciso, G. (2011). The effect of mafia on public transfers. Trinity economics papers, Trinity College Dublin, Department of Economics

[8] Becker, G. S. (1968). Crime and punishment: An economic approach. In The economic dimensions of crime (pp. 13-68). Palgrave Macmillan, London

[9] Budiakivska, V., & Casolaro, L. (2018). Please in my back yard: the private and public benefits of a new tram line in Florence. Banca d'Italia Working Paper 1161.

[10] Buonanno, P., Prarolo, G., & Vanin, P. (2016). Organized crime and electoral outcomes. Evidence from Sicily at the turn of the XXI century. European Journal of Political Economy, 41, 61-74

[11] Buonanno, P., Prarolo, G., & Vanin, P. (2016). Organized crime and electoral outcomes. Evidence from Sicily at the turn of the XXI century. European Journal of Political Economy

[12] Daniele, G., & Geys, B. (2015). Exposing politicians' ties to criminal organizations: the effects of local government dissolutions on electoral outcomes in southern Italian municipalities.

[13] Daniele, G. (2017). Strike one to educate one hundred: organized crime, political selection and politicians' ability. Journal of Economic Behaviour & Organization

[14] Dell, M. (2015). Trafficking networks and the Mexican drug war. American Economic Review, 105(6), 1738-79

[15] Dimico, A., Isopi, A., & Olsson, O. (2012). Origins of the Sicilian mafia: The market for lemons (No. 12/01). CREDIT Research Paper EVSTUDIO. (2016). The Five Minute Walk: Calibrated to the Pedestrian. Retrieved April 15, 2018, from http://evstudio.com/the-five-minute-walk-calibrated-to-the-pedestrian/

[16] Falcone, G., & Padovani, M. (1992). Men of honour: the truth about the Mafia. Fourth Estate.

[17] Frigerio, L., & Pati, D. (2007). L'uso sociale dei beni confiscati: La dimensione etica e culturale, le opportunit di sviluppo economico, il ruolo delle istituzioni e degli enti locali. Rome: Book Formativo

[18] Galletta, S. (2017). Law enforcement, municipal budgets and spillover effects: Evidence from a quasi-experiment in Italy. Journal of Urban Economics, 101, 90-105

[19] Garoupa, N. (2000). The economics of organized crime and optimal law enforcement. Economic Inquiry, 38(2), 278-288

[20] Garoupa, N. (2006). Optimal law enforcement and criminal organization. Journal of Economic Behaviour & Organization, 63(3), 461-474

[21] Gibbons, S., & Machin, S. (2008). Valuing school quality, better transport, and lower crime: evidence from house prices. Oxford Review of Economic Policy, 24(1), 99-119.

[22] Gibbons, S., Mourato, S., & Resende, G. M. (2014). The Amenity Value of English Nature: A Hedonic Price Approach. Environmental and Resource Economics, 57(March), 175-196.

[23] Hansen, Z. K., & Libecap, G. D. (2004). Small Farms, Externalities, and the Dust Bowl of the 1930s. Journal of Political Economy, 112(3), 665-694.

[24] Hilber, C. (2015). UK Housing and Planning Policies: the evidence from economic research. Centre for Economic Performance.

[25] Kuttim, M. (2016). The role of spatial and non-spatial forms of proximity in knowledge transfer. European Journal of Innovation Management, 19(4), 468-491.

[26] Libecap, G. D., & Lueck, D. (2011). The Demarcation of Land and the Role of Coordinating Property Institutions. Journal of Political Economy, 119(3), 426-467.

[27] Loberto, M., Luciani, A., & Pangallo, M. (2017). The potential of big housing data: an application to the Italian real-estate market. Banca d'Italia, MIMEO.

[28] Mastrobuoni, G. (2015). The Value of Connections: Evidence from the Italian-American Mafia. The Economic Journal, 125(586)

[29] Operti, E. (2018). Tough on criminal wealth: Exploring the link between organized crime's asset confiscation and regional entrepreneurship. Small Business Economics, 1-15

[30] Rossi-Hansberg, E., Sarte, P.-D., & Owens III, R. (2010). Housing Externalities. The Journal of Poitical Economy, 118(3), 1-8.

[31] Pinotti, P. (2013). Organized Crime, Violence, and the Quality of Politicians: Evidence from Southern Italy. Lessons from the Economics of Crime: What Reduces Offending, 175

[32] Pinotti, P. (2015). The causes and consequences of organised crime: Preliminary evidence across countries. The Economic Journal, 125(586)

[33] Sciarrone, R. (2011). Alleanze nell'ombra. Mafie ed economie locali in Sicilia e nel Mezzogiorno.

[34] Schneider, F. (2010). Turnover of organized crime and money laundering: some preliminary empirical findings. Public choice, 144(3-4), 473-486

[35] Torre, A. (2008). On the Role Played by Temporary Geographical Proximity in Knowledge Transmission. Regional Studies, 42(6), 869-889.

[36] WWC. (2016). Evidence Review 10 Area Based Initiatives: Enterprise Zones.

[37] Vaccaro, A., & Palazzo, G. (2015). Values against violence: Institutional change in societies dominated by organized crime. Academy of Management Journal, 58(4), 1075-1101

Tables

Table 1: Timing of re-allocation

	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 2: DiD (OMI zones)

Log euro per m^2					
	(1)	(2)	(3)	(4)	(5)
Confiscation	0.000417	0.000221			-0.000662
	(0.00104)	(0.00089)			(0.00083)
Re-allocation			0.00178*	0.00219*	0.00177*
			(0.00104)	(0.00131)	(0.00101)
OMI FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Re-all. time	Any	No re-all. years	Any	10+	Any
Observations	258,786	254,520	257,063	254,267	257,063
R-squared	0.965	0.966	0.961	0.966	0.966

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

Table 3: DiD - Heterogeneity analysis (OMI zones)

Log euro per m^2						Type of re-allocation					
		Only treated OMI		**Social**				**Institutional**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Confiscation (5 years)							0.012				0.0166
							(0.0188)				(0.0192)
1 year before re-all.	0.0102										
	(0.0143)										
Re-allocation	0.0329*	0.0218*		0.0204**	0.0359**			0.0177	0.0179		
	(0.0203)	(0.0116)		(0.0097)	(0.015)			(0.0161)	(0.0229)		
Re-allocation (5 years)						0.0228*	0.0230*			0.0178	0.0174
						(0.0121)	(0.0122)			(0.0192)	(0.0189)
OMI dummies	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓
Year dummies	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓
Re-all. time	10+	10+		Any	10+	10+	10+	Any	10+	10+	10+
Observations	254,267	2241		255,125	253,336	253,336	253,336	253,298	252,590	252,590	252,590
R-squared	0.965	0.957		0.965	0.965	0.965	0.965	0.965	0.966	0.965	0.965

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

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

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

Figures

Figure 1: Re-allocated real estate assets by year

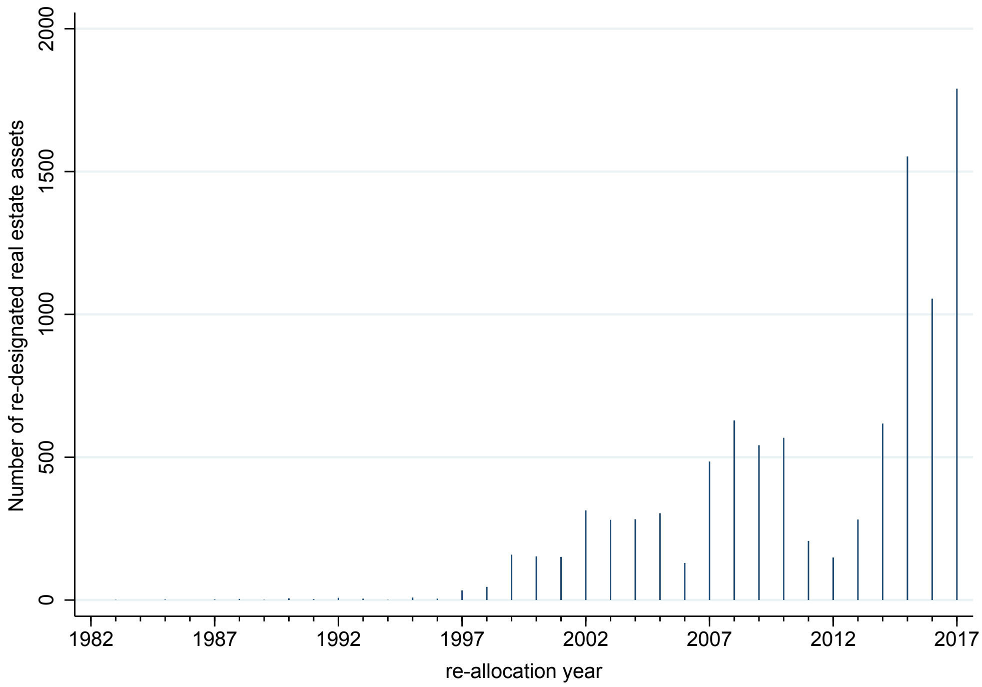

Figure 2: Re-allocations in Italy

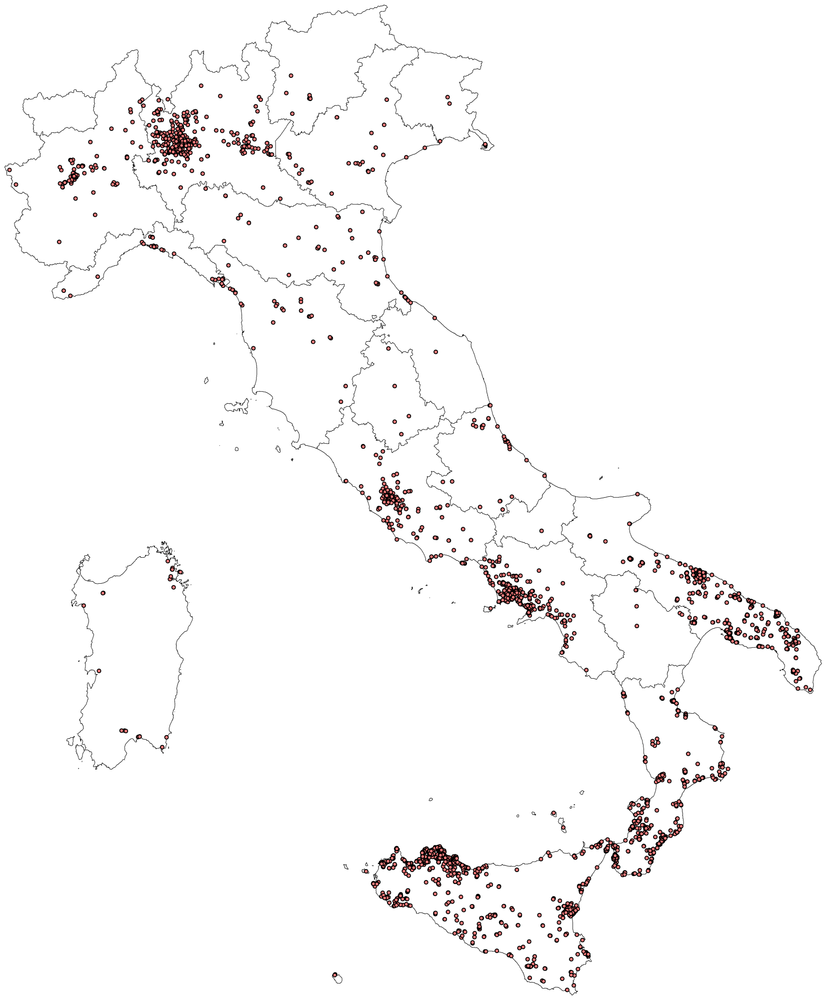

Figure 3: Re-allocation type

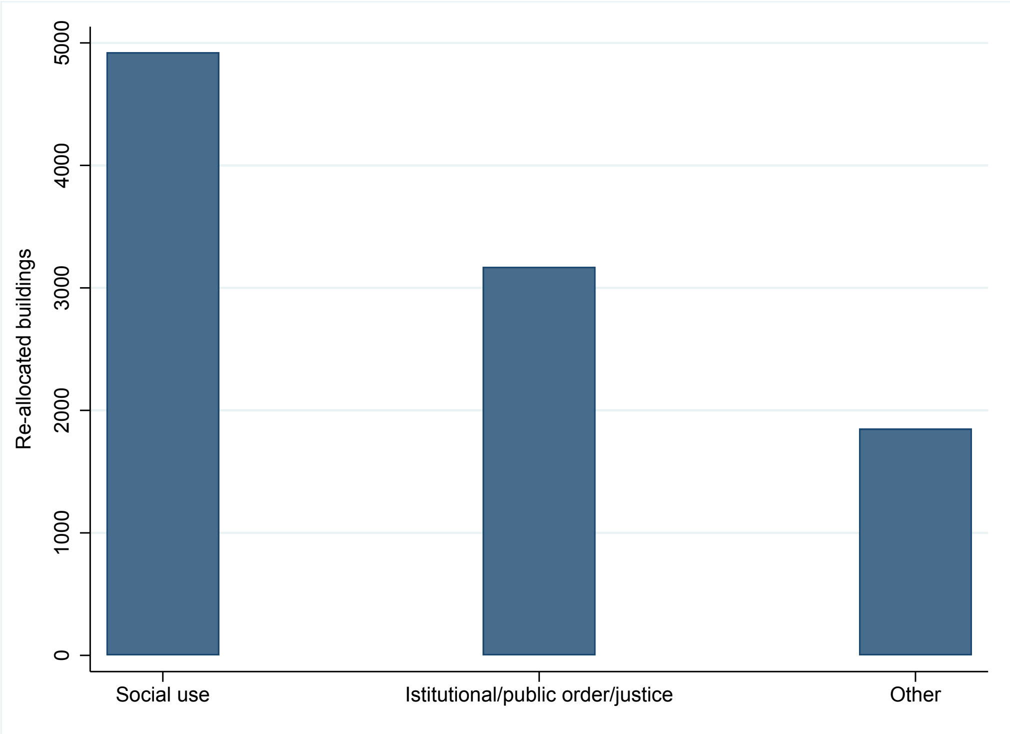

Figure 5: Buffer zones

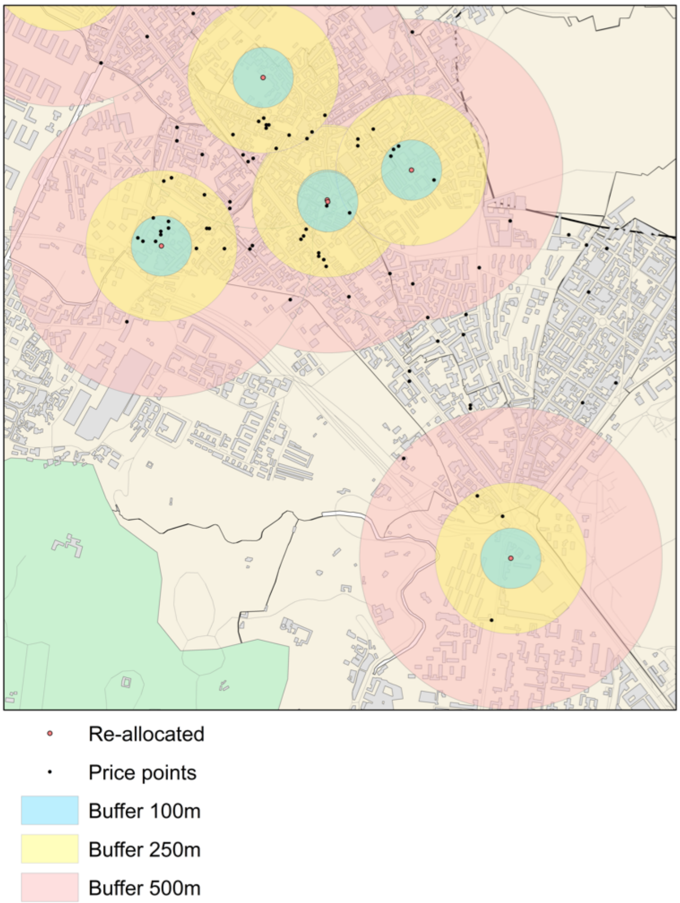

Figure 6: Event study - re-allocation

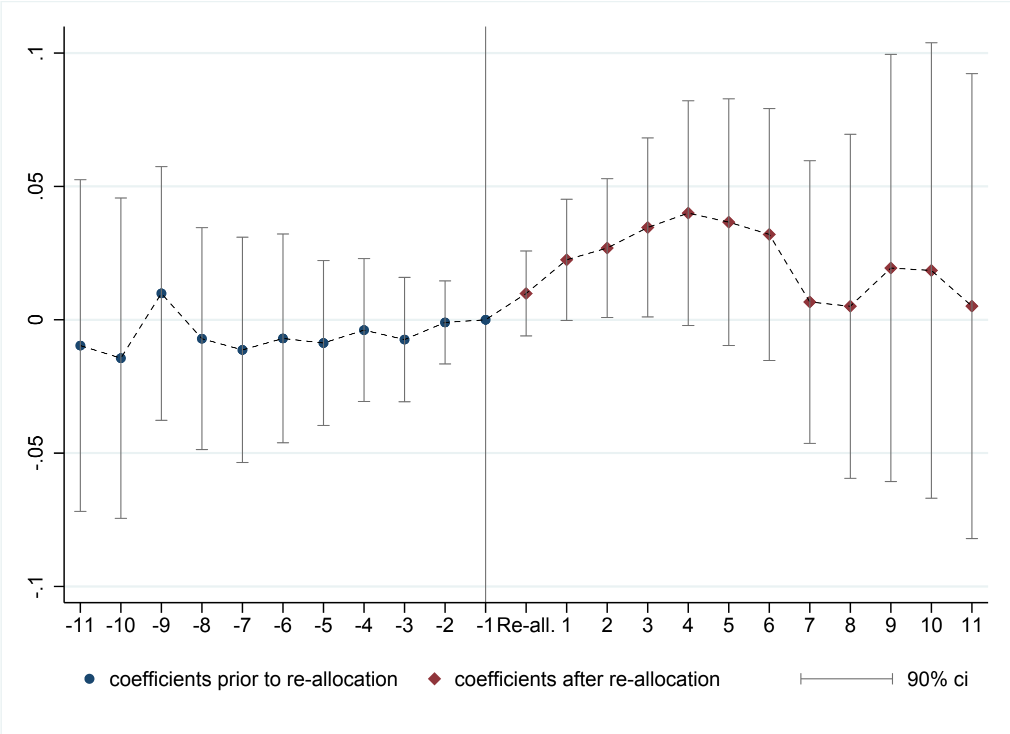

Figure 8: Sale point analysis - distance decay

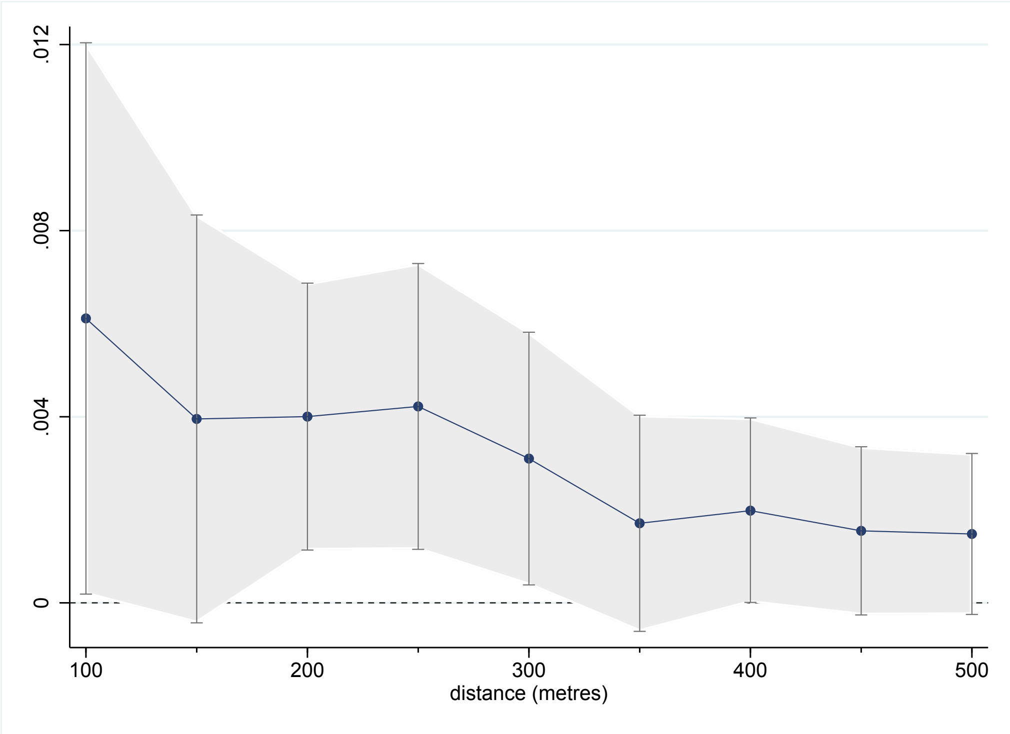

Table A3: Properties characteristics

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 A4: Descriptive statistics - treatment variables

Variable	Obs	Mean	Std. Dev.
OMI zones:			
Price €/m2	262,740	1188.544	778.8697
Re-allocation	388,884	0.016632	0.127889
Confiscation	388,884	0.013439	0.115143
Re-allocation (5 years)	388,884	0.012392	0.110627
Confiscation (5 years)	388,884	0.008139	0.089847
Properties:			
Price €/m2	52,651	2415.377	1525.311
Re-allocation (5 years)	52,651	0.166151	1.268978
Confiscation (5 years)	52,651	0.039069	0.720565
Re-allocation year	52,651	0.048793	0.607794
1 year after re-allocation	52,651	0.052155	0.614648
2 years after re-allocation	52,651	0.033998	0.593973
3 years after re-allocation	52,651	0.016961	0.285578
4 years after re-allocation	52,651	0.014245	0.196905

Table A5: Descriptive statistics - main covariates

Variable	Obs	Mean	Std. Dev.
Distance to green area	53,725	4305.6	6647.6
Distance to beach max 20km	53,725	3.35E+05	1.72E+05
Distance to city viewpoint 1km	53,725	10809.22	19962.38
Distance to a University	53,725	27780.23	50317.51
Distance to bus, tram or metro	53,725	755.63	3081.63
Distance to Intercity transport, railway	53,725	1750.82	6017.88
Distance to airport	53,725	17172.78	17593.43
Distance to commercial centre	53,725	14489.25	25858.58
Distance to church	53,725	406.91	729.59
Distance to state schools	53,725	994.23	6896.71
Noise - within 500m of a highway	53,725	0.06	0.23
Dummy industrial area	53,725	0.03	0.16
disINDUS	53,725	2665.21	5859.92
Distance to construction site	53,725	9124.55	19820.48
Month of offer	52,274	5	3.51
Lift dummy	53,725	0.41	0.49
Building height	53,725	14.05	8.04
Typology of building	48,148	2.62	1.24
Area of building	53,725	538.41	1141.17
Average typology of building of street	53,725	2.71	0.66
Property up for auction - dummy	53,725	0.02	0.14
Type of property	53,725	4.02	0.71
# of rooms	53,725	2.8	1.3
# of bathrooms	53,725	1.51	0.69
type of kitchen	53,725	1.46	0.7
Floor number	53,725	2.01	2.61
Parking with property	53,725	0.33	0.47
Periods year built	53,725	2.49	2.01
Property condition	53,725	2.19	1.08
Property heating type	53,725	0.93	0.73
AC dummy	53,725	0.27	0.44
Energy Efficiency	53,725	0.87	0.83