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Localised Effects of Re-allocated Real Estate Mafia Assets*

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Abstract

In an effort to tackle organised crime, the Italian State implements a policy stipulating that properties confiscated to individuals convicted of mafia-related crimes are re-allocated to a new use. The policy is meant to act as both an anti-mafia measure and a way to compensate local communities by converting real-estate assets into public amenities. We assess whether this scheme has an effect on the regeneration of local areas by assessing its impact on the value of properties in the vicinity of re-allocated assets and crime activity. The results unveil a positive effect of re-allocated real estate assets on house prices, driven by mafia strongholds, more deprived neighbourhoods, and areas with more inelastic housing supply. The findings suggest declining effects with distance from the re-allocation site, indicating that the policy impact is highly localised. Part of this effect appears due to a decrease in organised crime activity in the streets where re-allocations have taken place. These findings have implications for the effectiveness of policies aiming to improve the quality of neighbourhoods where mafia presence is more pronounced.

Keywords: organised crime, confiscation, hedonic analysis, urban regeneration policy, Italy.

JEL classification: K42, R32, H23.

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1 Introduction

Urban areas are often characterised by pockets of poverty, crime, and marginalisation (Rosenthal and Ross, 2015). In light of this, addressing urban deprivation by means of effective regeneration measures represents a key challenge for policymakers (Bailey and Robertson, 1997). Fostering the overall quality of cities often includes implementing interventions to tackle criminal activities or improve housing and public spaces, especially in underprivileged neighbourhoods (Atkinson and Helms, 2007; Koster and Van Ommeren, 2019).

This paper focuses on a large-scale, nationwide policy intended both as a measure to oppose organised crime and as a way to revitalise local urban areas. The 'Rognoni-La Torre' law (646/1982) stipulates the seizure of real estate asset previously owned by organised crime members or affiliates and, through re-allocations, the re-assignment of these assets to local communities by converting them into public housing amenities (e.g. centres for disadvantaged groups, green spaces, police stations). The intention of re-allocations, as conceived by Italian legislation, is thus to contribute to the development and revitalisation of local areas. The policy acts as a way to redistribute former mafia assets to local communities to provide opportunities in neighbourhoods with previous criminal presence. The re-assigned properties, in their new role, should stimulate the development of a 'culture of legality', favour local entrepreneurship, and help disadvantaged communities recover (Falcone, Giannone, and Iandolo, 2016).

While some descriptive and anecdotal evidence exists on the use and application of the policy (Camera dei Deputati, 2019; European Commission, 2014; Falcone, Giannone, and Iandolo, 2016), this evidence says little on its actual effectiveness. When discussed in the media, the monetary value of confiscated assets is systematically presented (e.g. Gabanelli and Grossi, 2020), but other local effects - let alone overall capitalisation effects - are seldom considered. Even though policies to recover organised crime assets are widely diffused in several countries across the world,[1] these measures have, to date and to our knowledge,

[1] According to the Asset Recovery Office of the European Commission (Bureau, 2016), organised crime

not been explored by the academic literature.

In this paper, we aim to fill this gap and investigate whether the re-allocation of mafia real estate assets produces any external effects on local neighbourhoods. Following the literature evaluating the impact of urban renewal policies, we capture spillover effects by examining how the monetary value of properties in the areas surrounding re-allocated assets responds to the implementation of the policy.

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 convert into higher local house prices (Santiago, Galster, and Tatian, 2001; Schwartz et al., 2006; Rossi-Hansberg, Sarte, and Owens III, 2010; Ooi and Le, 2013; Koster and Van Ommeren, 2019), others find they have no effect on the property value of surrounding areas (Lee and Murie, 1999; Ahlfeldt, Maennig, and Richter, 2017). It is worth noticing that almost all these studies focus on specific neighbourhoods of single cities where the programme has been implemented.[2] In contrast to that approach, we perform our analysis on cities located across 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: a nation-wide policy aimed at improving neighbourhoods by both tackling organised crime and increasing the stock of amenities.

Our analysis is based on a unique database which allows to aptly identify the policy's impact. We exploit detailed information on the exact location and timing of over 16,000 confiscated and re-allocated properties in Italy and investigate their spillover effect. As a preliminary step, we develop a panel model estimating whether homogeneous local housing markets across the entire Italian territory respond to real estate asset re-allocation. Next,

assets worth over 4 billion euros were recovered in Europe in 2014 alone (the last year for which data is available). Of this amount, over 1.6 billion euros were recovered in Italy.

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

exploiting information on over 53,000 geo-localised house sale points in the 55 major Italian cities for the 2011-2018 period, we provide an accurate examination of the impact of re-allocations on the housing value of neighbouring properties, as well as a detailed investigation of the spatial decay of the estimated effect. The sale-point specification produces precise and accurate estimates, thanks to the use of geo-referenced data as units of observation, and to the possibility of accounting for a very large set of property and amenity characteristics as controls. This setting allows us to minimise selection issue as well as to control for any potentially confounding housing market dynamics. In addition, detailed information on confiscated and re-allocated assets make it possible to identify the effect of the re-allocation policy by controlling for confiscation cases.

Our findings reveal a small positive external effect of re-allocation on neighbouring properties, decaying with distance and becoming insignificant 450m from the re-allocated asset. We also find that the conversion of confiscated buildings into new amenities increases local property value up to four years following the re-allocation(s). The higher the number of localised re-allocated assets, the larger the effect on neighbouring properties' monetary value.

Furthermore, we explore how three aspects of spatial heterogeneity drive the policy effect. First, the policy is found to be particularly effective in cities where mafia organisations are historically rooted. This suggests that a reduction in the disamenities associated with the presence of criminal organisations could play a significant role. Second, the positive effect is particularly visible in more deprived neighbourhoods, where local communities benefit the most from an increase in the provision of local public services. Finally, the policy effect is concentrated in areas characterised by physical constraints to residential development, a result implying the existence of heterogeneous local housing supply (Baum-Snow and Han, 2019). In these cases, each re-allocated asset increases the monetary value of surrounding properties within 150 metres by approximately 0.15-0.2% annually. The fact that estimates are more significant when we focus on areas characterised by high deprivation, strong mafia presence, and inelastic local housing supply suggests that the legislator's intent to improve the quality of some target-neighbourhoods may be effective.

A number of channels may be driving the uncovered effect. Property values are directly influenced by the stock of amenities of the kind of those chosen for the re-allocations: higher provision of green spaces, cultural facilities, social engagement centres, and similar buildings (Gibbons and Machin, 2008; Gibbons, Mourato, and Resende, 2014). Another possibility is that an increase in housing supply would reduce house prices (Glaeser, Gyourko, and Saks, 2005; Caldera and Johansson, 2013). However, the fact that the stronger impact of the re-allocation policy on housing value is visible in areas where organised crime is more rooted suggests that, at least in part, it may be driven by the effect the policy can have on disamenities such as the level of violence and crime, whose reduction also increases property prices (Gibbons, 2004, Linden and Rockoff, 2008, Ihlanfeldt and Mayock, 2010). In order to test for this possibility, we have constructed a dataset on yearly street-level organised crime presence in the city of Naples over the 2013-2018 period, exploiting information from annual DIA (Anti-mafia Investigation Directorate) reports. Our estimates show that the number of active *Camorra* - a mafia organisation rooted in the Naples area - families and the probability of finding any active family within Neapolitan streets significantly reduces after episodes of re-allocation taking place within those streets. This gives support to the hypothesis that re-allocations can have a negative impact on the intensity of crime activities.

In addition to contributing to the literature on urban renewal policy evaluation, this paper adds to the growing studies on the impact of organised crime (e.g. Acemoglu, Robinson, and Santos, 2013; Barone and Narciso, 2015; Pinotti, 2015; Buonanno, Prarolo, and Vanin, 2016; Ganau and Rodríguez-Pose, 2018; Alesina, Piccolo, and Pinotti, 2019; De Feo and De Luca, 2017; Le Moglie and Sorrenti, 2022; Di Cataldo and Mastrorocco, 2021). Specifically, within this literature, the paper relates to the studies examining the responsiveness of the housing market to mafia-related activities (Battisti et al., 2022) and to the works studying the societal implications of public policy initiatives against criminal organisations. Widely analysed anti-mafia policies in the literature are the Italian law allowing the dissolution of city councils upon clear evidence of links between mafia clans and local public officials[3] and the accomplice-witnesses regulation[4]. To our knowledge, no study has yet looked at confiscations and re-allocations of mafia real estate assets.

The remainder of the paper is organised as follows. Section 2 describes the legislative measures we evaluate, providing some key descriptive statistics. Section 3 presents our data. Section 4 introduces our empirical strategy. Section 5 presents our findings. Section 6 concludes.

[3] Acconcia, Corsetti, and Simonelli (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 dissolutions affect the quality of elected politicians and the proportion of public investments in neighbouring municipalities. Fenizia and Saggio (2020) show that firms winning procurement tenders before dissolutions are significantly less likely to do so afterwards.

[4] Acconcia, Corsetti, and Simonelli (2014) show the policy to be more effective the less efficient the prosecution system and the higher the internal cohesion of mafia organisations, while Garoupa (2007) analyses the policy within a principal-agent theoretical environment.

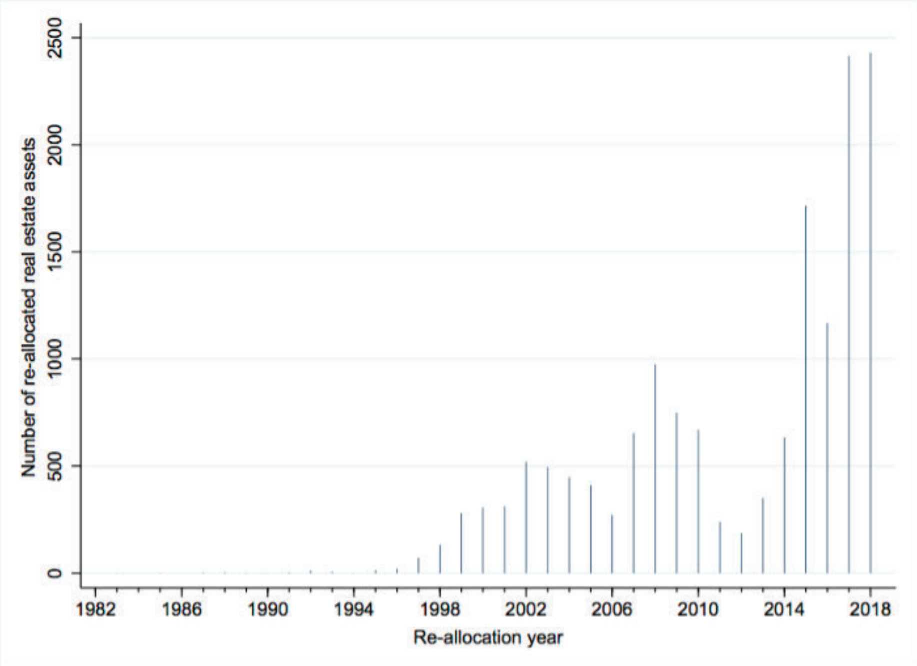
2 Institutional background: re-allocation of mafia assets

2.1 The 'Rognoni-La Torre' law

The rise in mafia activities throughout the 1980s and a series of violent attacks led the Italian 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), representing a turning point in the fight against organised crime. This bill introduced two key measures fighting 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 asset belonging to members of criminal associations, as well as to relatives, partners and other subjects who in the previous five years played a cover-up role for criminal organisations. To make law enforcement quick and effective, the law granted the judiciary full access to bank records in order to follow money trails (for more details on 'Rognoni-La Torre' law see section A of the Appendix).

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 and Pati, 2007). This is operated by the Italian State after the confiscation period has been completed. The procedure of re-allocation, already introduced in the 646/82 law, was regulated more clearly in 1996, when law 109/96 was promulgated. As can be seen in Figure 1, the number of re-allocations 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.

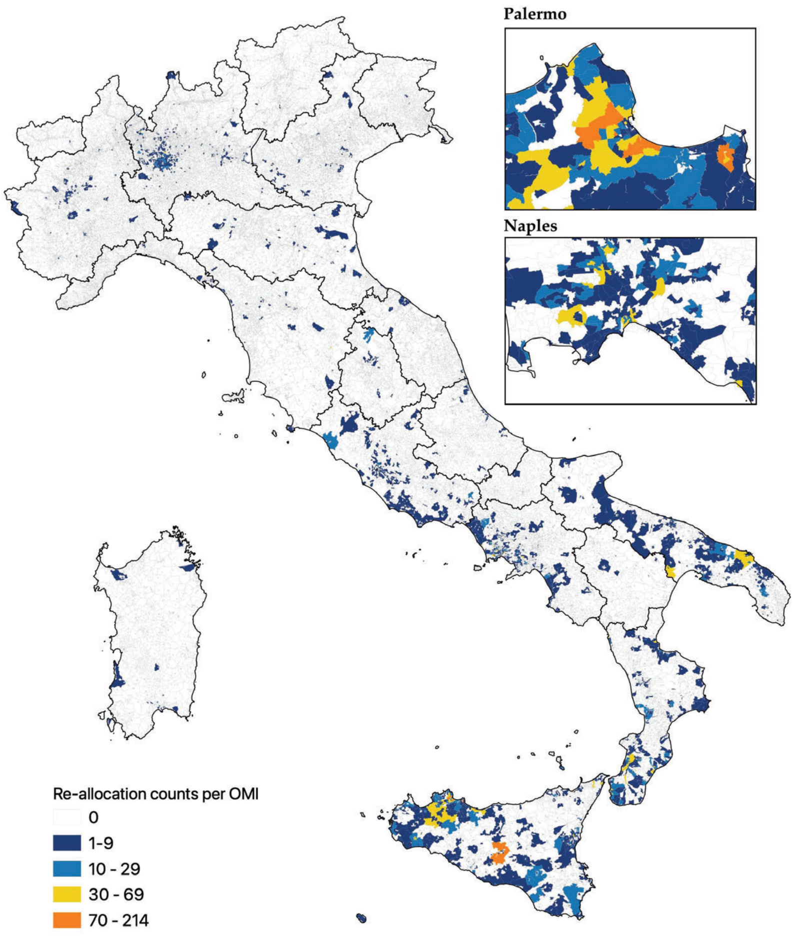
Figure 1: Re-allocated real estate assets by year



The approval of the 1996 law on re-allocation was the result of lobbying activity from the anti-mafia association *Libera*, who asked for a faster management of confiscated assets and the possibility to use re-allocated goods for social purposes. As a result, 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'. 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, eradicating the presence of the mafia in the areas where it is most deeply rooted (Dalla Chiesa, 2016; Falcone, Giannone, and Iandolo, 2016).

Figure 2 illustrates 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, Reggio-Calabria 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, Apulia, Calabria and Campania also present higher concentrations of re-allocated assets, which comes as no surprise given the publicised presence of mafia organisations in these regions.

Figure 2: Re-allocations in Italy



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 speeding 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 83 properties in total being re-allocated in the same year or the year following the confiscation, as visible in Table A1. The average length of the re-allocation procedure is sharply varying across the national territory, as illustrated in Table A1 in the Appendix, with no clear identifiable geographical pattern. Table A5, 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. Comparing column (4) with column (2) of Table A5, 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 municipality time-varying characteristics by means of municipality-year fixed effects.

Next, we examine how the length of re-allocation procedure correlates with the characteristics of local areas and the type of real estate asset being assigned to a new use. Table A6 reports the results of an exercise testing for the correlation between the duration of re-allocation procedures, computed as the difference between the year of re-allocation and the year of confiscation, and a number of variables measured either at the Census level or at the level of re-allocated asset. 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 A6 illustrates 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 inclusion of OMI fixed effects in the model.[5]

3 Data

Our empirical analysis relies on a novel dataset constructed from a wide range of sources. First, data on confiscated and re-allocated real estate assets was extracted from the National Agency for the Administration and Destination of Seized and Confiscated Assets from Organised Crime (ANBSC). This includes detailed information on 16,430 assets re-allocated between 1982 and 2018 on the whole Italian territory with their full address, date of confiscation and re-allocation, type of asset and of re-allocation, the local court responsible for completing the procedure, the administrative entity responsible for managing the asset once re-allocated. Each asset was geo-localised. Of these properties, a relatively small portion is sold on the housing market (693) or demolished (14). These assets are dropped from our sample because our goal is to assess the impact of the conversion of a building through the re-allocation process. We also exclude land assets (4,945) from sample.

As a preliminary analysis, we use housing transaction data at a micro-aggregated zone level (*Osservatorio del Mercato Immobiliare*, hereafter OMI), a spatial division of the Italian territory defined 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.[6] The dataset spans from 2005 to 2018. Almost all Italian

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

[6]According to the National Real Estate Agency, OMI areas are defined as: *'a continuous portion of the municipal area that reflects a homogeneous section of the local real estate market, where there are uniform prices for similar economic and socio-environmental conditions. This uniformity is translated into homogeneity in the positional, urban, historical-environmental, socio-economic characteristics of the settlements, as well as in the provision of services and urban infrastructure'*.

municipalities are composed of many OMI zones, with a minimum of 1 zone, a maximum of 326 zones (Rome) and an average (median) of 11.5 (5) zones. For each OMI zone of Italy and for each real estate asset typology, the dataset includes maximum and minimum selling prices of properties. In our analysis we refer to the former to construct our dependent variable.[7,8] In order to construct the largest possible time series, this dataset considers the value of prices of the most representative building category, i.e. civil properties in normal state of conservation which are usually private residential buildings. We retain over 35,000 OMI zones per year, 1882 of which have had at least one episode of re-allocation. Out of these, 652 have experienced re-allocations prior to 2005 and are excluded from our OMI analysis,[9] while 1261 have experienced re-allocations over the 2005-2018 analysed period, and no episodes before 2005. Figure 2 also zooms into the two major Italian cities with the largest number of re-allocations, Naples and Palermo, to show their OMI zones and re-allocations.

The main analysis exploits over 53,000 geo-localised house sale points, spanning from 2011 to 2018 and collected from *Immobiliare.it*, the biggest Italian real estate website. These data are based on real estate properties sold in the 55 major Italian cities,[10] with homogeneous coverage of the website across different cities as shown in Figure 3. The dataset provides 'asking prices' that we use as proxies for actual transaction prices.[11] The files have been

[7]Following Manzoli and Mocetti (2019), we refer to the maximum price for each OMI zone asset type. The values, computed for each semester, are subsequently averaged at the year level. As a robustness check, we have computed house prices also as an average of the minimum and maximum market values per zone. The results (available upon request) are robust to this change of dependent variable.

[8]OMI areas are drawn at the infra-municipality level, based on similar socio-economic and urban characteristics, building infrastructures and quality. 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 imperfections or attributing a reference price whenever the low number of transactions limits the representativeness of the reported values (Budiakivska and Casolaro, 2018).

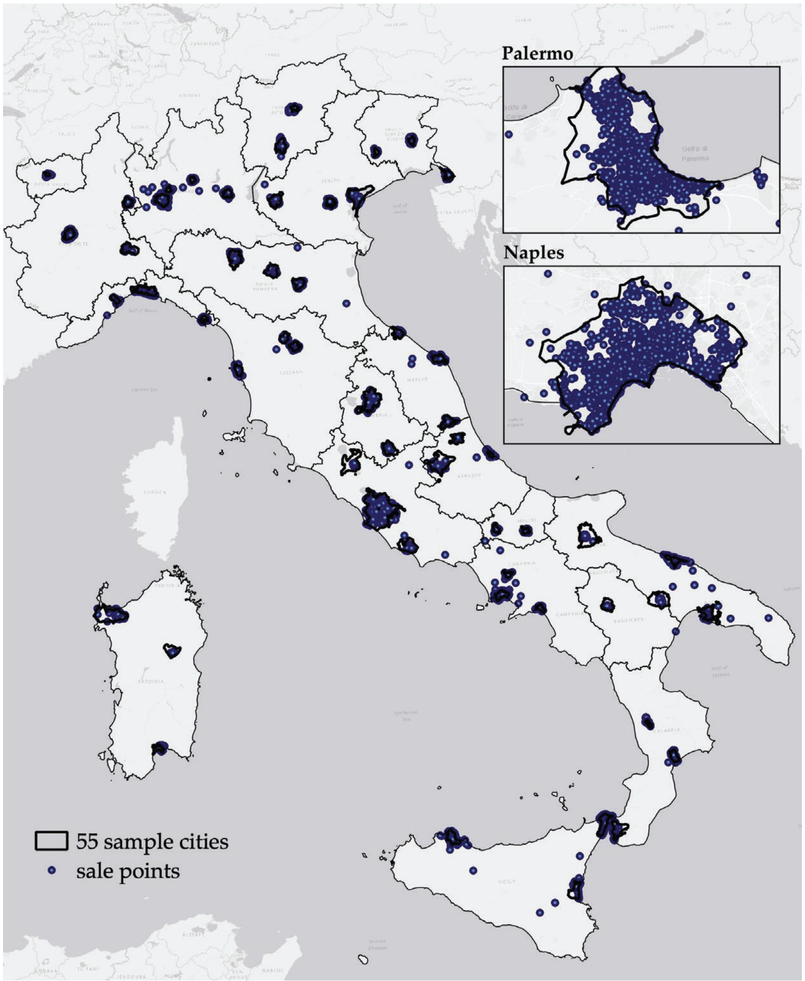
[9]Even with this necessary exclusion of pre-sample treated OMI zones, all major cities are well represented in sample, e.g. Rome (297 zones), Naples (107 zones), Milan (63 zones), Palermo (39 zones).

[10]These are: Alessandria, Ancona, Aosta, Ascoli Piceno, Bari, Bergamo, Bologna, Bolzano, Brescia, Cagliari, Campobasso, Caserta, Catania, Catanzaro, Cosenza, Florence, Foggia, Genoa, Isernia, La Spezia, L'Aquila, Latina, Livorno, Matera, Messina, Milan, Modena, Monza, Naples, Novara, Nuoro, Padua, Palermo, Parma, Perugia, Pesaro, Pescara, Pordenone, Potenza, Prato, Reggio Calabria, Rome, Salerno, Sassari, Savona, Taranto, Teramo, Terni, Turin, Trento, Trieste, Udine, Venice, Verona, Viterbo.

[11]Following Loberto, Luciani, and Pangallo (2018), we assume that the removal of the ad corresponds to the sale of the property.

compiled, cleaned and checked for duplicates through the website unique identifier for each advertisement.[12] We have excluded extreme values to avoid issues of outliers by trimming the highest 1% of the sample. Finally, some of the missing values were filled by us using the textual description of the ads. A paper by Loberto, Luciani, and Pangallo (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 3: Sale points across the sample cities



The micro-level dataset includes a wide range of structural attributes including floor space

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

in squared metres, building height, type of property (studio, apartment, house, villa), number bedrooms and bathrooms, floor, date of construction, garage or parking facility, and type of heating and energy consumption. In addition, a long list of controls is 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 (see Table A4). 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). We focus exclusively on *Immobiliare.it* sale points with most accurate coordinates. Descriptive statistics for treatment and control variables are reported in the Appendix (Tables A3, and A4).

4 Empirical Strategy

In order to estimate the effect of the re-allocation of mafia assets, we develop two empirical strategies. First, we preliminarly focus on the local homogeneous housing markets (OMI), to test if any re-allocation effect is visible at that level. Next, we perform our main analysis at the level of sale points, testing for the spillover effect of the policy on house prices, capturing the spatial decay of the estimated effect and investigating the heterogeneous treatment effect.

4.1 OMI areas

As a preliminary analysis we investigate the relationship between re-allocations and property prices at the OMI area level for the 2005-2018 period. In order to test for the effect of re-allocations of real estate assets on house prices, we rely on a differences-in-differences model accounting for the timing of re-allocation of one or more properties in each OMI zone. The estimated model is as follows:

$$\ln p_{jmt} = \alpha\, R_{jmt} + \beta\, C_{jmt} + \delta_j + \lambda_t + \phi_{mt} + \varepsilon_{jmt} \tag{1}$$

Where $\ln p_{jt}$, the natural logarithm of average housing prices per square meter in OMI j, municipality m and year t, is a function of a different set of variables. The key variable in the model is R_{jt} switching on for OMI j from the moment in which at least one property has been re-assigned to a new use until the end of the sample period. We control for C_{jmt}, a dummy switching on when confiscation(s) took place, until the moment of the re-allocation, and include time (λ_t), OMI (δ_j), and municipality-year (ϕ_{mt}) fixed effects. Standard errors are clustered at the level of OMI area. All OMI zones having re-allocations prior to the beginning of our sample period, 2005, a re excluded from sample. In cases of OMI zones having experienced more than one episode of re-allocation(s) in time, the R_{jt} treatment dummy takes value 1 from the moment of the first episode of re-allocation.

Given that the analysis takes the form of a TWFE difference-in-differences model, it is possible to test for parallel trends through a classic event study. To do so, we create q leads $(D_{r,s,t-2}, D_{r,s,t-3}, ..., D_{r,s,t-q})$ and lags $(D_{r,s,t+1}, D_{r,s,t+2}, ..., D_{r,s,t+q})$ dummy variables and estimate a model to check for anticipatory effects, excluding the first year before the re-allocation as reference category. The model is:

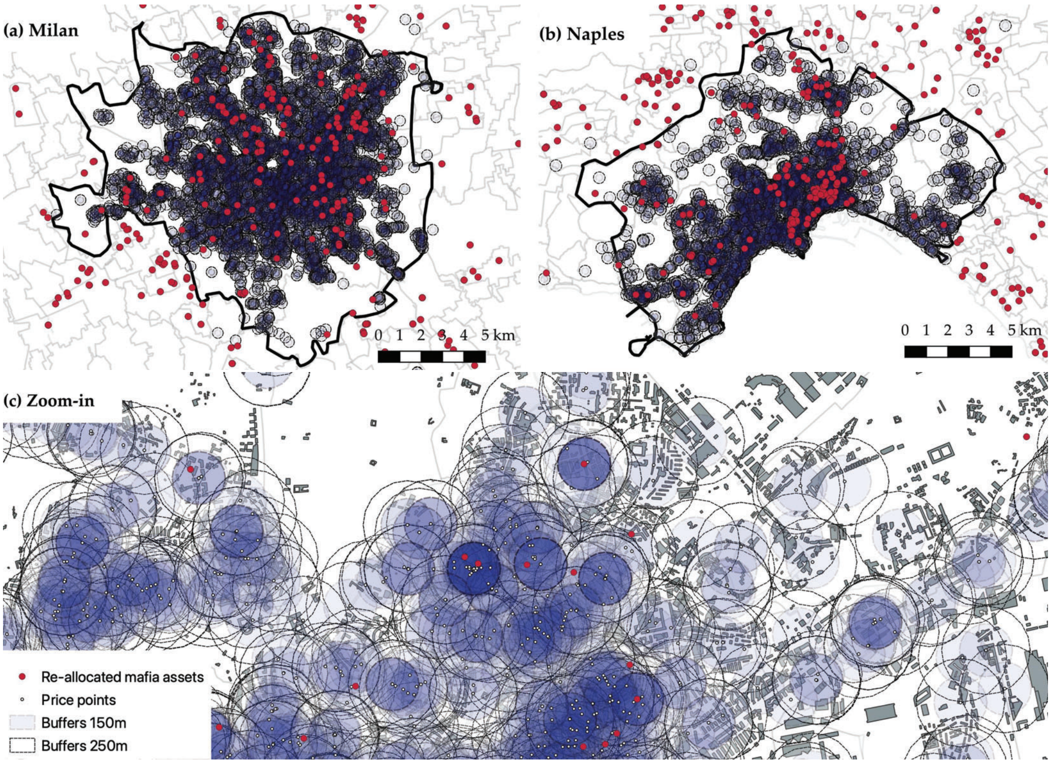
$$\ln p_{jmt} = \sum_{\tau=2}^{q} \delta_{-q}\delta_{-\tau} D_{jmt-\tau} + \sum_{\tau=1}^{q} \delta_{-q}\delta_{+\tau} D_{jmt+\tau} + \delta_j + \lambda_t + \phi_{mt} + u_{jmt}. \tag{2}$$

We estimate this both as a traditional TWFE and with the Sun and Abraham (2021) estimator, excluding late-treated from the control group and accounting for heterogeneous treatment effect.

4.2 Sale-point analysis

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

Figure 4: Buffer zones around sold buildings



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 minutes walking distance from the real estate asset, spatially translating the expected local effect (EVstudio, 2019; Gibbons and 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 very localised, with radii varying between 100m to 500m from re-allocated assets.[13] Figure 4 provides an illustration of our approach. All sale points with no assets in the buffer zone act as controls, while sale points located in the same OMI area with at least one re-allocated asset within their buffer radius and re-allocations occurring before the sale act as treated units. We expect that sales occurring *after* the re-allocations may be affected by them, while in sales occuring *before* re-allocations the policy should produce no effect on the price of the sold building. In practice, our analysis compares properties whose value is observed in the aftermath of nearby re-allocation(s)

[13]In choosing our buffer radii we follow the literature on the evaluation of the spillover effects of urban renewal policies (Linden and Rockoff, 2008; Schwartz et al., 2006; Rossi-Hansberg, Sarte, and Owens III, 2010; Ahlfeldt, Maennig, and Richter, 2017).

with that of properties located at distance from re-allocated assets. The analysis is performed within homogeneous local housing markets (OMI).

We drop from the sample any observation with no re-allocated asset within 2km distance, excluding in this way the large majority of OMI areas with no treated units. Exploiting information on each property's sale date, we can exploit the timing of the re-allocation and identify the impact of the policy on the prices of properties 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 re-allocated asset, identifying with precision the treatment area. To compute the external impact of the re-allocated real estate assets we estimate the following hedonic pricing model:

$$\ln p_{ijmt} = \beta_1\, R_{i,t-n(d)} + \beta_2\, C_{i,t-n}(d) + \beta_3\, R_{i,t+n}(d) + \rho X_j + \delta_j + \theta_m + \varepsilon_{ijmt} \tag{3}$$

where $\ln p_{ijmt}$ is the natural logarithm of house price per m^2 of real estate property i in OMI zone j, municipality m, sold in year t. $R_{i,t-n}$ is a treatment indicator defined as the number of buildings re-allocated within distance d from sale point i in year $t-n$ (n=1,2,3,4) after the re-allocation. The treatment variable captures the intensive margin effect of re-allocations on house prices of neighbouring buildings, a given period after the re-allocations. Similarly, $C_{i,t-n}$ is defined as number of buildings confiscated within radius d from building i in year $t-n$ before it was sold, and it controls for confiscations.

The variable $R_{i,t+n}$ (n=0,1,2) is a variable acting as placebo treatment, allowing us to test for differences in housing prices *before* re-allocation events. X_i is a vector of structural and amenity controls of property i, the latter which were constructed from multiple geographical datasets for all the Italian territory and ε_{ijmt} is the error term for property i. 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 OMI zone (δ_j) and municipality-year (θ_{mt}) fixed effects, thus accounting for any time-varying municipal variables and for year-of-sale-specific shocks. The model is estimated for the 2011-2018 period, for every distance d = 150, 200, 250, 300, 350, 400, 450, 500 from re-allocated assets. Standard errors are clustered at the OMI zone level so to correct for the presence of spatial autocorrelation. This research design allows to separate the effect of re-assignment of real estate assets on property values from correlated location effects (Koster, Ommeren, and Rietveld, 2012; Noonan and Krupka, 2011).

4.3 Estimation issues

In order to correctly identify the effect of confiscation or 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 Savona and Berlusconi (2015), 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 re-allocated assets. In this sense, Appendix Figure A1 is reassuring, in that it shows no obvious geographical/regional pattern in relation to the efficiency of local courts responsible for re-allocations. Re-allocation procedures exhibit a high degree of heterogeneity, with no clear differences in the average duration between Northern and Southern Italian regions. However, Table A5 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 and Casolaro, 2018). In Table A2, we exploit data retrieved from the 2011 Italian Census to test the balancing properties of our setting on a number of local area characteristics. Using the sale point dataset, we estimate a model where the dependent variable is the probability of having a nearby re-allocation, testing its correlation with pre-treatment buffer characteristics both at a 100m and a 500m distance threshold. Table A2 shows no significant difference within OMI areas when OMI fixed effects are controlled for, confirming the homogeneity of these geographical units.

In addition to OMI fixed effects, our hedonic models control for Census area characteristics (Table A7), further minimising any potential confounder within OMI areas. Moreover, the specifications account for generalised shocks in housing markets, as well as for any municipality-specific characteristics varying over time with municipality-year fixed effects. The latter control also 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.

Another possible issue relates to the fact that our study focuses on a policy implemented in two steps: first the confiscation, and then the re-allocation. For this reason, our analysis controls for the confiscation period or the number of confiscation cases. 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, 150m, where the probability of any labour/firm relocation is unlikely to be more concentrated than in the outer ring.

Finally, we include in our model variables referring to re-allocations taking place after properties have been sold, as a 'placebo' test to verify if they display any relationship with house prices, and expecting no effect.

5 Results

5.1 OMI-level analysis

We begin by showing the results of the preliminary analysis at the level of OMI areas, testing the relationship between re-allocations and house prices using municipal neighbourhoods as units of analysis in a staggered difference-in-differences setting. We focus on the entire Italian territory and rely on a panel between 2005 and 2018.

The results of the difference-in-differences analysis are reported in Table 1. Columns (1) to (4) report the result with the full sample of OMI zones, while column (5) restricts the sample of treated OMI zones to those having experienced re-allocation(s) involving more than one single asset. In other words, this specification excludes all local areas having the re-allocation of a single asset. In the first column, confiscation years are excluded from the sample.

In columns (1) and (2) the re-allocation dummy variable returns a positive significant coefficient, suggesting the presence of a positive correlation between OMI zones applying the policy and house prices. Confiscation is also positively related with the selling price of properties. When interacted fixed effects are included in the model, however, in the form of region-year (column (3)) or municipality-year (column (4)) dummies, the two coefficients become insignificant. This suggests that, when controlling for regional and municipality characteristics, property prices in OMI zones in the period following policy application are no different to pre-policy (or pre-confiscations) prices (relative to OMI that did not experience re-allocations). In column (5) we focus specifically on cases of multiple assets re-allocated. We estimate the full model by excluding the 564 OMI zones experiencing a single re-allocated asset, retaining as treated only the 589 zones experiencing two or more

Table 1: OMI-level estimates

Dep. variable: Log euro per m^2	(1)	(2)	(3)	(4)	>1 asset (5)
Re-allocations	0.0145*	0.0144**	-0.00461	-0.000342	0.0117**
	(0.00794)	(0.00722)	(0.00705)	(0.00426)	(0.00572)
Confiscations		0.0199***	0.00401	0.00480	0.00944
		(0.00650)	(0.00638)	(0.00422)	(0.00586)
OMI FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Region-year FE			Yes		
Municipality-year FE				Yes	Yes
Observations	313,372	316,474	314,668	291,982	284,417
R-squared	0.965	0.965	0.969	0.992	0.992

Notes. Standard errors clustered at the municipality level in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance. Dependent variable: average price per m^2 recorded for private properties in each OMI area. The Confiscations dummy switches on in the year of confiscation(s) until the year of re-allocation. The Re-allocations dummy equals one from the year of re-allocation(s) onwards. In columns (1)-(4) the analysis covers the whole sample of OMI zones. In column (1) confiscation years (i.e. Confiscations=1) are excluded. Column (5) excludes OMI with only one re-allocated asset and only considers OMI zones with more than one re-allocation(s). OMI zones experiencing re-alloctions pre-2005 excluded from sample.

re-allocations. In this case, the re-allocations dummy returns a positive coefficient, suggestive that, only in the case of multiple re-allocations, the price of within-OMI buildings has increased post-re-allocation relative to the period preceding the re-allocation episode.

This result, while interesting, cannot be interpreted as conclusive evidence of a causal effect of the policy on house prices. A wide number property-specific characteristics are unaccounted for in the estimates. However, while we do not interpret column (5)'s coefficient causally, it is still compelling to test for parallel trends through a classic event study. We do so by adding a set of leads and lags dummy variables and excluding the first year before the re-allocation as reference category. The results of the event study, shown in the Appendix (Figure A2), display insignificant pre-treatment dummy variables, consistent with the idea of parallel trends and no anticipatory effects, and illustrate some weak evidence of an increase in house prices in the very first years post re-allocations.

In order to dig deeper into this preliminary evidence obtained at the local housing market level, we zoom into OMI zones with our sale-point analysis, verifying whether the effect is more clearly visible at the level of individual real estate properties, and if so, testing how geographically localised the effect is.

5.2 Sale-point analysis

To analyse the relationship between asset re-allocation and house prices more accurately, we exploit micro-data on individual properties. Table 2 reports the results for the hedonic analysis conducted at the sale point level using three distance thresholds around sale points: 150 metres, 250 metres and 500 metres buffer radii. The sample is composed of sold properties in the 55 largest Italian cities. All specifications include structural, building, pre-existing amenity and socio-economic controls, as well as OMI and municipality-year fixed effects. The full model reporting the coefficient of control variables is shown in Table A8 of the Appendix.

Specifications in columns (1), (3) and (5) include a cumulative treatment proxy, labeled 'Re-allocations', corresponding to the sum of the neighbouring assets re-allocated over a 4-year period before the sale of each property at the stated distance.[14] Columns (2), (4) and (6) add a similar variable for confiscated assets, labeled 'Confiscations', to control for confiscation cases and a control for the number of re-allocated assets up to three years after the property sale within each sale point's buffer (variable 'Placebo re-allocations'). If re-allocations have an effect on house prices, we should expect only post-re-allocations' sales to be affected, while all sales occurred *before* re-allocations should not be impacted.

The estimates report a small but positive and consistently significant coefficient, indicating the presence of an externality from the re-allocation of real estate mafia assets. For each additional re-allocated asset, neighbouring property prices are expected to rise by up

[14] We have data on the confiscated assets and sales occurring in each trimester. Our 'Confiscations' control corresponds to the number of assets confiscated over the 48 trimesters before the sale.

to 0.15%, relative to buildings who do not experience re-allocations.

The relatively low magnitude of coefficients is probably due to the highly localised nature of re-allocations. The magnitude is higher when considering a smaller buffer (150m vs. 250m), and becomes insignificant at 500 metres, consistent with the fact that, the closer are the re-allocations, the larger is the effect. This result holds when controlling for the number of confiscated assets within short distances before the sale, which seemingly do not affect the value of the market price of the property, an interesting result in itself. Finally, the 'placebo' variable referring to the number of re-allocations taking place after the sale returns no significant coefficient, as one would expect if the effect of the increase in property value is driven by pre-sale re-allocations, not post-sale ones.

Table 2: Sale point analysis by distance

Dep. variable: Log euro per m^2	Buffer radius: 150 metres		250 metres		500 metres	
	(1)	(2)	(3)	(4)	(5)	(6)
Re-allocations	0.00142***	0.00154***	0.000932***	0.00106***	0.000462*	0.000441
	(0.000320)	(0.000292)	(0.000294)	(0.000268)	(0.000252)	(0.000295)
Placebo re-allocations		0.000154		-0.000101		-0.000251
		(0.000510)		(0.000323)		(0.000278)
Confiscations		-8.03e-05		0.000380		-0.000818
		(0.00106)		(0.00112)		(0.000740)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
OMI FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,160	48,456	51,160	48,456	51,160	48,456
R-squared	0.785	0.785	0.785	0.785	0.785	0.785

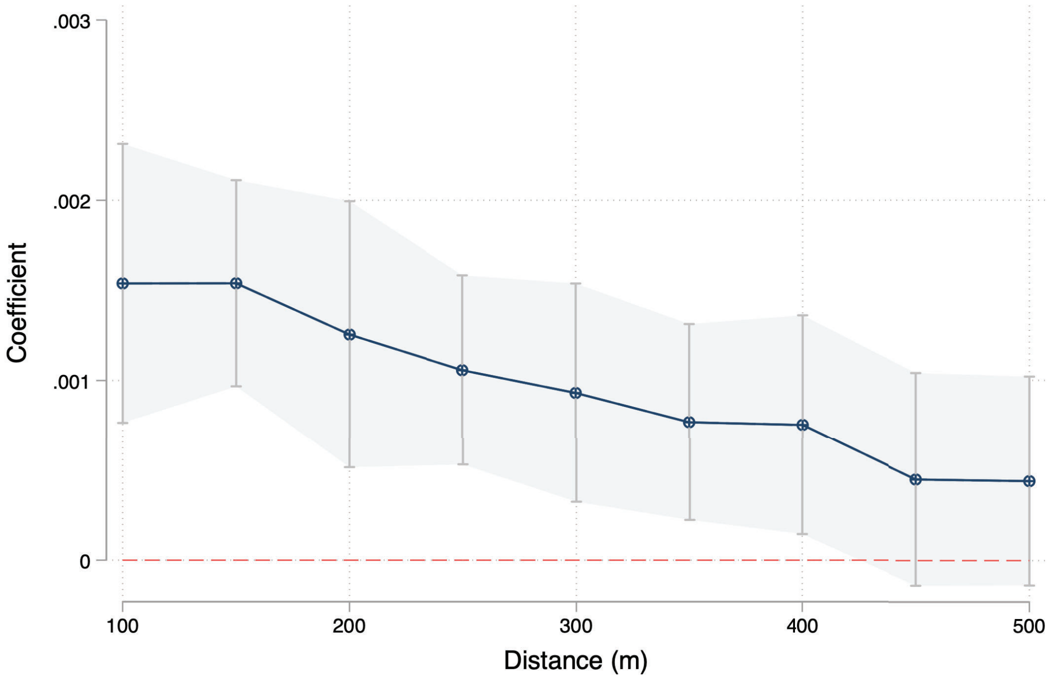
Notes. Robust standard errors clustered at the OMI level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance. Dependent variable: price recorded for each sale point i in year t. Explanatory variables are constructed in relation to the sale point. Re-allocations: nr of re-allocations up to 4 years before the sale of the building, within its buffer zone. Placebo re-allocations: nr of re-allocations up to 3 years after the sale of the building, within its buffer zone. Confiscations: nr of confiscations up to 4 years before the sale of the building, within its buffer zone. Columns (1)-(2): buffer 150m around sold property; columns (3)-(4): buffer 250m around sold property; columns (5)-(6): buffer 500m around sold property. Controls: sale property, amenity, socio-economic characteristics.

The differences in results between our OMI and sale-point analysis is likely due to the spatial precision of the second strategy, guaranteeing a more precise identification of the policy effect. Controlling for property observable characteristics and unobservable time-invariant area characteristics, we improve the identification of the effect of the re-allocation policy on the properties located in the immediate neighbourhood around the seized assets.

We estimate the full timing of the re-allocation(s) events in Table A7 in the Appendix, reporting a set of variables referring to re-allocation events up to three years before and four years after the sale of each property. All year-specific variables referring to re-allocations in the pre-sale period return positive coefficients, which are significant in many cases. The largest effect in magnitude appears to materialise in the immediate aftermath of operative re-allocations at buffer of 250 metres, i.e. in the first year following the re-allocation events. The fact that the result materialises within such a short distance from re-allocated assets reduces endogeneity concerns possibly 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 at 150 to 250 metres from the treatment sites than in the rest of the OMI area is very low.

All in all, the findings are consistent with the existence of a localised positive externality arising from the re-allocation of confiscated assets. In order to investigate the distance decay of the policy, in Figure 5 we combine the estimated coefficients from 150 to 500 metres, with relative 95% confidence intervals, controlling for confiscations and all other set of controls and fixed effects. Figure 5 allows us to appreciate the spatial decay characterising the cumulative treatment. At larger distances from the re-allocated assets the coefficients are decreasing. Overall, the policy is found to have a positive and significant effect at 150m, 200m, 250m, 300m, 400m. The declining coefficient suggest the transactions localised further than the 400m threshold to be less affected. At 450 metres distance the coefficient is still positive, but no longer significant.

Figure 5: Sale point analysis - distance decay



By allowing for multiple re-allocations within the same buffer area, the results suggest that the impact of re-allocations on property prices is larger the higher the number of re-allocations - i.e. in presence of a higher density of re-allocated real estate assets. This is what we investigate next. Using a 150 (250) buffer, roughly 2000 (4000) sale points appear as treated, i.e. having at least one nearby re-allocation within their buffer, preceding the sale. Out of these, around half of sale points experience only one single re-allocation, while the other half experiences two or more neighbouring re-allocated assets. In Table 3 we select treated sale points and test the impact of re-allocations when the re-allocated buildings in the four years preceding the sale are one, more than one, more than five, more than ten, more than fifteen. At the same time, in these estimates we also account for potential issues due to outliers by excluding all sale-points having experienced over 50 nearby re-allocations during the 4-years pre-sale window[15]. The results in Table 3 clearly illustrate that one single re-allocation alone is incapable of influencing the value of neighbouring

[15]With a 150m buffer this implies having a maximum of 32 re-allocations per treated sale point, while with 250m it implies a maximum of 49 re-allocations.

buildings (column (1)), while for a larger number of real estate assets are re-allocated, every re-allocation has an impact on the value of closeby buildings (columns (2)-(5)). The magnitude of the treatment variable increases, the larger is the number of re-allocations. For buildings with ten or more re-allocations within 150 metres, any extra re-allocation converts into a 0.4% increase in house prices (column (4), Panel A).

5.3 Spatial heterogeneity

Having uncovered a general effect of re-allocations on the value of surrounding properties, in this section we explore the heterogeneity of the policy effect. To begin with, given that re-allocations are primarily an anti-mafia policy, we investigate whether they produce larger impacts in urban areas where organised crime groups are more rooted and where they invest the most. These are also the areas where most re-allocations have occurred.

While organised crime activities are nowadays spread across the entire Italian territory (and beyond), mafia regional strongholds are well known[16] Our assumption is that the policy might be more effective where criminal organisations are more rooted and re-allocated assets could send a stronger signal to the local housing market. To test this hypothesis, we exploit the geographical extension of our dataset and replicate the model focusing exclusively on provinces characterised by higher mafia strongholds. These are defined on the basis of an indicator developed by Bernardo et al. (2021)[17], examining the sensitivity of organised crime and developing weights of crime variables to define the highest and lowest intensity of organised crime presence across Italian provinces.[18] Figure A3 in the Appendix illustrates the spatial distribution of the mafia intensity index.

[16]Organised crime maintains its strongest presence in the areas where it was originally formed. According to Transcrime (2013), the Cosa Nostra (Sicily), 'Ndrangheta (Calabria), Camorra (Campania) and Sacra Corona Unita (Apulia) preserve their strongholds in their regions of origin.

[17]Other studies mapping local mafia intensity across the Italian territory are, among others, Marselli and Vannini (1997); Calderoni (2011); and Dugato, Calderoni, and Campedelli (2020)).

[18]This is obtained by using the stochastic dominance efficiency (SDE) methodology on a set of commonly used crime indicators. The index gives more weight to infrequent events occurring in a limited number of provinces and makes use of the widest set of indicators available. It is based on the following set of variables: mafia murders, mafia-type associations, councils dissolved, assets confiscated, extortion, arson, usury, money laundering, drug, corruption

Table 3: Sale point analysis - one vs. many re-allocated assets

Dep. variable: Log euro per m^2	1 asset (1)	>1 asset (2)	>5 assets (3)	>10 assets (4)	>15 assets (5)
Panel A: 150 metres					
Re-allocations	-0.00211	0.00224*	0.00219	0.00406**	0.00394**
	(0.0132)	(0.00122)	(0.00143)	(0.00192)	-0.00199
Placebo re-allocations	0.00269	0.000067	0.00180	0.00229	0.00201
	(0.00190)	(0.000532)	(0.00162)	(0.00177)	-0.00173
Confiscations	0.000374	0.000974	0.00164	0.00112	0.00125
	(0.00137)	(0.00171)	(0.00219)	(0.00196)	-0.00197
Observations	47,870	47,683	47,204	47,154	47,138
R-squared	0.785	0.784	0.784	0.784	0.784
Panel B: 250 metres					
Re-allocations	-0.0143	0.00152	0.00179*	0.00199*	0.00203*
	(0.0126)	(0.00102)	(0.00107)	(0.00106)	(0.00110)
Placebo re-allocations	0.000801	0.000074	-0.000116	0.000956	0.000869
	(0.00224)	(0.000294)	(0.00193)	(0.00206)	(0.00212)
Confiscations	0.00246	0.000120	0.00162	0.00207	0.00173
	(0.00157)	(0.00123)	(0.00204)	(0.00211)	(0.00213)
Observations	46,965	47,006	45,841	45,667	45,629
R-squared	0.784	0.783	0.782	0.782	0.782
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
OMI FE	Yes	Yes	Yes	Yes	Yes
Municipality-year FE	Yes	Yes	Yes	Yes	Yes

Notes. Clustered standard errors at OMI level in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance. Dependent variable: price recorded for each sale point i in year t. Explanatory variables constructed in relation to timing of sale points. Re-allocations: nr re-allocations up to 4 years before the sale of the building, within its buffer zone; column (1): sale points with more than one re-allocation within buffer excluded; column (2): sale points with only one and >50 re-allocations within buffer excluded; column (3): sale points with 5 or less and >50 re-allocations within buffer excluded; column (4): sale points with 10 or less and >50 re-allocations within buffer excluded; column (5): sale points with 15 or less and >50 re-allocations within buffer excluded; Placebo re-allocations: nr re-allocations up to 3 years after the sale of the building within buffer. Confiscations: nr confiscations up to 4 years before the sale of the building within buffer. Panel A: buffer 150m around sold property; Panel B: buffer 250m around sold property. Controls: sale property, amenity, socio-economic characteristics.

Besides the presence of criminal organisations, the policy is likely to be more effective in deprived areas, where the provision of an additional local service can benefit local communities the most. For this reason, we map local deprivation across census blocks using the deprivation index developed by Caranci and Costa (2009) and used by the Italian Institute for Statistics (ISTAT). The index is based on 5 variables, measured at the census block-level, retrieved from the 2011 Italian Census: share of residents with at most a primary education degree, local unemployment rate, share of tenants, share of single parent families and crowding of dwellings (number of family members per 100 m^2). Variables are first standardised over the whole population and then aggregated with equal weights. We further standardised the composite index at the regional level, to bypass the extreme between-region inequality that characterise the Italian territory and create a measure of local deprivation that is assumed to be more in line with the perception of local communities.[19]

Finally, we consider within-city heterogeneity in housing supply elasticity. Baum-Snow and Han (2019) show that local development constraints can determine significant differences in local housing market structures across neighbourhoods. Consequently, even a homogeneous shock will have heterogeneous effects on the territory based on the differences in the elasticity of supply. To build an indicator of housing supply elasticity we abstain from using local land use regulations, possibly endogenous to local shocks (Fischel, 2005), and exploit instead physical constraints. Following Accetturo et al. (2021), we build it as the principal component of four dimensions: land consumption, land slope, fraction of surface covered by water bodies, and land fragmentation. Land slopes are retrieved from Copernicus Land Monitoring Service (see Figure A4b)[20]; the fraction of surface covered by water is drawn from CLMS Corine Land Cover produced by the European Environment Agency (EEA) (Figure A4a); land fragmentation is captured by patch density – a proxy of the uneven distribution of different land types over the territory – and is drawn again from the EEA (Figure A4c). Finally, we exploit Census block-level data to produce a measure of house vacancy to complement data on artificial surfaces.

[19]Due to the spatial inequality that characterise Italian regions, any unstandardised measure of local inequality would label large parts of poorer Southern cities as deprived, while overlooking the significant inequalities that characterise most Northern regions

[20]The raster is based on EU-DEM v1.0, a digital surface model (DSM) representing the first surface as illuminated by the sensors.

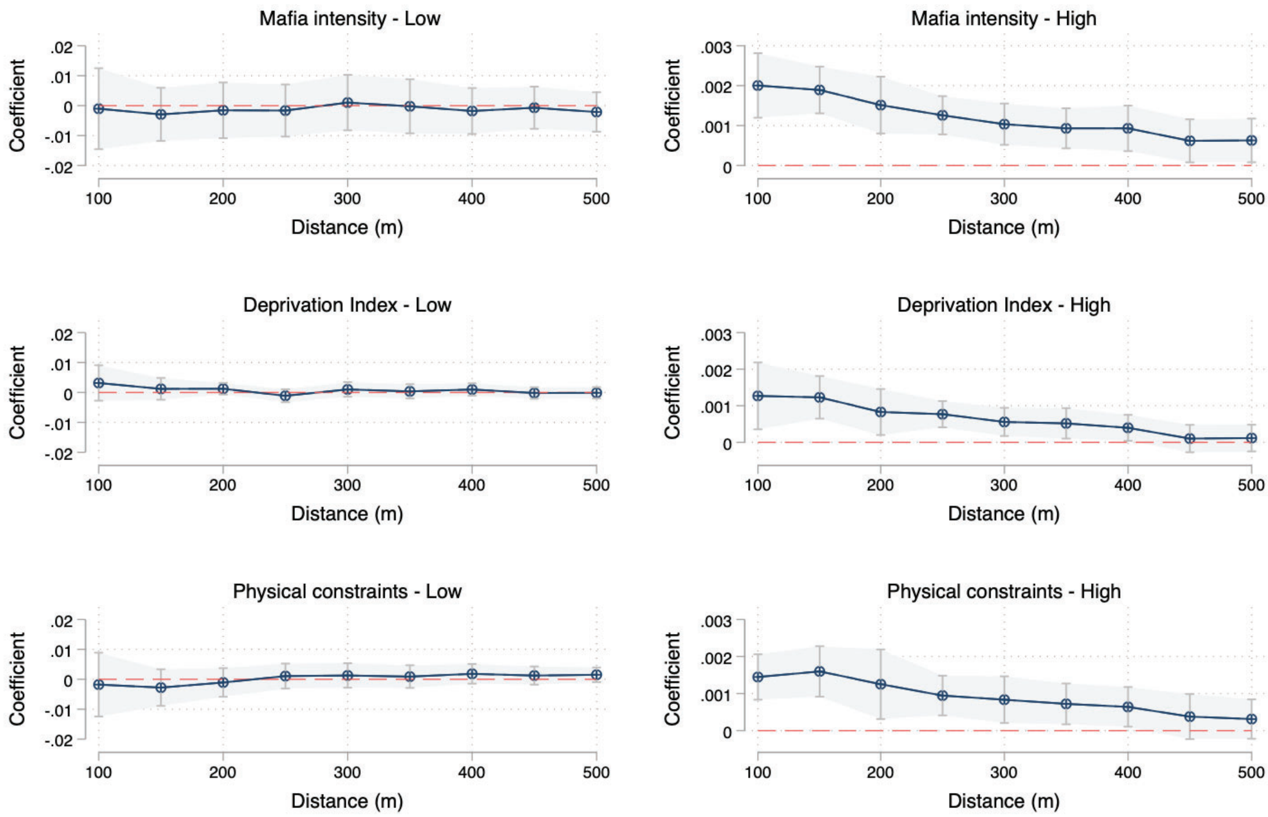
Table 4: Mafia-intensive areas, deprived areas and physical constraints

Dep. variable:	buffer: 150m					
Log euro per m^2	Mafia intensity		Local deprivation		Physical constraints	
	low	*high*	*low*	*high*	*low*	*high*
	(1)	(2)	(3)	(4)	(5)	(6)
Re-allocations	-0.00293	0.00189***	0.00120	0.00123***	-0.00278	0.00160***
	(0.00453)	(0.000298)	(0.00185)	(0.000297)	(0.00312)	(0.000346)
Placebo re-allocations	0.00472	4.87e-05	0.000268	0.000581	0.00387	-0.000358
	(0.00389)	(0.000497)	(0.00385)	(0.000475)	(0.00351)	(0.000441)
Confiscations	0.00200	-0.000276	0.00137	0.00199	-0.00128	0.000163
	(0.00683)	(0.00102)	(0.00137)	(0.00822)	(0.00201)	(0.00119)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
OMI FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,961	14,889	10,675	20,377	24,189	24,068
R-squared	0.770	0.821	0.782	0.747	0.774	0.795

Notes. Clustered standard errors at the OMI level in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance. Dependent variable: price recorded for each sale point i in year t. Re-allocations: number of re-allocated assets up to 4 years before the transaction within buffer zone. Placebo re-allocations: number of re-allocated assets taking place up to 2 years after the transaction within buffer zone. Confiscations: number of confiscated assets events taking place up to 4 years before the transaction within buffer zone. Columns (1)-(2) report the effect of property re-allocation in the cities reporting below- and above-median scores of the Mafia Intensity index described in section 5.3. Column (3)-(4) report the effect of property re-allocation in the OMI areas characterised by hlow and high deprivation (respectively below the 1st and above the 3rd quartile of the deprivation index). Columns (5)-(6) report the effect of property re-allocation in the OMI areas characterised by below- and above-median housing supply elasticity, as proxied by the first principal component of land consumption, land slope, fraction of surface covered by water bodies, and land fragmentation. All specifications include Structural controls, Building controls, Amenity controls, Socio-economic controls, OMI fixed effects, municipality-year fixed effects.

The results of the model estimated by focusing on the aspects of heterogeneity discussed are shown in Table 4 and Table A9. As visible in columns (2), (4) and (6) of Table 4, the effect of re-allocations on house prices only appears for areas with high mafia intensity, higher deprivation levels, and higher physical constraints. In columns (1), (3), and (5) indicating areas with low mafia intensity, low deprivation levels, and low physical constraints, the treatment variable is always statistically insignificant. The overall estimated effect thus appears to be driven by the most disadvantaged neighbourhoods and those provinces characterised by higher mafia activity. In terms of magnitude, the effect of re-allocations is the highest in cities located in areas with stronger mafia presence, where neighbouring property prices are expected to rise by 0.19% in the period following each re-allocation. Table A9 shows that the effect is visible also at 250 metres from re-allocations, and holds at 500 metres for mafia-intensive areas. Figure 6 illustrates the distance decay effect for the three dimensions of spatial heterogeneity examined.

Figure 6: Distance decay by deprivation level, mafia intensity and physical constraints



5.4 Size of the effect and channels

Despite the fact that a proper cost-benefit analysis is beyond the scope of this study, it is possible to discuss the magnitude of the policy effect. To our knowledge, this is the first study to investigate the impact of re-allocation policies on property prices. As a result, it is not an immediate benchmark to compare our results with. However, our result can be compared with studies analysing the effect of crime at a similar spatial scale. Thaler (1978) finds that a one standard deviation increase in the incidence of property crime reduces home values by about 3%. A more significant effect is reported by Gibbons (2004), that finds a standard deviation decrease in local density of criminal damage to be associated with a 10% price increase in the average Inner London property.

Our results can also be analysed in relation to studies investigating the effect of local amenities on property prices. Indeed, the creation of amenities by means of re-allocations may be one of the channels through which the policy produces its impact on house prices. On the one hand, the re-allocation policy could serve as an engagement device for the local community (Falcone, Giannone, and Iandolo, 2016). Non-profit organisations could use assets located in critical areas to organise bottom-up initiatives and sustain institutional change. On the other hand, assets can be used by local councils to improve the local provision public services in areas characterised by high demand and limited resources. In both cases, the increase in local amenities would foster housing demand for a previously more deprived and less attractive neighbourhood, an explanation coherent with the fact that the effect of the policy is stronger in more disadvantaged areas. Machin (2011) reviews 11 studies investigating the nexus between school quality and housing prices, finding a median change of 4% in housing prices following a standard deviation change in school quality. Similarly, the presence of sex offenders reduce property prices by 2-4% (Linden and Rockoff, 2008; Pope, 2008). On the other hand, changes in toxic emissions from industrial plants is associated with a 10% change in house price (Currie et al., 2015).

Hence, with respect to the house price effect of other amenities, our estimates appear to be lower. However, the policy considered is likely to be significantly cheaper for local authorities. Moreover, the strategic position of re-allocated assets, mostly located in deprived neighbourhood, and the fact that the impact is stronger in more deprived census areas, is such that the policy is likely to particularly benefit more disadvantaged social groups.

The re-allocation effect may materialise through the creation of amenities, but it may also be the result of different dynamics, directly related with the activity of organised crime. The re-allocation can weaken criminal organisations, both directly reducing its ability to extract resources from the territory and acting as a deterrent against future penetrations.[21], as well as a signal of the State's presence to local communities given that the asset provides new public services for citizens. Thus, the re-allocation could have *per se* an effect on the perception of impunity that often characterises criminal organisations. A weaker presence of criminal groups is expected to materialise into a higher value of buildings in the area where re-allocations take place (Gibbons, 2004, Linden and Rockoff, 2008, Ihlanfeldt and Mayock, 2010). We investigate this possibility in the next section.

5.5 Re-allocations and organised crime activity

The evidence shown so far suggests that re-allocations can impact property values in deprived areas, though the effect is highly localised. 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 dynamic 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 (Riccardi and Soriani, 2016).

In this section, we run an empirical exercise to provide some indications regarding the mechanisms behind our results. We exploit 2013-2018 annual reports produced by the DIA, the Anti-Mafia Investigation Directorate, reporting very detailed information on the major territories under the influence of mafia organisation. In particular, the DIA maps illustrate the power exerted by each single mafia family on the territory. The DIA data are updated every year and make it possible to follow the evolution of mafia presence in small neighbourhoods and even in single streets (see Figure A5). The city of Naples represents the ideal testing ground, not only for its large number of re-allocated assets but also because of the high variability over time in terms of *Camorra* (the main criminal organisation rooted in the region) activity. According to DIA reports, around 80% of the 14,098 streets

[21] This dynamic is consistent with the model proposed by Garoupa (2007), where a higher punishment for the employer fosters a decrease in the number of agents and in information diffusion.

of Naples have had one or more mafia families active in the streets during 2013-2018. In addition, over 70% of streets have experienced changes in criminal activity over the same period, with the number of active mafia families increasing, or decreasing, or remaining the same in number but changing balance of power.

Thanks to this data, we have constructed a street-level panel dataset on organised crime presence in Naples. To identify cases of re-allocations within streets, we have exploited again buffers, identifying as 'treated' a street experiencing re-allocations within its buffer radius. Due to the high heterogeneity recorded in street-level data, we focus on a 100 to 200 metres radius from each street.[22] A representation of our strategy, zooming into some streets of Naples, is shown in Figures 7 and A5c.

Figure 7: Buffer zones around streets

Exploiting the constructed dataset, we estimate the following model:

$$Mafia\ families_{sjt} = \alpha R_{sjt} + \beta C_{sjt} + \sigma_s + \lambda_t + \delta_{jt} + \varepsilon_{sjt} \quad (4)$$

[22]Out the total 14,098 streets in sample, 963 (2375) have experienced close-by re-allocations if we consider 100 (200) metres radius. Among these, using a 100 (200) metres radius, 182 (884) streets have experienced episodes of re-allocations. In the period 2013-2018 there have been 173 re-allocations in the city of Naples, of which 8 in 2013, 78 in 2015, 25 in 2016, 41 in 2017, and 21 in 2018. The average re-allocation time in the city is 12.5 years.

where $Mafia\, families_{sjt}$ is the number of *Camorra* families active in street s, OMI zone j, year t. R_{sjt} is the re-allocation dummy, switching on from the year of the first re-allocation episode taking place in street s to the end of the period. As our model is estimated for 2013-2018, all streets having experienced re-allocations prior to 2013 are excluded from sample. C_{sjt} is a variable controlling for the confiscations that took place in street s and the length of the re-allocation process. The specification controls for time-invariant street-specific factors (σ_s), time shocks (λ_t) and OMI-year fixed effects (δ_{jt}). The re-allocation episodes can take place in any moment during 2013-2018. As such, the model takes the form of a Two-Way-Fixed-Effects with variation in treatment timing (Goodman-Bacon, 2021).

In Table 5 we regress the number of families operating in one street over the re-allocation dummy variable, using a 100 meters and 200 metres radii. In column (1), Panel A, street and year fixed effects are included. Re-allocations are found to have a negative effect on the number of families per road. When OMI-year FE are included (column (2), Panel A), the coefficient for re-allocations, although losing magnitude, remains negative and significant. Overall, a significant and negative effect is found for the re-allocation of former mafia assets. In columns (3)-(4), Panel A we estimate the same specification using a 200 meters buffer radius around streets, confirming the results.

Our sale-point analysis indicates that the effect of re-allocations on house prices is visible particularly at the extensive margin, i.e. that a larger number of re-allocated assets produce stronger effects. We investigate whether the same applies to this setting by splitting the sample of treated streets along this dimension. We look at streets with one single re-allocated asset vs. streets with more than one re-allocated asset over the 2013-2018 period. Table 5, Panel B, displays the result. The effect of re-allocations on mafia families' presence discussed above appears driven especially by streets with more than one re-allocated asset, as the magnitude of the treatment dummy appears larger when re-allocations involve more than one single asset.[23] In sum, Table 5 seems to indicate that the effect the policy has

[23]In some cases, this refers to many assets being re-allocated in the same address, i.e. part of the same flat complex.

Table 5: Street-level analysis on mafia activity

Dep. variable: Nr of mafia families	100m buffer (1)	(2)	200m buffer (3)	(4)
Panel A: full sample of re-allocated				
Re-allocations	-0.449***	-0.134***	-0.414***	-0.164***
	(0.0595)	(0.0365)	(0.0412)	(0.0272)
Confiscations	Yes	Yes	Yes	Yes
Roads FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
OMI-year FE		Yes		Yes
Observations	71,814	71,808	71,814	71,808
R-squared	0.850	0.946	0.851	0.946
Panel B: 1 vs. many re-allocated				
	1 asset	>1 assets	1 asset	>1 assets
Re-allocations	-0.0439	-0.131**	-0.1000***	-0.225***
	(0.0452)	(0.0589)	(0.0341)	(0.0426)
Confiscations	Yes	Yes	Yes	Yes
Roads FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
OMI-year FE	Yes	Yes	Yes	Yes
Observations	70,146	69,696	66,306	67,470
R-squared	0.947	0.947	0.950	0.947

Notes. ***, **, and * indicate 0.01, 0.05, and 0.1 levels of significance. Dependent variable: number of mafia families recorded in each street of Naples. Re-allocations: dummy variable taking value 1 from the first re-allocation episode experienced by a street until the end of the period. Time period: 2013-2018. Columns (1)-(2): 100 metres buffer around each street; Columns (3)-(4): 200 metres buffer around each street. Panel B, columns (1), (3): streets experiencing re-allocation of more than one building excluded from sample; Panel B, columns (2), (4): streets experiencing re-allocation of only one building excluded from sample. The sample covers all streets of Naples, except those having experienced re-allocations prior to 2013. Clustered standard errors at the street level in parentheses.

on mafia activity is also higher, the larger the number of re-allocated assets in a given street.

As the OMI analysis, the street-level study takes the form of a TWFE difference-in-differences model. As such, it is possible to look at the temporal dynamics around the treatment event with an event study. We create q leads ($D_{r,s,t-2}$, $D_{r,s,t-3}$, ..., $D_{r,s,t-q}$) and lags ($D_{r,s,t+1}$, $D_{r,s,t+2}$,

..., $D_{r,s,t+q}$) dummy variables and include them in the model to check for anticipatory effects, using the first year before re-allocation as reference category. The model is:

$$Mafia\,families_{st} = \sum_{\tau=2}^{q} \delta_{-q}\delta_{-\tau}D_{s,t-\tau} + \sum_{\tau=1}^{q} \delta_{-q}\delta_{+\tau}D_{s,t+\tau} + \sigma_s + \lambda_t + \delta_{zt} + u_{st} \tag{5}$$

The results of both Two-way Fixed Effects (TWFE) and Sun and Abraham (2021) event studies using 100 metres buffers are shown in Figure A6. They are reassuring regarding the absence of pre-trends between treatment and control units, and they display a temporal dynamic of the effect materialising short after the re-allocation and lasting for several periods afterwards. They confirm a clear reduction in the number of mafia families per street following the re-allocation.

The results suggest that re-allocations decreases the number of active mafia families in the neighbourhood where re-allocation takes place. A decrease in the number of families may not, however, necessarily correspond to a reduction in the actual power of criminal groups on a territory. In Table A10 we run a similar exercise, but this time we use two different outcome variables: a dummy taking value 1 if a change of power occurs in street s in year t (Panel A), and a dummy taking value of 1 if mafia presence is recorded in the street and 0 otherwise (Panel B). A positive coefficient is found in the first case and a negative one in the second, thus suggesting that re-allocations indeed modify the local mafia system of power by decreasing the probability of finding active families in treated streets. While this does not represent conclusive evidence regarding the effect of the policy on mafia activity, it supports the hypothesis that at least part of the effect of the re-allocation policy is obtained through the eradication of the pervasive presence of the mafia in the treated areas.

6 Conclusions

In an effort to tackle criminal organisations, the Italian State allows for the re-allocation of assets confiscated to the mafia 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 processes by testing their external effects on the monetary value of properties in the surrounding areas. Our estimates, making use of unique micro-level datasets, unveil a short-term positive relationship between re-allocation cases and the property price of neighbouring buildings, materialising in mafia-intensive regions and areas with physical constraints. Our preferred estimates stipulate that any additional re-allocated asset increases the monetary value of surrounding properties within 150 and 250 metres at approximately 0.1-0.15% annually.

In addition, the effect decays with distance, as it is no longer visible beyond 400m from re-allocated assets and it is weak when using homogeneous local housing markets as units of analysis. This indicates that the effect, while significant, is extremely localised. Furthermore, it appears that single-asset re-allocations produce little or no effect, while a larger number of re-allocations determines a statistically significant increase in the monetary value of neighbouring properties, up to 0.4% increase per asset when neighbouring re-allocations are ten or more. These findings suggests that re-allocations lead to small but significant spillover effects. However, these seem to add value only to certain local areas within mafia-rigged territories and deprived neighbourhoods.

A possible interpretation of the fact that the policy mainly shows its impact in mafia-rigged territories relates with the typology of re-allocated assets in those areas. Mafia organisations generally own both operational and economic assets. The former are critical resources to exercise sovereignty over their market, possibly directly used by criminal members, whereas the latter are investments and money laundering machines (Operti, 2018). Operational assets such as real estate properties serve both as inputs for illicit activities, insurance systems against the detection of family members of the organisation, and institutional signals for the entire community. More mafia-rigged territories likely involve a combination of both operational and economic assets, while in less mafia-rigged areas the re-allocated assets were more likely investments made by criminal organisations for money laundering purposes. A possibility is that citizens more easily recognise and are aware of the conversion of former operational mafia assets through re-allocations, thus valuing properties more in areas where this kind of re-allocations have been made.

One way to explain the larger impact in more deprived areas, instead, may be related to the fact that the re-allocation measure is conceived as an engagement device for the local community (Falcone, Giannone, and Iandolo, 2016). Non-profit organisations use assets located particularly in critical areas at higher disadvantage to organise bottom-up initiatives and sustain institutional change. This process may also contribute to the revitalisation of the targeted areas through the attraction of competitive firms and skilled workers (Storper and Venables, 2004). All this would capitalise into higher house prices in these neighbourhoods.

Spillover effects are also driven by areas with less elastic local housing market structures, where physical constraints are high. This result is in line with the literature on housing supply elasticity postulating a high degree of heterogeneity in price responsiveness to local demand shocks across different neighbourhoods (Baum-Snow and Han, 2019).

The effect we obtain may be the result of the improved attractiveness of a previously more deprived and less attractive neighbourhood, thanks to the new amenities. This explanation is linked to the fact that the effect of the policy is stronger in more disadvantaged areas. However, another possibility is that the policy is capable of reducing criminal activity, thus increase the value of neighbourhoods in this way. With the available data, we are not currently able to fully disentangle the extent to which the estimated effect is due to the eradication of the presence of criminal organisations or exclusively amenity effect. However, an exercise conducted at the street level on the Naples case-study suggests that at least a part of the effect could be associated with a reduction of intensity of mafia activities in the streets where re-allocations occur.

In all cases, what emerges with clarity from our study is that the policy of re-allocating real estate assets recovered from criminal organisations can have the capacity of increasing the localised value of buildings in the their surroundings, particularly under some specific conditions. The fact that the policy effect on real estate prices is only visible when we focus on areas characterised by strong mafia presence, high deprivation, and inelastic local housing supply suggests that the legislator's intent to improve the quality of some target-neighbourhoods through re-allocations may be effective. Provided the 'anti-mafia' original nature of the legislative tool we evaluated, the fact that it appears capable of increasing the value of poorer neighbourhoods characterised by strong mafia presence, and that it also seems to impact criminal activities, may be seen as strong evidence in favour of the idea that re-allocation truly revitalise territories in highest need, where the policy was arguably expected to produce its larger impacts. It also suggests that the legislators may adapt the policy to the context of the re-allocated assets. For example, assets in non-mafia areas could simply be sold and the proceeds invested in alternative urban regeneration policies.

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 rather can be implemented in both more and less developed areas. Nevertheless, we have shown that its effective application has been in deprived local areas characterised by high unemployment and more unattractive buildings, and cities where the presence of organised crime is stronger. The timing of re-allocations may vary sharply across the country and may depend on local courts, with the confiscation period often lasting over ten years. Our results indicate that efforts should be made in speeding up the re-allocation procedures, particularly where the policy has displayed its stronger capacity to add value - and hence possibly regenerate - local territories. An effective and more rapid implementation of the re-allocation policy may favour the revitalisation of local areas at higher disadvantage where mafia groups hold the upper hand.

References

Accetturo, A. et al. (2021). "Housing supply elasticity and growth: Evidence from Italian cities". In: *Journal of Economic Geography* 21.3, pp. 367–396.

Acconcia, A., G. Corsetti, and S. Simonelli (2014). "Mafia and public spending: Evidence on the fiscal multiplier from a quasi-experiment". In: *American Economic Review* 104.7, pp. 2185–2209.

Acemoglu, D., J. A. Robinson, and R. J. Santos (2013). "The monopoly of violence: Evidence from Colombia". In: *Journal of the European Economic Association* 11.suppl_1, pp. 5–44.

Ahlfeldt, G. M., W. Maennig, and F. J. Richter (2017). "Urban renewal after the Berlin Wall: a place-based policy evaluation". In: *Journal of Economic Geography* 17.1, pp. 129–156.

Alesina, A., S. Piccolo, and P. Pinotti (2019). "Organized crime, violence, and politics". In: *The Review of Economic Studies* 86.2, pp. 457–499.

Atkinson, R. and G. Helms (2007). *Securing an urban renaissance: Crime, community, and British urban policy*. Policy Press.

Bailey, N. and D. Robertson (1997). "Housing renewal, urban policy and gentrification". In: *Urban studies* 34.4, pp. 561–578.

Barone, G. and G. Narciso (2015). "Organized crime and business subsidies: Where does the money go?" In: *Journal of Urban Economics* 86, pp. 98–110.

Battisti, M. et al. (2022). "Shooting down the price: Evidence from Mafia homicides and housing prices". In: *Papers in Regional Science*.

Baum-Snow, N. and L. Han (2019). "The microgeography of housing supply". In: *Work in progress, University of Toronto*.

Bernardo, G. et al. (2021). "Measuring the presence of organized crime across Italian provinces: a sensitivity analysis". In: *European Journal of Law and Economics* 51.1, pp. 31–95.

Budiakivska, V. and L. Casolaro (2018). "Please in my back yard: the private and public benefits of a new tram line in Florence". In: *Bank of Italy Temi di Discussione (Working Paper) No* 1161.

Buonanno, P., G. Prarolo, and P. Vanin (2016). "Organized crime and electoral outcomes. Evidence from Sicily at the turn of the XXI century". In: *European Journal of Political Economy* 41, pp. 61–74.

Bureau, E. C. A. (2016). "Does crime still pay? Criminal asset recovery in the EU". In.

Caldera, A. and Å. Johansson (2013). "The price responsiveness of housing supply in OECD countries". In: *Journal of Housing Economics* 22.3, pp. 231–249.

Calderoni, F. (2011). "Where is the mafia in Italy? Measuring the presence of the mafia across Italian provinces". In: *Global Crime* 12.1, pp. 41–69.

Camera dei Deputati (2019). *XVI Legislature - Disegni di Legge e Relazioni - Senato della Repubblica*.

Caranci, N. and G. Costa (2009). "Un indice di deprivazione a livello aggregato da utilizzare su scala nazionale: giustificazioni e composizione". In: *Un indice di deprivazione a livello aggregato da utilizzare su scala nazionale*, pp. 1000–1021.

Currie, J. et al. (2015). "Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings". In: *American Economic Review* 105.2, pp. 678–709.

Dalla Chiesa, N. (2016). "Il riuso sociale dei beni confiscati. Le criticitá del modello lombardo". In: *Rivista di Studi e Ricerche sulla criminalitá organizzata* 2.2, pp. 15–25.

Daniele, G. and B. Geys (2015). "Organised crime, institutions and political quality: Empirical evidence from italian municipalities". In: *The Economic Journal* 125.586, F233–F255.

De Feo, G. and G. D. De Luca (2017). "Mafia in the ballot box". In: *American Economic Journal: Economic Policy* 9.3, pp. 134–67.

Di Cataldo, M. and N. Mastrorocco (2021). "Organised crime, captured politicians and the allocation of public resources". In: *Journal of Law, Economics, and Organization* forthcoming.

Dugato, M., F. Calderoni, and G. M. Campedelli (2020). "Measuring organised crime presence at the municipal level". In: *Social Indicators Research* 147.1, pp. 237–261.

European Commission (2014). *Confiscation and asset recovery*. URL: https://home-affairs.ec.europa.eu/policies/internal-security/organised-crime-and-human-trafficking/confiscation-and-asset-recovery_en.

EVstudio (2019). *The Five Minute Walk: Calibrated to the Pedestrian*. URL: https://evstudio.com/the-five-minute-walk-calibrated-to-the-pedestrian/.

Falcone, R., T. Giannone, and F. Iandolo (2016). *BeneItalia. Economia, welfare, cultura, etica: la generazione di valori nell'uso sociale dei beni confiscati alle mafie*.

Fenizia, A. and R. Saggio (2020). *Can the Mafia's Tentacles Be Severed? The Economic Effects of Removing Corrupt City Councils*. Tech. rep.

Fischel, W. A. (2005). *The homevoter hypothesis: How home values influence local government taxation, school finance, and land-use policies*. Harvard University Press.

Frigerio, L. and D. Pati (2007). "L'uso sociale dei beni confiscati–Programma di formazione sull?utilizzazione e la gestione dei beni confiscati alla criminalitá organizzata". In: *Libera–Associazioni, nomi e numeri contro le mafie, Roma* 60.

Gabanelli, M. and M. Grossi (2020). "Mafia, l'odissea dei beni confiscati e la mappa dei 17 mila immobili ancora da assegnare". In: *Corriere della Sera*.

Galletta, S. (2017). "Law enforcement, municipal budgets and spillover effects: Evidence from a quasi-experiment in Italy". In: *Journal of Urban Economics* 101, pp. 90–105.

Ganau, R. and A. Rodríguez-Pose (Mar. 2018). "Industrial clusters, organized crime, and productivity growth in Italian SMEs". In: *Journal of Regional Science* 58 (2), pp. 363–385.

Garoupa, N. (2007). "Optimal law enforcement and criminal organization". In: *Journal of Economic Behavior & Organization* 63.3, pp. 461–474.

Gibbons, S. (2004). "The costs of urban property crime". In: *The Economic Journal* 114.499, F441–F463.

Gibbons, S. and S. Machin (2008). "Valuing school quality, better transport, and lower crime: evidence from house prices". In: *oxford review of Economic Policy* 24.1, pp. 99–119.

Gibbons, S., S. Mourato, and G. M. Resende (2014). "The amenity value of English nature: a hedonic price approach". In: *Environmental and Resource Economics* 57.2, pp. 175–196.

Glaeser, E. L., J. Gyourko, and R. E. Saks (2005). "Why have housing prices gone up?" In: *American Economic Review* 95.2, pp. 329–333.

Goodman-Bacon, A. (2021). "Difference-in-differences with variation in treatment timing". In: *Journal of Econometrics* 225.2, pp. 254–277.

Ihlanfeldt, K. and T. Mayock (2010). "Panel data estimates of the effects of different types of crime on housing prices". In: *Regional Science and Urban Economics* 40.2-3, pp. 161–172.

Koster, H. R., J. van Ommeren, and P. Rietveld (2012). "Bombs, boundaries and buildings: a regression-discontinuity approach to measure costs of housing supply restrictions". In: *Regional Science and Urban Economics* 42.4, pp. 631–641.

Koster, H. R. and J. Van Ommeren (2019). "Place-based policies and the housing market". In: *Review of Economics and Statistics* 101.3, pp. 400–414.

Le Moglie, M. and G. Sorrenti (2022). "Revealing 'mafia inc.'? Financial crisis, organized crime, and the birth of new enterprises". In: *Review of Economics and Statistics* 104.1, pp. 142–156.

Lee, P. and A. Murie (1999). "Spatial and social divisions within British cities: beyond residualisation". In: *Housing Studies* 14.5, pp. 625–640.

Linden, L. and J. E. Rockoff (2008). "Estimates of the impact of crime risk on property values from Megan's laws". In: *American Economic Review* 98.3, pp. 1103–27.

Loberto, M., A. Luciani, and M. Pangallo (2018). *The potential of big housing data: an application to the Italian real-estate market*. Banca d'Italia, Eurosistema.

Machin, S. (2011). "Houses and schools: Valuation of school quality through the housing market". In: *Labour Economics* 18.6, pp. 723–729.

Manzoli, E. and S. Mocetti (2019). "The house price gradient: evidence from Italian cities". In: *Italian Economic Journal* 5.2, pp. 281–305.

Marselli, R. and M. Vannini (1997). "Estimating a crime equation in the presence of organized crime: evidence from Italy". In: *International Review of law and Economics* 17.1, pp. 89–113.

Noonan, D. S. and D. J. Krupka (2011). "Making or picking winners: Evidence of internal and external price effects in historic preservation policies". In: *Real Estate Economics* 39.2, pp. 379–407.

Ooi, J. T. and T. T. Le (2013). "The spillover effects of infill developments on local housing prices". In: *Regional Science and Urban Economics* 43.6, pp. 850–861.

Operti, E. (2018). "Tough on criminal wealth? Exploring the link between organized crime's asset confiscation and regional entrepreneurship". In: *Small Business Economics* 51.2, pp. 321–335.

Pinotti, P. (2015). "The economic costs of organised crime: Evidence from Southern Italy". In: *The Economic Journal* 125.586, F203–F232.

Pope, J. C. (2008). "Fear of crime and housing prices: Household reactions to sex offender registries". In: *Journal of Urban Economics* 64.3, pp. 601–614.

Riccardi, M. and C. Soriani (2016). "Mafia infiltration in legitimate companies in Italy: From traditional sectors to emerging businesses". In: *Organised crime in European businesses*. Routledge, pp. 139–160.

Rosenthal, S. S. and S. L. Ross (2015). "Change and persistence in the economic status of neighborhoods and cities". In: *Handbook of regional and urban economics* 5, pp. 1047–1120.

Rossi-Hansberg, E., P.-D. Sarte, and R. Owens III (2010). "Housing externalities". In: *Journal of political Economy* 118.3, pp. 485–535.

Santiago, A. M., G. C. Galster, and P. Tatian (2001). "Assessing the property value impacts of the dispersed subsidy housing program in Denver". In: *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management* 20.1, pp. 65–88.

Savona, E. and G. Berlusconi (2015). "Organized crime infiltration of legitimate businesses in Europe: A pilot project in five European countries. Final report of project ARIEL: assessing the risk of the infiltration of organized crime in EU MSs legitimate economies: a pilot project in 5 EU countries". In.

Savona, E. and M. Riccardi (2015). *From Illegal Market to Legitimate Businesses: The Portfolio of Organised Crime in Europe*. European Commission - Directorate-General Home Affairs. URL: https://www.transcrime.it/wp-content/uploads/2015/12/ocp.pdf.

Schwartz, A. E. et al. (2006). "The external effects of place-based subsidized housing". In: *Regional Science and Urban Economics* 36.6, pp. 679–707.

Storper, M. and A. J. Venables (2004). “Buzz: face-to-face contact and the urban economy”. In: *Journal of economic geography* 4.4, pp. 351–370.

Sun, L. and S. Abraham (2021). “Estimating dynamic treatment effects in event studies with heterogeneous treatment effects”. In: *Journal of Econometrics* 225.2, pp. 175–199.

Thaler, R. (1978). “A note on the value of crime control: evidence from the property market”. In: *Journal of Urban Economics* 5.1, pp. 137–145.

Transcrime (2013). *Gli investimenti delle mafie e Il riutilizzo dei beni confiscati*. URL: https://www.transcrime.it/investimentioc/.

Appendices

This appendix presents additional text, tables and figures that complement the main paper.

A Institutional background

A.1 The 'Rognoni-La Torre' law

The 'Rognoni-La Torre' law (646/1982) stipulates the seizure of real estate asset previously owned by organised crime members or affiliates and, through re-allocations, the re-assignment of these assets to local communities by converting them into public housing amenities. The 'Rognoni-La Torre' law (646/1982) prescribes four steps to obtain the final confiscation:

- The properties of suspects of belonging to mafia groups are scrutinised by the competent tribunal;
- The seizure is decided upon by a panel of 3 judges. The asset goes under judiciary administration;
- The judges provide a motivation for confiscation. The asset goes under first degree confiscation;
- If appealed, the confiscation decision is reviewed by the Court of Appeal. The order can be 'revocation' or confirmation (second degree confiscation).[24]

The two broader categories of re-allocations are: 'social use' and 'institutional, justice and public order'. The former category includes 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. 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, eradicating the presence of the mafia in the areas where it is most deeply rooted (Dalla Chiesa, 2016; Falcone, Giannone, and Iandolo, 2016). This is because real estate properties have a strong symbolic meaning for criminal groups as they are a physical representation of their power

[24] 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

on the local territory. These properties 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 (Savona and Riccardi, 2015) - the confiscation policy is a way to harm their business model and earnings.

Only 83 properties in total were re-allocated in the same year or the year following the confiscation, as visible in Table A1.

Table A1: Timing of re-allocations

	Years between confiscation and re-allocation					
	0-1	2-3	4-5	6-7	8-9	10+
	All re-allocations					
Nr re-allocated real estate properties	83	599	1706	2947	2783	8167
% of total (16,285)	0.5	3.7	10.5	18.1	17.5	50.2
	OMI sample 2005-2018					
Nr re-allocated real estate properties	30	312	940	1620	1417	4850
% of total (9169)	0.3	3.4	10.3	17.7	15.5	52.9
	Sale points in cities sample 2011-2018					
Nr re-allocated real estate properties	0	20	172	330	269	1360
% of total (2151)	0	0.9	8	15.3	12.5	63.2
	Naples sample 2013-2018					
Nr re-allocated real estate properties	0	0	1	12	25	134
% of total (172)	0	0	0.6	7	14.5	77.9

Source: own elaboration with ANBSC data. OMI sample, Sale points in cities sample, and Naples sample exclude all re-allocated assets that (1) have been sold in the property market, or (2) have been demolished, or (3) are terrains.

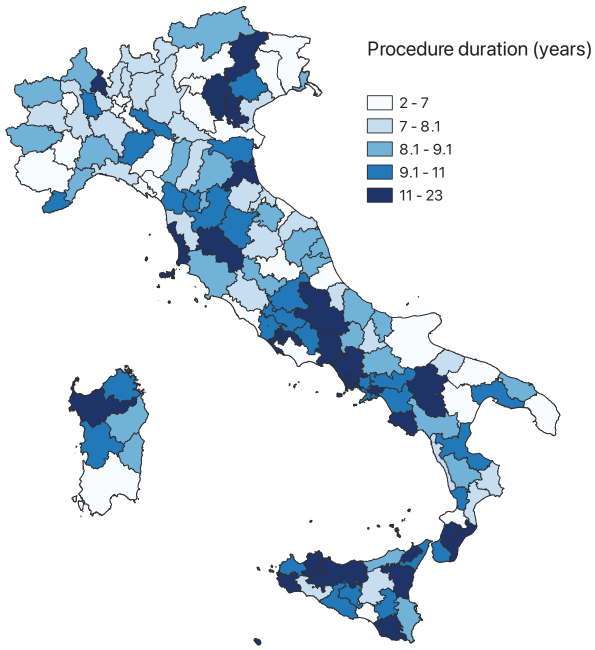
A.2 Local area characteristics

Table A2: Re-allocation and local area characteristics: balancing test

Dep. variable: Re-allocation dummy	Local area characteristics: Large households (>5 members)	Unemployed	Rented households	1st gen. migrants	Buildings in bad condition
	(1)	(2)	(3)	(4)	(5)
Panel A: 150m buffer					
	6.635***	4.447***	0.729***	-0.822***	2.139***
	(1.794)	(1.098)	(0.198)	(0.313)	(0.760)
OMI FE	No	No	No	No	No
Observations	52,416	52,405	52,416	52,436	52,431
R-squared	0.001	0.005	0.002	0.001	0.002
	-0.173	0.630	0.139	0.0778	0.205
	(1.852)	(0.688)	(0.102)	(0.174)	(0.721)
OMI FE	Yes	Yes	Yes	Yes	Yes
Observations	52,327	52,314	52,327	52,346	52,342
R-squared	0.120	0.120	0.120	0.120	0.120
Panel B: 500m buffer					
	86.68***	49.65***	8.593***	-10.19***	26.45***
	(20.86)	(9.721)	(1.597)	(3.182)	(3.683)
OMI FE	No	No	No	No	No
Observations	52,416	52,405	52,431	52,436	52,431
R-squared	0.012	0.030	0.017	0.006	0.002
	2.117	-1.316	-0.273	1.488	0.459
	(8.195)	(2.141)	(0.510)	(1.123)	(2.064)
OMI FE	Yes	Yes	Yes	Yes	Yes
Observations	52,416	52,314	52,327	52,346	52,342
R-squared	0.012	0.627	0.627	0.627	0.627

Notes. Clustered standard errors in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance. Dependent variable: Re-allocation dummy. The model estimate the probability of re-allocation taking place in the buffer around each sale point (dummy=1 if in the neighbourhood of a sale point there has been at least one re-allocation, 0 otherwise) based on a number of pre-treatment buffer characteristics, measured both at 100m and 500m distance threshold. Explanatory variables, reported on top of each column: share of households composed of at least 5 members, unemployment rate, share of rented households, share of 1st generation migrants, share of buildings in bad conditions.

Figure A1: Re-allocation duration by Court



The figure shows the average time required for local cohorts to re-allocate confiscated mafia assets.

B Data

B.1 Descriptive Statistics

Variables collected from *Immobiliare.it* the biggest Italian real estate website are reported in Table A3. Descriptive statistics for treatment and control variables are reported in Table A4 .

Table A3: 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

The table illustrates the main variable types available in the hedonic dataset

Table A4: Descriptive statistics: outcome, treatment variables and sale point characteristics

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 (buffer 250m):			
Ln price €/m2	52,161	7.62	0.574
Re-allocations	53,627	0.29	3.038
Confiscations	53,627	0.072	1.11
Placebo re-allocations	50,057	0.26	2.885
3^{rd} year *before* re-allocation	52,844	0.055	0.573
2^{nd} year *before* re-allocation	52,844	0.093	2.135
1^{st} year *before* re-allocation	53,627	0.082	0.839
1^{st} year *after* re-allocation	53,627	0.0955	0.999
2^{nd} years *after* re-allocation	53,627	0.087	2.108
3^{rd} years *after* re-allocation	53,627	0.066	0.818
4^{th} years *after* re-allocation	53,627	0.042	1.438
Distance to green space	53,224	6,647.60	4,305.60
Distance to beach max 20km	53,224	172,000	335,000
Distance to city viewpoint 1km	53,224	19,962.30	10,809.20
Distance to a University	53,224	50,317.50	27,780.20
Distance to bus, tram or metro	53,224	3,081.60	755.6
Distance to Intercity transport, railway	53,224	6,017.80	1,750.80
Distance to airport	53,224	17,593.40	17,172.70
Distance to commercial centre	53,224	25,858.50	14,489.20
Distance to church	53,224	729.5	406.9
Distance to state schools	53,224	6,896.70	994.2
Noise - within 500m of a highway	53,224	0.23	0.06
Dummy industrial area	53,224	0.16	0.03
Distance to factory	53,224	5,859.90	2,665.20
Distance to construction site	53,224	19,820.40	9,124.50
Month of offer	51,786	3.51	5
Lift dummy	53,224	0.49	0.41
Building height	53,224	8.04	14.05
Typology of building	53,224	1.24	2.62
Area of building	53,224	1,141.10	538.4
Average typology of building in street	53,224	0.66	2.71
Property up for auction	53,224	0.14	0.02
Type of property	53,224	0.71	4.02
Number of rooms	53,224	1.3	2.8
Number of bathrooms	53,224	0.69	1.51
Type of kitchen	53,224	0.7	1.46
Floor number	53,224	2.61	2.01
Parking with property	53,224	0.47	0.33
Periods year built	53,224	2.01	2.49
Property condition	53,224	1.08	2.19
Property heating type	53,224	0.73	0.93
Air conditioning	53,224	0.44	0.27
Energy Efficiency	53,224	0.83	0.87

The bottom part of the table reports descriptive statistics for the sale-point-level variables used in the analysis.

B.2 Additional tests

Table A5 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.

Table A5: 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

Notes. 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 A6 reports the results of an exercise testing for the correlation between the duration of re-allocation procedures, computed as the difference between the year of re-allocation and the year of confiscation, and a number of variables measured either at the Census level or at the level of re-allocated assets.

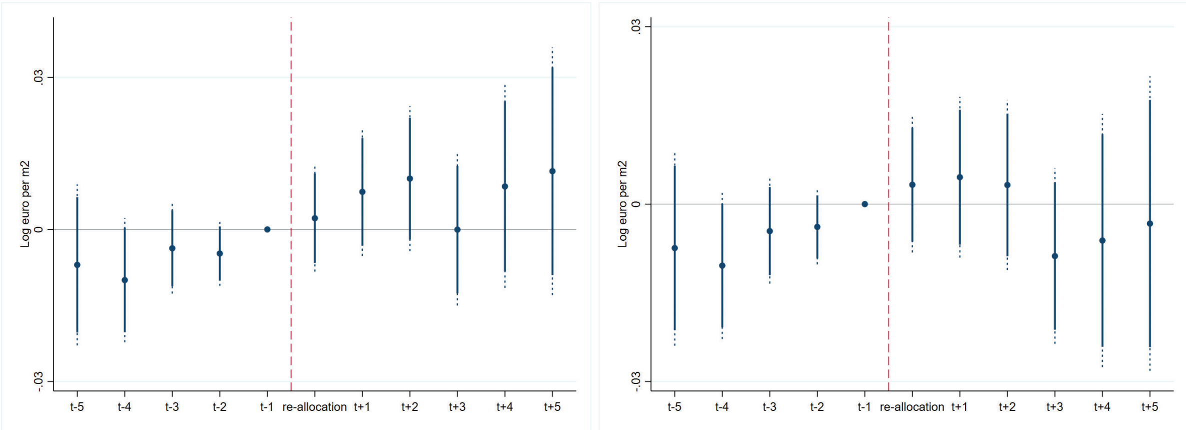
Table A6: Re-allocation timing and local area/building characteristics

Dep. variable: Re-allocation timing	(1) Primary school pop	(2) Ln pop	(3) Unemployed	(4) Rented pop	(5) Buildings in bad conditions
	0.272	0.232**	5.045**	3.978***	1.328*
	(1.061)	(0.0975)	(2.366)	(1.229)	(0.742)
Observations	14,667	14,667	14,667	14,709	14,804
R-squared	0.000	0.004	0.004	0.012	0.003
OMI FE	No	No	No	No	No
	0.0361	0.0352	0.989	-0.262	-0.316
	(0.388)	(0.0924)	(1.552)	(0.897)	(0.528)
Observations	13,996	13,996	13,994	14,037	14,129
R-squared	0.635	0.635	0.634	0.634	0.632
OMI FE	Yes	Yes	Yes	Yes	Yes

Notes. The table illustrates the relation between the length of re-allocation procedure and characteristics of the area where the confiscation took place. Independent variable: percentage of residents with primary education or less, Log population, percentage of unemployed, percentage of families being rented, buildings in bad conditions as percentage of total in local area. Robust standard errors are clustered at the OMI level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

C Results

Figure A2: Event Study: OMI



(a) Two-way Fixed Effects

(b) Sun and Abraham (2021)

The figure shows the event study using ln house prices as dependent variable. Continuous lines refer to 90% confidence intervals, dotted lines refer to 95% confidence intervals. OMI zones with only one case of re-allocation excluded from sample.

Table A7: Sale point analysis year by year

Dep. Variable:	Buffer radius: 150m			Buffer radius: 250m			Buffer radius: 500m		
Log euro per m^2	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Re-allocations	0.00142***	0.00154***		0.000932***	0.00106***		0.000462*	0.000441	
	(0.000320)	(0.000292)		(0.000294)	(0.000268)		(0.000252)	(0.000295)	
Placebo re-allocations		0.000154			-0.000101			-0.000251	
		(0.000510)			(0.000323)			(0.000278)	
Confiscations		0.000080	-0.00101		0.000380	0.000158		-0.000818	-0.00140*
		(0.00106)	(0.00117)		(0.00112)	(0.00113)		(0.000740)	(0.000794)
Timing referring to the moment of sale of the building:									
3^{rd} year *before* re-allocation			-0.000159			-0.000708			0.000192
			(0.00542)			(0.00340)			(0.000640)
2^{nd} year *before* re-allocations			-0.000365			-0.000214			-0.000949**
			(0.000292)			(0.000232)			(0.000374)
1^{st} year *before* re-allocations			-0.00598			-0.00445			-0.00111
			(0.00538)			(0.00280)			(0.00104)
1^{st} year *after* re-allocations			0.00766			0.00570***			0.00138
			(0.00601)			(0.00220)			(0.00110)
2^{nd} year *after* re-allocations			0.00125***			0.000639***			0.000502***
			(0.000277)			(0.000235)			(0.000153)
3^{rd} year *after* re-allocations			0.00183			0.00217*			0.000282
			(0.00230)			(0.00129)			(0.000499)
4^{th} year *after* re-allocations			0.00131**			0.000243			0.000241
			(0.000574)			(0.000443)			(0.000273)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
OMI FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,160	48,456	51,160	51,160	48,456	51,160	51,160	48,456	51,160
R-squared	0.785	0.785	0.785	0.785	0.785	0.785	0.785	0.785	0.785

Notes. Clustered standard errors at the OMI level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance. Dependent variable: price recorded for each sale point i in year t. Re-allocations: nr of re-allocations up to 4 years before the sale of the asset, within its buffer zone. Placebo re-allocations: nr of re-allocations up to 3 years after the sale of the asset, within its buffer zone. Confiscations: nr of confiscations up to 4 years before the sale of the asset, within its buffer zone. Columns (1)-(2): buffer 150m around sold property; columns (3)-(4): buffer 250m around sold property; columns (5)-(6): buffer 500m around sold property. Controls: sale properties, amenities, socio-economic characteristics. Explanatory variables are constructed in relation to the sale point. 2/1 years before re-allocation: nr of reallocations within buffer of a building sold 2/1 years before re-allocation(s). Re-allocation year: nr of reallocations within buffer of a building sold in the same year of re-allocation(s). 1-4 years after re-allocation: nr of reallocations within buffer of a building sold 1/2/3/4 years before re-allocation(s).

Table A8 reports the estimate for each of the controls of the sale point analysis.

Table A8: Sale point analysis controls

Dep. variable: Log euro per m^2	Buffer radius: 150 metres	250 metres	500 metres
	(1)	(2)	(3)
Re-allocations	0.00154***	0.00106***	0.000441
	(0.000292)	(0.000268)	(0.000295)
Property up for auction	-0.389***	-0.389***	-0.389***
	(0.0248)	(0.0248)	(0.0247)
Box	-0.423***	-0.423***	-0.423***
	(0.0352)	(0.0352)	(0.0352)
Attic	0.101***	0.101***	0.101***
	(0.0151)	(0.0151)	(0.0151)
Loft	-0.0671**	-0.0672**	-0.0672**
	(0.0277)	(0.0276)	(0.0277)
Appartment	0.0146	0.0146	0.0145
	(0.0123)	(0.0123)	(0.0123)
House	-0.0706***	-0.0706***	-0.0706***
	(0.0180)	(0.0180)	(0.0180)
Villa	-0.0130	-0.0130	-0.0130
	(0.0163)	(0.0163)	(0.0163)
Building	-0.121***	-0.121***	-0.121***
	(0.0386)	(0.0386)	(0.0386)
Number of rooms	-0.0136***	-0.0136***	-0.0136***
	(0.00170)	(0.00170)	(0.00170)
Number of bathrooms	0.0618***	0.0618***	0.0618***
	(0.00379)	(0.00379)	(0.00379)
Type of kitchen	-0.0321***	-0.0320***	-0.0321***
	(0.00378)	(0.00378)	(0.00378)
Floor number	0.00576***	0.00575***	0.00576***
	(0.000791)	(0.000791)	(0.000792)
Parking	0.0517***	0.0517***	0.0518***
	(0.00420)	(0.00420)	(0.00420)
Lift	0.0780***	0.0780***	0.0781***
	(0.00454)	(0.00454)	(0.00455)
Refurbished	0.196***	0.196***	0.196***
	(0.0105)	(0.0105)	(0.0105)
Heating	0.0315***	0.0315***	0.0314***
	(0.00591)	(0.00591)	(0.00591)
Air conditioning	0.0383***	0.0383***	0.0383***
	(0.00523)	(0.00523)	(0.00523)
High energy efficiency	0.122***	0.122***	0.122***
	(0.00960)	(0.00960)	(0.00960)
Distance to green space	-4.74e-06	-4.71e-06	-4.78e-06
	(4.44e-06)	(4.44e-06)	(4.44e-06)
Distance to water (5 km)	-9.33e-06*	-9.34e-06*	-9.32e-06*

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Table A8 – continued from previous page

Dep. variable:	Buffer radius:		
Log euro per m2	150 metres	250 metres	500 metres
	(1)	(2)	(3)
	(5.34e-06)	(5.35e-06)	(5.34e-06)
Distance to beach	-1.91e-06	-1.93e-06	-1.89e-06
	(3.42e-06)	(3.42e-06)	(3.42e-06)
Distance to a view	-1.15e-05***	-1.15e-05***	-1.15e-05***
	(4.13e-06)	(4.13e-06)	(4.13e-06)
Distance to bus or tube	-9.53e-07	-9.65e-07	-8.30e-07
	(8.37e-06)	(8.37e-06)	(8.37e-06)
Distance to train or bus station	8.35e-06	8.39e-06	8.34e-06
	(6.43e-06)	(6.43e-06)	(6.44e-06)
Distance to airport	9.25e-06**	9.25e-06**	9.25e-06**
	(3.92e-06)	(3.92e-06)	(3.92e-06)
Distance to commercial centre	3.17e-06	3.17e-06	3.21e-06
	(4.32e-06)	(4.32e-06)	(4.32e-06)
Distance to church	3.83e-06	3.82e-06	3.71e-06
	(8.44e-06)	(8.44e-06)	(8.44e-06)
Distance to state school	-2.96e-06	-3.00e-06	-3.03e-06
	(1.21e-05)	(1.21e-05)	(1.21e-05)
Noise (within 500m of a highway)	-0.00590	-0.00579	-0.00609
	(0.00922)	(0.00923)	(0.00918)
Inside an industrial area	-0.0233*	-0.0233*	-0.0234*
	(0.0127)	(0.0127)	(0.0127)
% of population with higher education	0.297***	0.297***	0.297***
	(0.0197)	(0.0197)	(0.0197)
% of migrant population	-0.193***	-0.193***	-0.193***
	(0.0226)	(0.0226)	(0.0226)
Population density	-1.53e-06***	-1.53e-06***	-1.53e-06***
	(0.0963)	(0.0963)	(0.0963)
Year FE	Yes	Yes	Yes
OMI FE	Yes	Yes	Yes
Municipality-year FE	Yes	Yes	Yes
Observations	48,456	48,456	48,456
R-squared	0.785	0.785	0.785

Figure A3: Mafia intensity

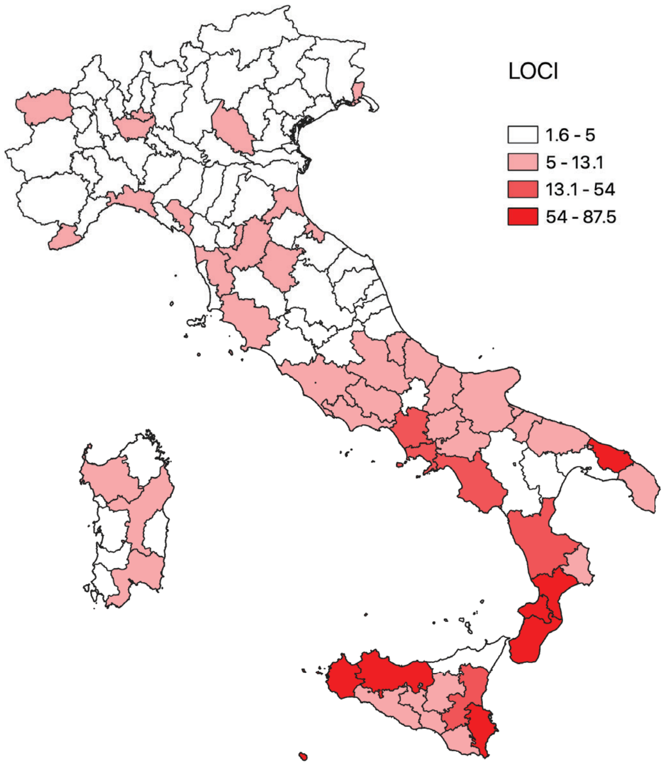


Figure A4: Physical constraints to residential development

(a) Land use (b) Land slope (c) Fragmentation

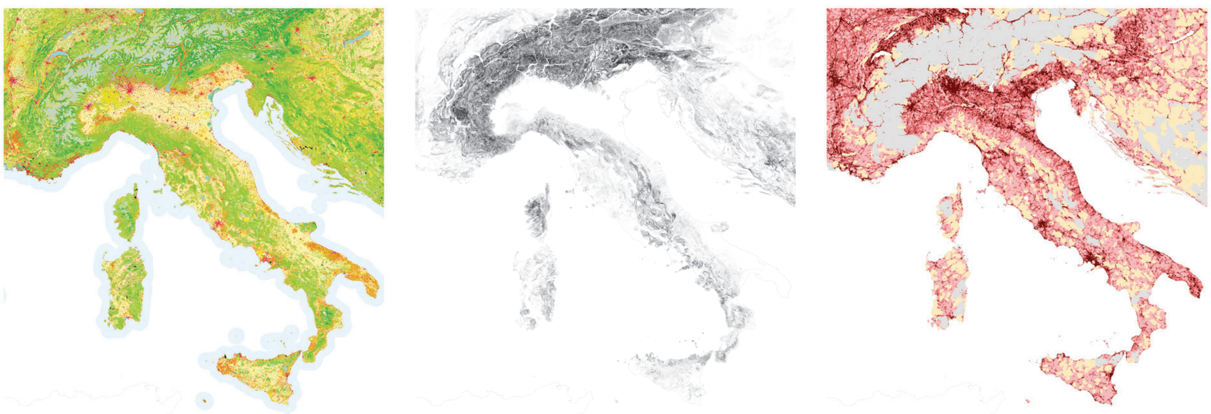


Table A9: Heterogeneity analysis by buffer distances

Dep. Variable: Log euro per m^2	Mafia intensity *low*	*high*	Local deprivation *low*	*high*	Physical constraints *low*	*high*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: buffer 250m						
Re-allocations	-0.00164	0.00126***	-0.00111	0.000769***	0.00107	0.000946***
	(0.00444)	(0.000244)	(0.00110)	(0.000183)	(0.00213)	(0.000273)
Placebo re-allocations	-0.000567	-2.08e-05	8.98e-05	0.000251	0.000559	-0.000364
	(0.00296)	(0.000314)	(0.00271)	(0.000225)	(0.00272)	(0.000342)
Confiscations	-0.00210	0.000690	0.000304	0.00140	-8.64e-05	0.000576
	(0.00496)	(0.000952)	(0.00108)	(0.00604)	(0.00135)	(0.00182)
Observations	32,961	14,889	10,675	20,377	24,189	24,068
R-squared	0.771	0.821	0.785	0.768	0.765	0.795
Panel B: buffer 500m						
Re-allocations	-0.00212	0.000628**	-0.000129	0.000116	0.00151	0.000312
	(0.00335)	(0.000278)	(0.000972)	(0.000186)	(0.00124)	(0.000270)
Placebo re-allocations	-0.00152	-0.000052	0.000311	-0.000386	0.000564	-0.000591
	(0.00158)	(0.000270)	(0.00153)	(0.000431)	(0.00119)	(0.000322)
Confiscations	-0.00150	-0.000671	-0.00176	-0.000841	-0.000946	-0.000313
	(0.00168)	(0.000773)	(0.00118)	(0.00183)	(0.000878)	(0.00133)
Observations	32,961	14,889	10,675	20,377	24,189	24,068
R-squared	0.770	0.821	0.782	0.747	0.774	0.795
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
OMI FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-year FE	Yes	Yes	Yes	Yes	Yes	Yes

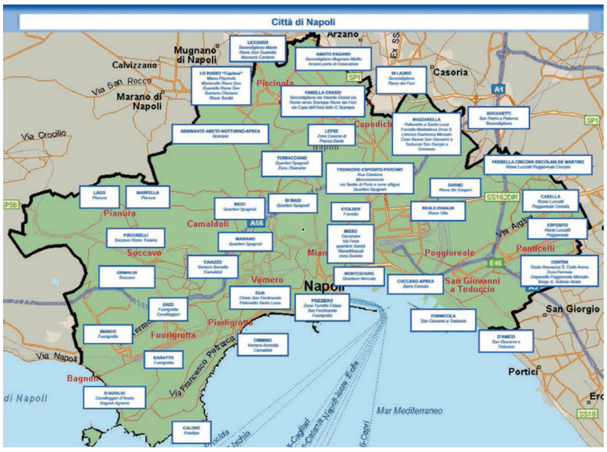
Notes. Clustered standard errors at the OMI level in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance. Dependent variable: price recorded for each sale point i in year t. Re-allocations: number of re-allocated assets up to 4 years before the transaction within buffer zone. Placebo re-allocations: number of re-allocated assets taking place up to 2 years after the transaction within buffer zone. Confiscations: number of confiscated assets events taking place up to 4 years before the transaction within buffer zone. Columns (1)-(2) report the effect of property re-allocation in the cities reporting below- and above-median scores of the Mafia Intensity index described in section 5.3. Column (3)-(4) report the effect of property re-allocation in the OMI areas characterised by hlow and high deprivation (respectively below the 1st and above the 3rd quartile of the deprivation index). Columns (5)-(6) report the effect of property re-allocation in the OMI areas characterised by below- and above-median housing supply elasticity, as proxied by the first principal component of land consumption, land slope, fraction of surface covered by water bodies, and land fragmentation. All specifications include Structural controls, Building controls, Amenity controls, Socio-economic controls, OMI fixed effects, municipality-year fixed effects.

D Re-allocations and organised crime activity

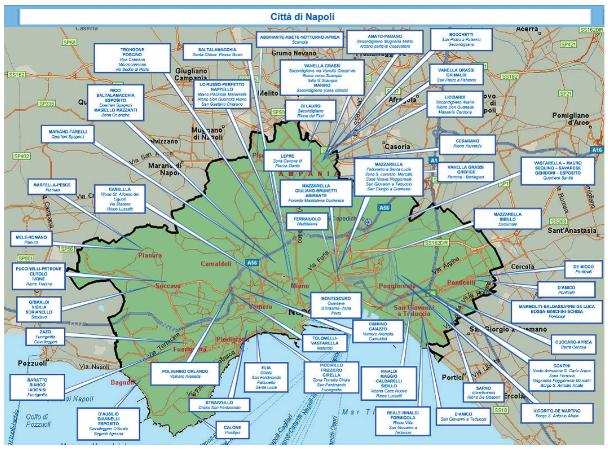
Figures A5a and A5b are retrieved from DIA reports shows the spatial distribution of mafia families in Naples in 2013 and 2018. Figure A5c shows the Naples road network and the buffer constructed within 100m from both side of each road.

Figure A5: Mafia families in Naples, Anti-Mafia Directorate (DIA) reports

(a) Mafia families in Naples, 2013



(b) Mafia families in Naples, 2018



(c) Street-level dataset

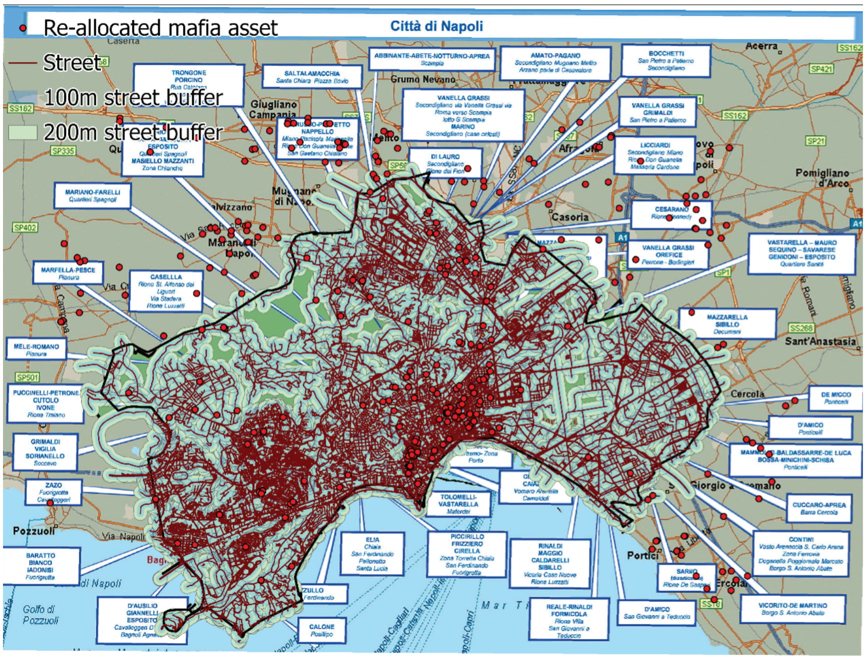
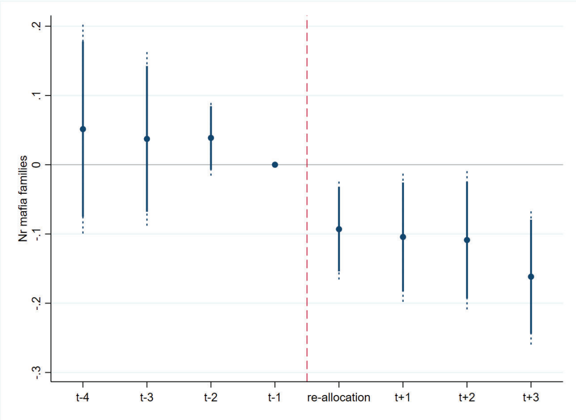
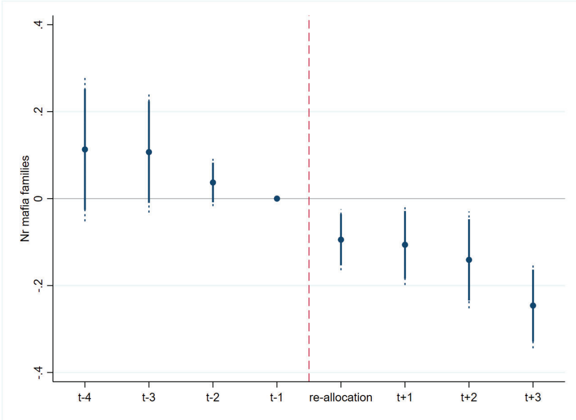


Figure A6: Event Study - re-allocation and mafia families

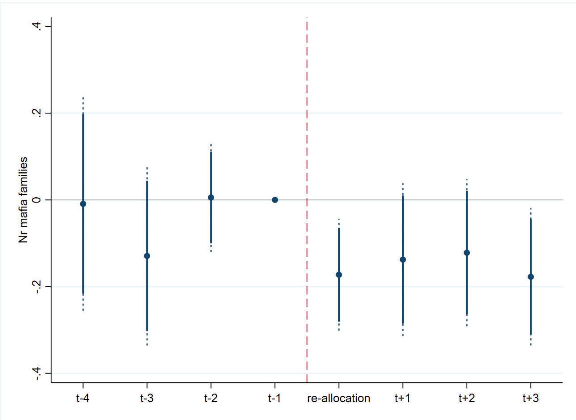
(a) TWFE



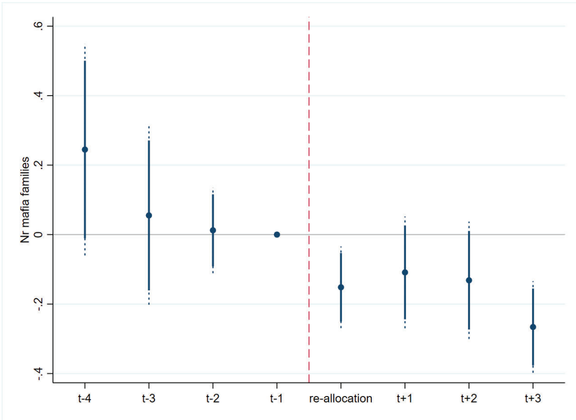
(b) Sun and Abraham (2021)



(c) TWFE >1 asset



(d) Sun and Abraham (2021) >1 asset



The figure shows the event study using nr of *Camorra* families in Naples' streets as dependent variable. Continuous lines refer to 90% confidence intervals, dotted lines refer to 95% confidence intervals. Figures (a), (b): full sample. Figures (c), (d): streets with single re-allocation cases excluded from sample.

Table A10: Street-level analysis, mafia change of power and mafia dummy

	100m buffer		200m buffer	
	(1)	(2)	(3)	(4)
Panel A: Dep. var.: mafia change of power				
Re-allocation	0.0450***	0.0309**	0.0496***	0.0644***
	(0.0139)	(0.0123)	(0.00856)	(0.00700)
Observations	61,230	61,225	61,230	61,225
R-squared	0.532	0.807	0.533	0.807
Panel B: Dep. var.: mafia dummy				
Re-allocation	-0.0134	-0.00784	-0.0275***	-0.0180***
	(0.00818)	(0.00795)	(0.00494)	(0.00469)
Observations	73,476	73,470	73,476	73,470
R-squared	0.878	0.951	0.878	0.951
Confiscations	Yes	Yes	Yes	Yes
Roads FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
OMI-year FE		Yes		Yes

Notes. The table reports the estimation results for linear probability models. Panel A: the dependent variable is the change in the composition of mafia families controlling street s in year t; Panel B: the dependent variable is a dummy equal to 1 if mafia activity is recorded in the street. The sample covers all Naples roads. Robust standard errors are clustered at the OMI level and reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.