Localised Effects of Confiscated and 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 the confiscation of real estate assets from individuals convicted of mafia-related crimes. These assets are then re-allocated to new uses. The policy of confiscation (*confisca*) and re-allocation (*destinazione*) 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 affects local areas, by estimating its impact on the value of buildings in the vicinity of confiscations and re-allocations. The results unveil a negative effect of confiscations and a positive effect of re-allocations on house prices. Both these effects are observable in the periods that immediately follow confiscations and reallocation cases, and appear to be highly localised. Part of the increase in property values induced by re-allocations could be driven by a decrease in organised crime activity in the streets where re-allocations have taken place. These findings have implications for the effectiveness of anti-mafia policies aiming to improve the quality of neighbourhoods where criminal presence is more pronounced.

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JEL classification: K42, R32, H23.

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1 Introduction

In an effort to tackle organised crime, the Italian State implements a nation-wide policy stipulating the confiscation of real estate properties for individuals convicted of mafia-related crimes. Similar confiscation regimes are present throughout Europe, as a way to prevent crime perpetrators from benefiting from their crimes (Boucht, 2019). Such policies can influence local communities in several connected ways. Confiscations are intended to harm organised crime businesses and can send signals of criminal activity to local residents. A key feature of the Italian policy is to allow for the conversion of confiscated assets into public amenities by means of 're-allocations', in order to contribute to the revitalisation of local economies. Notably, most assets are transformed into local amenities such as centres for disadvantaged groups, police stations, or green spaces. In essence, the confiscation (*confisca*) and re-allocation (*destinazione*) policy is meant to act as both a deterrence measure and a way to compensate local communities, through the redistribution of former mafia assets and the provision of opportunities in neighbourhoods plagued by criminal activities.

While some descriptive and anecdotal evidence exists on the use and application of the policy (Camera dei Deputati, 2019; European Commission, 2014; Falcone et al., 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, not been explored by the academic literature.

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

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 35,000 confiscated and over 16,000 re-allocated properties in Italy and investigate their spillover effects. Exploiting information on over 50,000 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 confiscations and 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. We compare our estimates with a naive model estimated at the level of homogeneous local

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

housing markets across Italy.

Our findings reveal a relatively small negative external effect of confiscation and an equally small positive effect of re-allocation on neighbouring properties, both temporary and highly localised. We find that the confiscation of mafia assets and their conversion into new amenities modify local property values in the first years immediately following confiscation or re-allocation events, but disappear in the medium/long term. Our results also indicate that a clustered and coinciding set of re-allocations produces a sizeable positive effect on surrounding buildings.

While the depressing effect of confiscation on house prices is visible in different urban contexts across Italy, the re-allocation policy is found to be particularly effective in increasing the value of housing in cities where mafia organisations are historically rooted. This suggests that a reduction in the disamenities associated with the presence of criminal organisations could significantly contribute to the regeneration of neighbourhood plagued by mafia activities.

While we are not aware of empirical evidence assessing the external effects of confiscations of mafia assets, this paper adds to the growing studies on the impact of organised crime (e.g. Acemoglu et al., 2013; Barone and Narciso, 2015; Pinotti, 2015; Buonanno et al., 2016; De Feo and De Luca, 2017; Ganau and Rodríguez-Pose, 2018; Alesina et al., 2019; Di Cataldo and Mastrorocco, 2021; Le Moglie and Sorrenti, 2022;). 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.[2].

The paper also contributes to the literature on localised urban renewal policies. The evidence produced by previous studies assessing the external effects of regeneration policies on property prices is mixed. While some works reveal that localised investments to revitalise urban areas are capitalised into higher local house prices (Santiago et al., 2001; Schwartz et al., 2006; Rossi-Hansberg et al., 2010; Ooi and Le, 2013; Koster and Van Ommeren, 2019), others find they have no effect (P. Lee and Murie, 1999; Ahlfeldt et al., 2017). It is worth noticing that almost all these studies focus on specific neighbourhoods of single cities where the programme has been implemented.[3] 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.

A number of channels may be driving the uncovered effects. Confiscations can be viewed as disamenities, while re-allocations involve the creation of new amenities, directly affecting property prices (Gibbons, 2004; Gibbons and Machin, 2008; Gibbons et al., 2014). Another possibility is that house prices are influenced by the variation in housing supply (Glaeser et al., 2005; Caldera and Johansson, 2013). However, the fact that the stronger im-

[2]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 (Acconcia et al., 2014; Daniele & Geys, 2015; Fenizia & Saggio, 2020; Galletta, 2017)

[3]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.

pact 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 the level of violence and crime, whose reduction increases property prices (Linden and Rockoff, 2008; Ihlanfeldt and Mayock, 2010). In order to test for this possibility, we have estimated the impact of the policy on criminal activity, focusing on the city of Naples. We show that the number of active mafia families within Neapolitan streets significantly reduces after re-allocation episodes, suggesting that re-allocations can have a negative impact on the intensity of crime activities.

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.

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

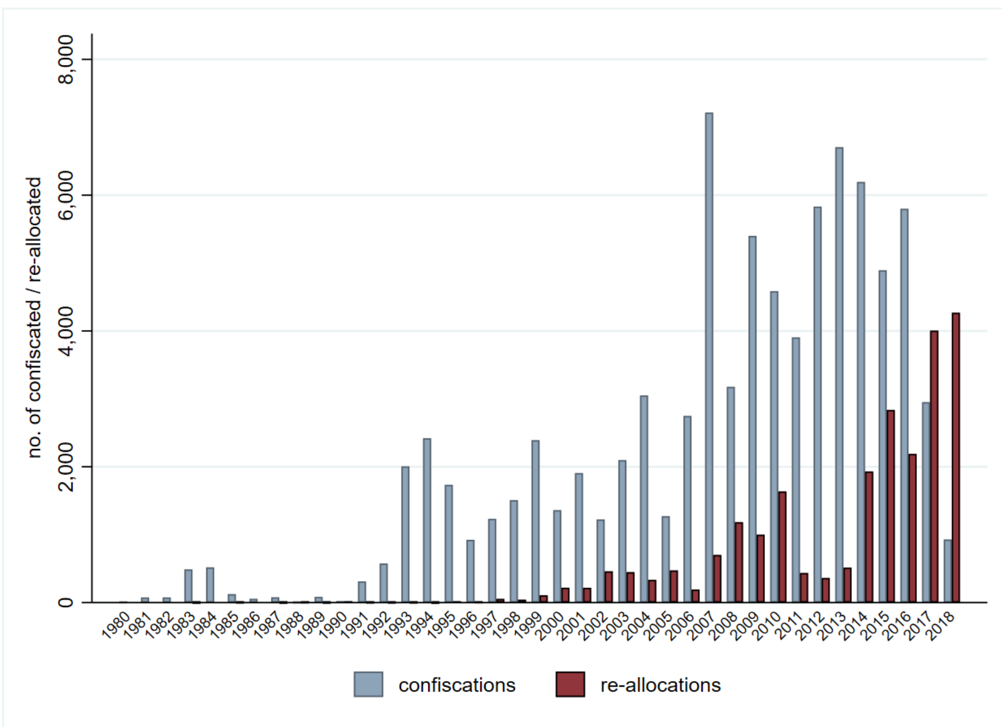
2.1 The 'Rognoni-La Torre' law

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. Any individual condemned with article 416-bis would immediately have their assets confiscated (for more details on 'Rognoni-La Torre' law and confiscation process see section A of the Appendix).

Figure 1 reports the number of confiscations from 1980 until 2018, as registered in the database elaborated by the National Authority for Mafia-Confiscated Assets (hereafter ANBSC). As we can see, confiscations started increasing in the early 1990s, following a set of deadly terrorist attacks operated by the Sicilian mafia.[4]

A fundamental step in the management procedure of confiscated 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 shown 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: Confiscated and re-allocated real estate assets by year



The approval of the 1996 law on re-allocation was the result of lobbying activity from the

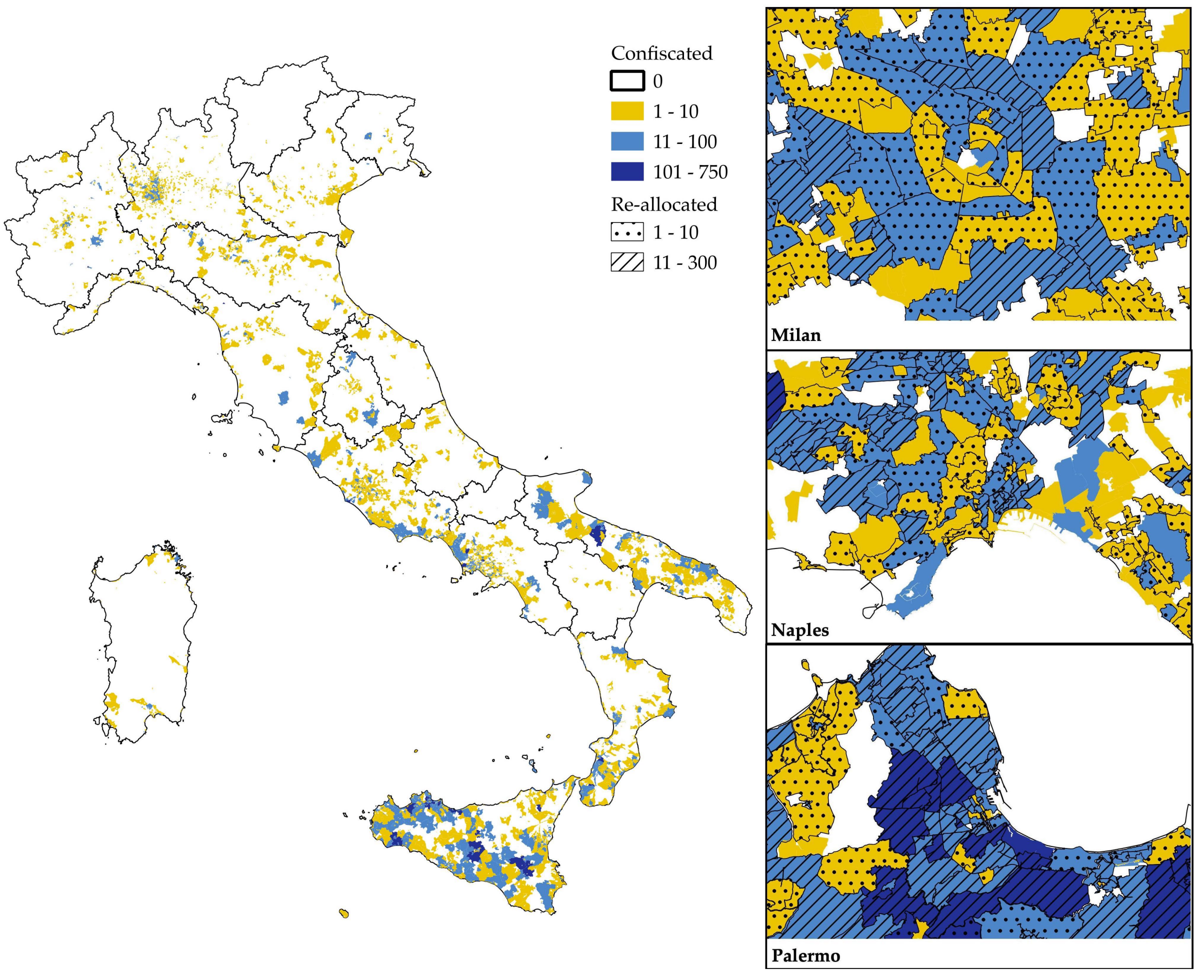
[4]The decrease in confiscations visible in 2018 is due to the fact that not all assets confiscated in the last few years have to date been included in the digital system of the ANBSC.

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. As discussed in more detail in section A of the Appendix, 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. 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 et al., 2016).

Figure 2 illustrates the geographical location of confiscated and 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.

The average time of re-allocations has been of over 8 years from the confiscation of assets,

Figure 2: Confiscations and Re-allocations in Italy



with no significant patterns correlating the length of the re-allocation procedure with the characteristics of local areas, or the type of real estate asset being assigned to a new use, once time-invariant characteristics of local neighbourhoods are accounted for. We do find some evidence of a correlation between the length of the process and the characteristics of the local administration, or different average speeds of re-allocation of different courts across the country. All this is controlled for in the analysis (more details in Appendix B).

3 Data

Our empirical analysis relies on a novel dataset constructed from a wide range of sources. First, data on confiscated and on re-allocated real estate assets were confidentially shared by the National Authority for Mafia-Confiscated Assets (ANBSC). This dataset includes detailed information on all confiscated assets (*confische*) across Italy, both those already re-allocated and those not yet re-allocated, included in the ANBSC managing system, with their exact address, date of confiscation, local court imposing the confiscation and type of asset. The dataset also includes all re-allocated assets (*destinazioni*) across Italy, with their date of confiscation and re-allocation, exact address, type of asset, type of re-allocation, local court responsible for completing the procedure, administrative entity responsible for managing the asset. Of these properties, a relatively small portion is sold on the housing market (1,423, or 4.3%) or demolished (14). These assets are dropped from our sample, given our goal is to assess the impact of confiscations and of the conversion of assets through re-allocation. We also drop terrains from sample. We are left with 30,758 not yet re-allocated and 21,554 re-allocated assets. 13,176 were confiscated and 10,004 were re-allocated in the 55 Italian cities used in the analysis, of which 8,012 confiscated and 5,471 re-allocated during the 2011-2018 sample period.

Second, the 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,[5] with homoge-

[5]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,

neous coverage of the website across different cities as shown in Figure D1. The dataset provides 'asking prices' that we use as proxies for actual transaction prices.[6] The files have been compiled, cleaned and checked for duplicates through the website unique identifier for each advertisement.[7] 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. Loberto et al. (2018) focus on the comparison between *Immobiliare.it* data and OMI data (see Appendix C), showing that the *Immobiliare.it* data provides an appropriate picture of the Italian housing market, consistent with official sources.

The *Immobiliare.it* dataset includes a wide range of structural attributes of sold buildings, including floor space in squared metres, building height, type of property (studio, apartment, house, villa), number of bedrooms and bathrooms, floor, date of construction, garage or parking facility, and type of heating and energy consumption.

We complement our dataset with a list of variables collected from 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, which we can associate to each sold building. These include a series of indicators for the presence of amenities (in the pre-sample period), 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 D2). Finally, data on labour market, education, real

Palermo, Parma, Perugia, Pesaro, Pescara, Pordenone, Potenza, Prato, Reggio Calabria, Rome, Salerno, Sassari, Savona, Taranto, Teramo, Terni, Turin, Trento, Trieste, Udine, Venice, Verona, Viterbo.

[6] Loberto et al. (2018) calculate a 12% discount between *Immobiliare.it* sale-adverts and OMI-data.

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

estate quality, and demographic characteristics from the 2011 Italian Census were obtained from the Italian Institute of Statistics (ISTAT).

Descriptive statistics of all variables are reported in Appendix D.

4 Empirical Strategy

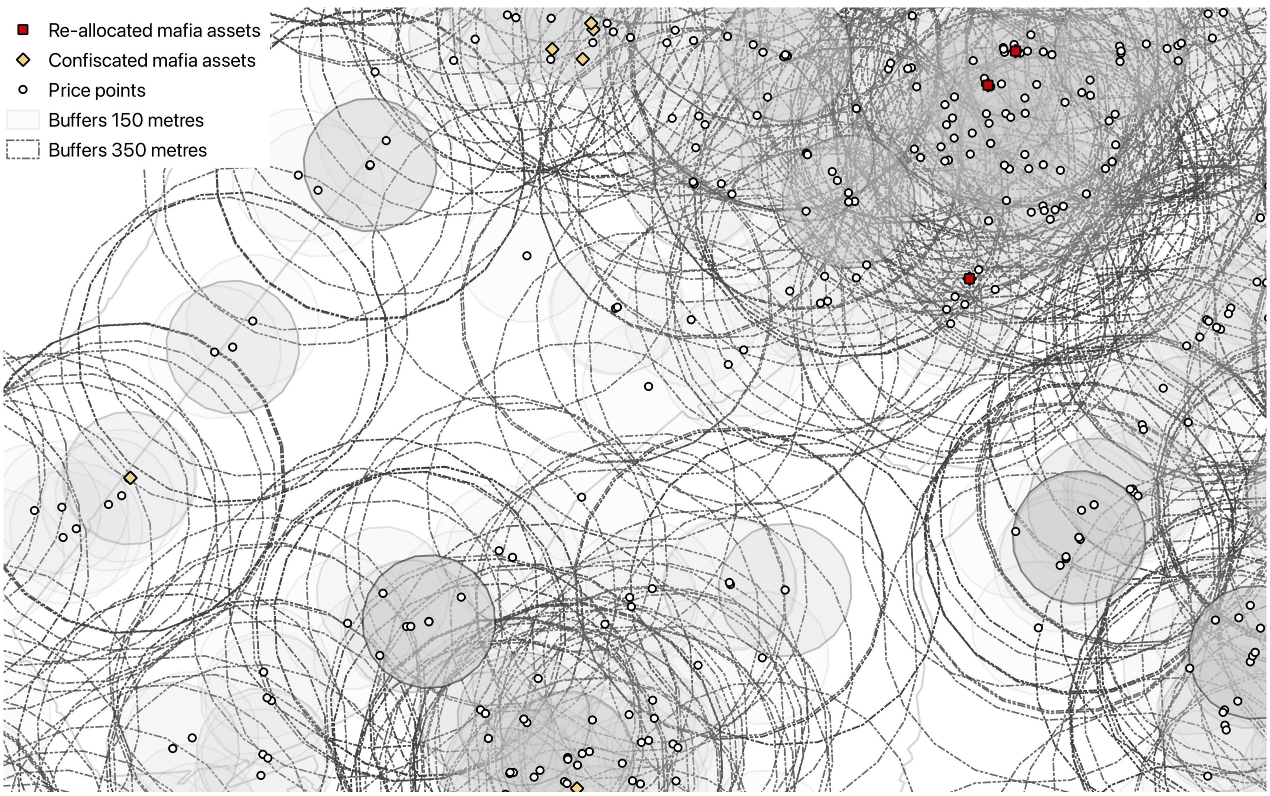
Our main analysis is performed as a comparison of sale points located *within* the same homogeneous micro-aggregated local housing market (OMI) defined by the Italian Revenue Agency. For each OMI area, we have compiled information on their average housing value over time, which we use for preliminary estimates performed at that level (this dataset and related estimates are described in Appendix C).

We estimate 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 Baseline model

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. 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 et al., 2017), our first assumption lies in expecting a very localised effect of confiscated assets on surrounding real estates.

Figure 3: Buffer zones around sold buildings



We begin by drawing perimeters up to 500m radii around each sold building. These buffers roughly correspond to an average 5 minutes walking distance from buildings, spatially translating the expected local effect (EVstudio, 2019; Gibbons & Machin, 2008). Given the punctuality of the policy, we expect externalities to be very localised.[8] Figure 3 provides an illustration of our approach. All sale points with no assets in their 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.

[8]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 et al., 2010; Ahlfeldt et al., 2017).

We expect that sales occurring *after* confiscations or re-allocations may be affected, while sales occurring *before* confiscations or re-allocations 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 confiscation(s)/re-allocation(s) with that of properties located at a given distance from confiscated or re-allocated assets. The analysis is performed within homogeneous local housing markets (OMI).

By utilising details on the sale date of each property and the timing of the confiscation/re-allocation, we can determine the effect of the policy on the prices of properties located near confiscations/re-allocations. This method allows us a highly accurate focus on the neighbourhood of the confiscated asset, identifying the treatment area with precision. To compute the external impact of the confiscated and the re-allocated real estate assets we estimate the following hedonic pricing model:

$$\ln p_{ijmt} = \beta_1 C_{i,t+n}(d) + \beta_2 R_{i,t+n}(d) + \rho X_i + \delta_j + \theta_{mt} + \varepsilon_{ijmt} \quad (1)$$

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. The two treatment indicators are $C_{i,t-n}$ and $R_{i,t-n}$. $C_{i,t-n}$ is defined as the number of buildings confiscated within radius d from building i in year $t+n$ (n=1,2,3) before it was sold. Similarly, $R_{i,t+n}$ is the number of buildings re-allocated within distance d from sale point i in year $t+n$ after the re-allocation. The treatment variables capture the intensive margin effect of confiscations and of re-allocations on house prices of neighbouring buildings, a given period after the confiscations or the re-allocations.

X_i is a vector of structural and amenity controls of property i, the latter which were constructed from multiple geographical datasets for 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. Local time-invariant factors, time-varying municipal characteristics, and year-of-sale-specific shocks are accounted for by adopting OMI zone (δ_j) and municipality-year (θ_{mt}) fixed effects. The model is estimated for the 2011-2018 period, for every distance d = 100, 150, 200, 250, 300, 350, 400, 450, 500 from sold assets. Standard errors are clustered at the OMI zone level so to correct for the presence of spatial auto-correlation. This research design allows to separate the effect of the policy on property values from correlated location effects (Koster et al., 2012; Noonan and Krupka, 2011).

We also study the timing of the policy effect by distinguishing between buildings sold before and buildings sold after the confiscation(s) and re-allocation(s) events. We compute the number of events for each sold building and each year before and after the sale, and estimate the following model:

$$\ln p_{ijmt} = \sum_{\tau=1}^{q} \varphi_{-\tau} C_{i,t-\tau} + \sum_{\tau=1}^{q} \varphi_{+\tau} C_{i,t+\tau} + \sum_{\tau=1}^{q} \gamma_{-\tau} R_{i,t-\tau} + \sum_{\tau=1}^{q} \gamma_{+\tau} R_{i,t+\tau} + \rho X_i + \delta_j + \theta_{mt} + \varepsilon_{ijmt} \tag{2}$$

where $C_{i,t+n}$ and $R_{i,t+n}$ refer to confiscations and re-allocations that took place before the sale of building i, similar to those in equation 4.1 but disaggregated by year, while $C_{i,t-n}$ and $R_{i,t-n}$ allow to examine the value of real estates for each year prior to confiscations and re-allocation events.

4.2 Estimation issues

In order to correctly identify the effect of confiscated/re-allocated assets 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 confiscated assets. In this sense, Appendix Figure A1a 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 A2 shows some evidence that the duration of the re-allocation procedure may vary depending on the political colour of the local government administrating the municipality where the asset is located.

In order to deal with these issues, we include a number of controls in our models. To start with, we always include municipality-times-year and 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). Thanks to this approach, our baseline model absorbs all the variation across municipalities and time-invariant OMI-level unobservables. Nevertheless, it might still be the case that confiscation and re-allocations are not randomly distributed across space. For instance, a judge might choose to speed-up the confiscation/re-allocation process for assets localised in strategic areas.

In Tables B1, B2, and B3, we exploit data retrieved from the 2011 Italian Census to test the balancing properties of our setting. In panel A, Table B1, we analyse the relationship between the time required to confiscate an asset and local characteristics.[9] In panel B, we focus on the length of the re-allocation procedure, i.e. the time between confiscation and re-allocation. In Tables B2 and B3, our main treatment variables - the number of confiscated assets or the number of re-allocated assets within short distance from sale points - are regressed on a set of Census characteristics aggregated at the buffer-level (150 metres or 350 metres). All these estimates are performed with and without the inclusion of OMI fixed effects. In all these tests, once OMI fixed effects are included, we find no significant correlation between local characteristics and the timing of the policy, and (with just one exception) no significant relationship between the number of confiscation/re-allocations and local characteristics.

[9] The dependent variable is the number of years between the confiscation of the first asset to a mafia family (defined on the basis of the surname of the convicted members) and each subsequent confiscation. This variable can be considered a good proxy for the time between conviction and confiscation.

Overall, these exercises confirm the homogeneity of OMI areas. In addition, we choose to include a set of controls in our hedonic models for census area characteristics (Table E1), further minimising any potential confounder within OMI. Moreover, the specifications account for generalised shocks in housing markets, as well as for any municipality-specific characteristics varying over time with municipality-year interacted fixed effects. The latter control also accounts 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 being implemented in two steps: first the confiscation, and then the re-allocation. Having accurate information on each confiscated and each re-allocated asset over time allows us to correctly and precisely determine the number of confiscated and re-allocated assets, and re-construct the exact timing of the policy events prior to/after the sale of each neighbouring building. Using this information, we can estimate event study-like models testing for significant differences in house prices in the immediate surroundings of areas where confiscations and re-allocations will take place. All our specifications include variables referring to both steps of the policy in the model, thus accounting for both. The two-steps treatment may give rise to one additional concern, namely the fact that the policy 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, where the probability of any labour/firm relocation is unlikely to be more concentrated than in the outer ring.

5 Results

Table 1 reports the results of the hedonic analysis conducted at the sale point level using four distance thresholds around sale points: 150 metres, 250 metres, 350 metres, and 450 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 E1 of the Appendix.

The specifications include the two cumulative treatment proxies. 'Confiscations' and 'Re-allocations' correspond to the sum of neighbouring assets confiscated / re-allocated over a 3-year period before the sale of each property at the stated distance. The estimates report a negative significant coefficient of confiscations and a positive significant coefficient of re-allocations, both reducing in magnitude (in absolute value) with distance from the sold property. Column 1 shows that each confiscated asset converts into a decrease in neighbouring properties' value of up to 0.7% per asset, for confiscations occurring within 150 metres of sold buildings. Conversely, for each additional re-allocated asset, the price of surrounding properties increases by up to 0.5% per asset, for re-allocations taking place within 150 metres of sold buildings. This indicates the presence of significant externalities deriving from the application of the anti-mafia policy. We also conducted the analysis at the OMI level, discussed in Appendix C, using aggregate units of observation. However, this approach does not allow to detect any clear policy impact on house prices, possibly because the effect is highly spatially confined.

Table 1: Sale point analysis by distance

Dep. variable: Log euro per m^2	Buffer radius: 150 metres (1)	250 metres (2)	350 metres (3)	450 metres (4)
Confiscations	-0.00703***	-0.00289**	-0.00223**	-0.00219***
	(0.00226)	(0.00129)	(0.00101)	(0.000766)
Re-allocations	0.00515**	0.00350**	0.00221***	0.000702
	(0.00227)	(0.00170)	(0.000658)	(0.000836)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
OMI FE	Yes	Yes	Yes	Yes
Municipality-year FE	Yes	Yes	Yes	Yes
Observations	50,485	50,485	50,485	50,485
R-squared	0.786	0.786	0.786	0.786

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered at OMI level in parenthesis. Dependent variable: price recorded for each sale point i in year t. Re-allocations: nr of re-allocations up to 3 years before the sale of the building, within buffer zone. Confiscations: nr of confiscations up to 3 years before the sale of the building, within buffer zone. Column (1): buffer 150m around sold property; column (2) buffer 250m; column (3): buffer 350m; column (4): buffer 450m. Controls: sale property, amenity, socio-economic characteristics.

In order to better illustrate the distance decay of the policy, in Figure 4 we combine the estimated coefficients of confiscations and re-allocations from 150 to 500 metres, with relative 90% confidence intervals, for models estimated with the full set of controls and fixed effects. Figures 4a and 4b allow us to appreciate the spatial decay characterising the cumulative treatments. As seen in Figure 4a, at shorter distances from confiscations the coefficients are more negative, while they become progressively less negative moving away from the asset. Similarly, moving away from the re-allocated assets, the positive coefficients decrease in magnitude (Figure 4b). The declining coefficients suggest a rapid spatial decay of the policy effect, with the transactions localised further than 400m away from the asset looking mostly unaffected.

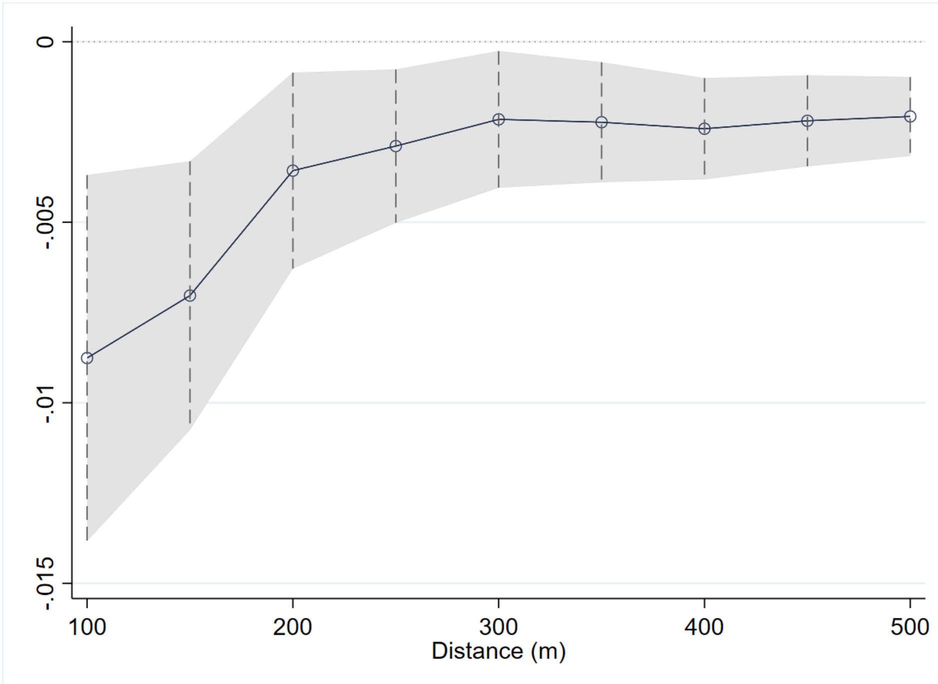
While the coefficient of confiscation remains marginally significant at 500 metres, this does not imply that the effect of confiscated assets reaches that distance. The statistical significance of the effect at very small distances is quite strong, making the coefficient still significant at 500 metres in within-OMI estimates with few controls. If, however, the model is estimated using sale point comparisons within municipalities, excluding OMI fixed effects, the control group becomes much larger and the estimated coefficient of confiscations is only significant up to 200 metres (Appendix Figure E1).[10]

The magnitude of coefficients is higher when considering a smaller buffer distance, consistent with the fact that, the closer the confiscations or the re-allocations, the larger are the effects. The fact that the impact materialise within such a short distance from confiscated and re-allocated assets reduces endogeneity concerns, possibly due to the presence of time-varying confounding dynamics at the OMI level. The likelihood that these dynamics are stronger at such a short distance from the treatment sites than in the rest of the OMI area is very low.

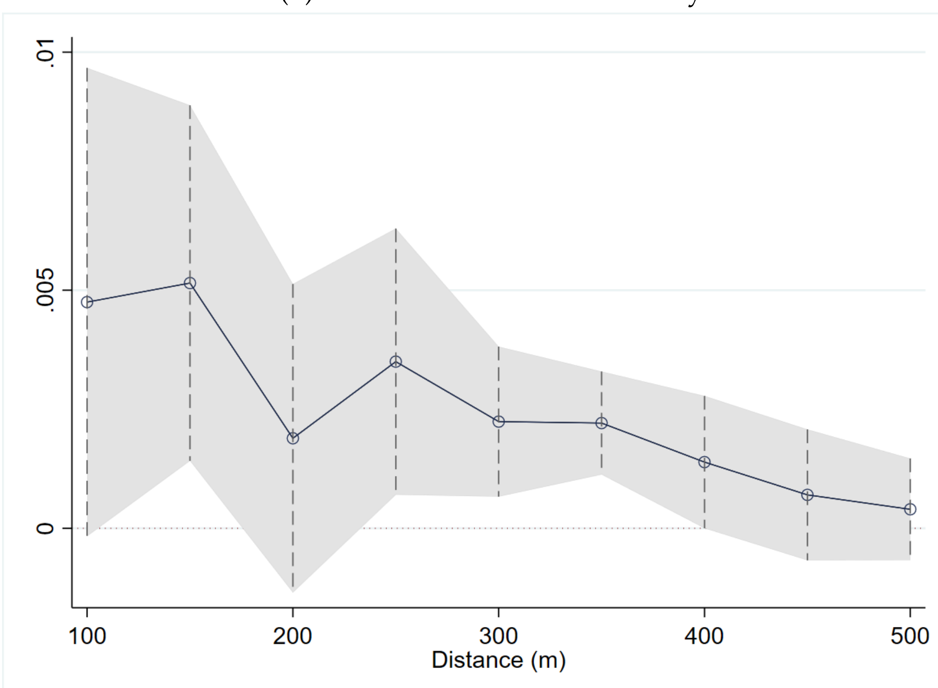
[10] As an alternative estimation method, rather than using buffers we have estimated the baseline model - with OMI and municipality-year fixed effects, and controls - adopting rings around confiscations/re-allocations. Figure E2 reports the result of estimates including a set of variables referring to the number of confiscations/re-allocations up to three years before sales at 0 to 100 metres, 100 to 400 metres, 400 to 700 metres, and 700 to 1000 metres from confiscations/re-allocations. It confirms that the negative effect of confiscations and the positive effect of re-allocations converges to zero at higher distances from the policy events.

Figure 4: Distance decay effect

(a) Confiscation - distance decay



(b) Re-allocation - distance decay



Coefficients of a model estimating differences in house price for buildings located within 150-500m of confiscations/re-allocations and sold up 3 years after confiscations/re-allocations. Dashed lines around point estimates refer to 90% CIs. Treatment variable: number of confiscated/re-allocation assets within buffer.

5.1 Timing of the policy impact

If the policy has an effect on house prices, we should expect only post-confiscation and post-re-allocation sales to be affected, while all sales occurred *before* the application of the policy should not be impacted. To verify this, we estimate model 4.1, exploring the timing of the policy impact by including a set of variables referring to the number of confiscated and re-allocated assets each year before and after the sale of each property. We report the estimated effect on sold buildings in the period surrounding the confiscation/re-allocation events, four years prior and three years after those events.

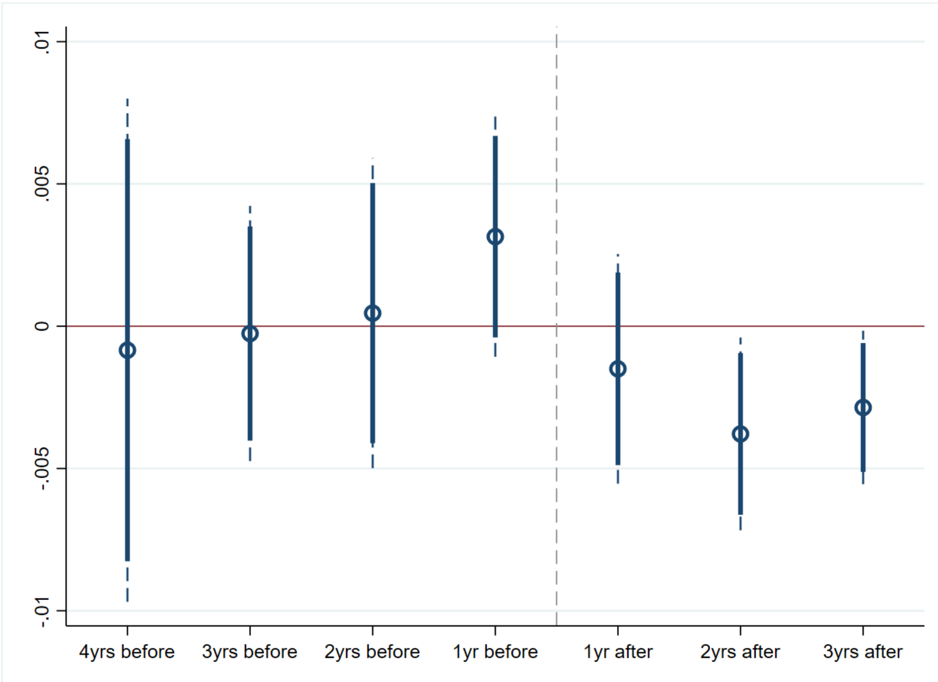
The results for 350 metres buffer are summarised in Figure 5, while the results for a 250 metres buffer are in Figure E3. Crucially, they show that all year-specific variables referring to sales preceding confiscations and re-allocations return insignificant coefficients, as one would expect if the policy displays no anticipatory effects.

Looking at the effect of confiscations in Figures 5a and E3a, we note a significant decrease in the value of nearby buildings from the second year after confiscation events. Figure 5b and E3b, illustrate the effect of re-allocations, showing a positive jump in house prices materialising in the immediate aftermath of operative re-allocations, i.e. in the first year following the re-allocation events.

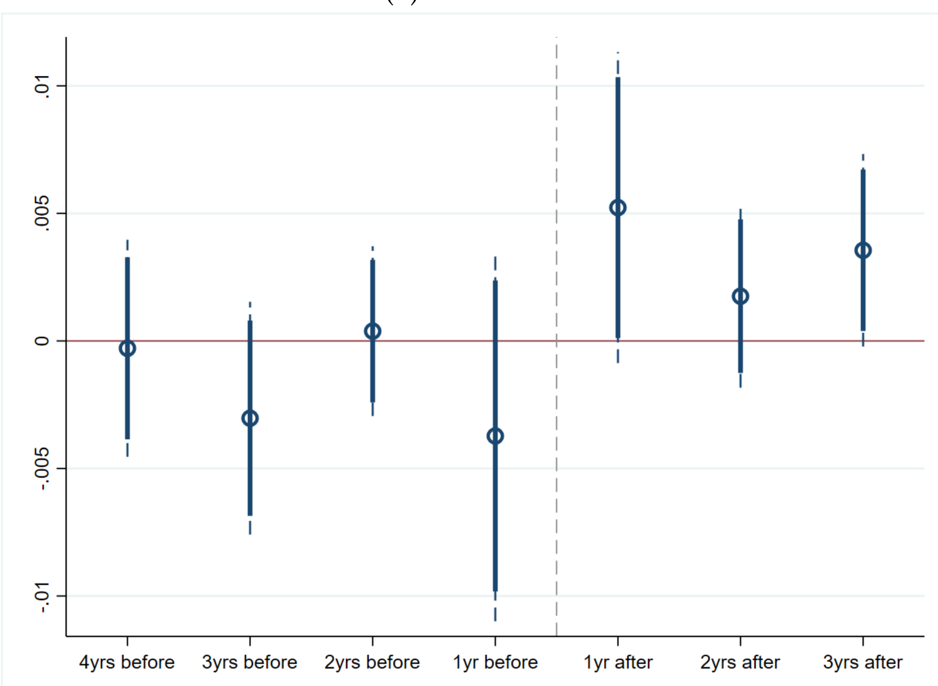
So far, the analysis has focused on the relationship between the number of assets confiscated/re-allocated in the neighbourhood and housing prices. This approach does not allow us to distinguish between extensive-margin treatment - the occurrence of a single confiscation/re-allocation event, regardless of the number of properties involved - and intensive-margin

Figure 5: House values before/after confiscations and re-allocations (350m)

(a) Confiscation



(b) Re-allocation



Coefficients of a model estimating year-by-year differences in house price for buildings located within 350m of confiscations/re-allocations and sold up to 4 years before and 3 years after confiscations/re-allocations. Continuous (dashed) lines around point estimates refer to 90% (95%) CIs. Treatment variable: number of confiscated/re-allocation assets within buffer.

treatment. To test if the results are exclusively driven by the extensive-margin treatment, we replicate the year-by-year analysis using dummy variables for confiscations/re-allocations by each period before and after the policy application, rather than using a count measure of confiscated/re-allocated buildings. The results for 250 and 350 metres buffers are displayed in Figure E4. While the impact of confiscation and re-allocation seems visible at 250 metres, all post-re-allocation coefficients are insignificant at 350 metres (Figure E4d), consistent with the idea that, at that distance, a larger number of assets is needed in order to induce an increase in the value of neighbouring buildings.

Next, we test for an effect of confiscation/re-allocations in the medium/long-term, looking at their impact on house prices up to 9 years after the policy event(s). The results in Figure E5 show that the variation in house prices induced by the policy is short-lived. Buildings sold 4 to 9 years after the event do not display any significant difference in house prices. The short duration of the recorded effects may be ascribed to different factors, including the rapid adjustment of local housing markets, made possible by the substantial number of unoccupied properties in Italian cities, or the post-policy decisions taken by local administrators in the medium-term, in terms of allocation of resources and local services.

5.2 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. 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 confiscations and re-allocations have occurred.

While organised crime activities are currently spread throughout Italy (and beyond), mafia regional strongholds are well known.[11] A possibility is that the policy is more effective where criminal organisations are more rooted and re-allocated assets 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),[12] 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.[13] Figure E6 in the Appendix illustrates the spatial distribution of the mafia intensity index.

For ease of interpretation, we construct a dummy that distinguishes between high and low mafia intensity at province level on the basis of the median value of the mafia intensity indicator. We interact this dummy with our treatment indicators in the baseline model. The results of the model are shown in Table 2. While signs of the negative effect of confiscation on house prices are visible in both more mafia-intensive and less mafia-

[11]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.

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

[13]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 2: Confiscations and re-allocation in mafia-intensive areas

Dep. variable: Log euro per m2	(1) 150m	(2) 250m	(3) 350m	(4) 450m
Low mafia intensity × Confiscations	-0.0183**	-0.00807	-0.00613	-0.0101*
	(0.00854)	(0.0104)	(0.00664)	(0.00521)
High mafia intensity × Confiscations	-0.00692***	-0.00273**	-0.00234**	-0.00202**
	(0.00224)	(0.00127)	(0.00106)	(0.000793)
Low mafia intensity × Re-allocations	0.0363	-0.0167	-0.0183	-0.0253
	(0.0226)	(0.0347)	(0.0266)	(0.0183)
High mafia intensity × Re-allocations	0.00388	0.00374**	0.00237***	0.000865
	(0.00238)	(0.00168)	(0.000750)	(0.000922)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
OMI FE	Yes	Yes	Yes	Yes
Municipality-year FE	Yes	Yes	Yes	Yes
Observations	50,350	50,350	50,350	50,350
R-squared	0.786	0.786	0.786	0.786

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered at OMI level in parenthesis. Dependent variable: price recorded for each sale point i in year t. Re-allocations: number of re-allocated assets up to 3 years before the transaction within buffer. Confiscations: number of confiscated assets events taking place up to 3 years before the transaction within buffer. Mafia intensity is a binary dummy variable, distinguishing cities with high mafia intensity (1) from those with low mafia intensity (0) at the at the median of Bernardo et al. (2021)'s index as described in section 5.2. Low Mafia intensity indicates areas with below-media scores. High mafia intensity indicates areas with above-median scores. All specifications include: Structural controls, Building controls, Amenity controls, Socio-economic controls, OMI fixed effects, municipality-year fixed effects.

intensive areas, the positive effect of re-allocations on house prices appears to be driven particularly by re-allocations in areas of higher mafia activity. It is unsurprising that confiscations would have a negative effect on housing prices across all cities in Italy, since the underlying mechanisms (social stigma and expected negative externalities from an empty property) are relevant regardless of the location of the asset. On the other hand, the findings suggest that re-allocation policies are only effective in areas where mafia organisations are more rooted, thanks to the higher utility associated with the creation of new social and institutional amenities in areas which are generally considered abandoned by the Italian

State. It is possible that cities with smaller mafia presence, which tend to be more socio-economically successful, may not pay as much attention to the introduction of new social and institutional facilities.[14]

5.3 Size of the effects and channels

Despite the fact that a proper cost-benefit analysis is beyond the scope of this study, we can discuss the magnitude of the policy effect. To our knowledge, this is the first study to investigate the impact of confiscation/re-allocation policies on property prices. As a result, there is no immediate benchmark to compare our results with. However, our findings 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. Confiscations could be seen as a disamenity for various reasons. First, in signalling the presence of criminal operations or criminal investments in a given area. Second, because the management of confiscated assets often involves construction or restoration work that may result in noise pollution or other disturbances. Conversely, the creation of amenities by means of re-allocations may be a channel through

[14] Our dataset comprises distinct applications of reallocated structures, namely social purposes and institutional roles. Both assets reallocated for social and institutional objectives demonstrate positive effects of comparable magnitude, with no discernible determinant.

which this aspect of the policy produces positive impact on house prices. On the one hand, the re-allocation policy could serve as an engagement device for the local community (Falcone et al., 2016). Non-profit organisations could use assets located in critical areas to organise bottom-up initiatives and sustain institutional change. On the other hand, assets can be used by local councils to improve the local provision of public services in areas characterised by high demand and limited resources. In both cases, the increase in local amenities would foster housing demand in previously more deprived and less attractive neighbourhoods. 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). We find that the extensive-margin effect of confiscations and re-allocations in the years immediately following the policy application is up to -3% for confiscations within 250 metres (Figure E4a) and up to +2% for re-allocations within 250 metres (Figure E4c). However, the re-allocation effect appears much clearer if we count the number of re-allocated assets in the vicinity of buildings, where every additional asset leads to a 0.3-0.5% increase in house prices.

Hence, with respect to other hedonic price studies, our estimates on the impact of confiscations and re-allocations appear to be somewhat lower. However, the policy considered is likely to be significantly cheaper for local authorities. The strategic position of confiscated/re-allocated assets, mostly located in deprived neighbourhood, is such that the policy is likely to particularly benefit more disadvantaged social groups.

The policy effect may materialise through the creation of amenities, but it may also be the result of different dynamics, directly related to the activity of organised crime. Both the confiscation and the re-allocation can weaken criminal organisations, both directly reducing their ability to extract resources from the territory and acting as a deterrent against future penetrations, as well as a signal of the State's presence to local communities. Thus, the policy could have an effect on the presence of criminal groups, which in turn is expected to influence the value of buildings (Gibbons, 2004, Linden and Rockoff, 2008, Ihlanfeldt and Mayock, 2010). We investigate this possibility in the next section.

5.4 Policy effect on organised crime activity

To provide some indications regarding a possible link between the policy and organised crime activity, 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 organisations (more details in Appendix F). We focus on the city of Naples, which represents the ideal testing ground not only for its large number of confiscated/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 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.

Thanks to this data, we construct a street-level panel dataset on organised crime presence in Naples. To assign cases of confiscations/re-allocations within streets, we also exploit buffers, identifying as 'treated' streets experiencing confiscations/re-allocations within their buffer radius. We focus on a 50, 100 and 200 metres radii from each street.[15] A representation of our strategy, zooming into some streets of Naples, is shown in Figures F1c and F2.

Using the constructed dataset, we estimate a Two-Way Fixed Effects (TWFE) model exploiting the staggered treatment of confiscations and re-allocations, testing their effect on the number of mafia families active in a given street and year. We regress the number of families operating in one street over confiscation and re-allocation dummy variables, using different buffer radii. The model and regression results are illustrated in Appendix F.1. Overall, no effect of confiscations is found, while re-allocations appear to be negatively related to the number of active families in a street. We take this interesting result and look at the temporal dynamics around the re-allocation event with an event study, estimated with TWFE and Sun and Abraham (2021) estimators (model discussed in Appendix F.2).

The results using 100 metres buffers are shown in Figure F3. They show no pre-trends and display the temporal dynamic of the effect, materialising shortly after the re-allocation and lasting for several years afterwards. They indicate a clear significant reduction in the number of active mafia families per street following the re-allocations in those streets. A decrease in the number of families may not, however, necessarily correspond to a reduction in the overall power and degree of control of criminal groups on a local territory. For this reason, these results should be interpreted with caution.[16] While we cannot provide

[15] Out the total 14,098 streets in sample, 985 (2140) have experienced confiscations and 963 (2375) have experienced re-allocations if we consider 100 (200) metres radius, in the 2013-2018 period. In these years, there have been 189 confiscations and 173 re-allocations in the city of Naples. None of these 189 confiscated assets were re-allocated prior to 2018. The average re-allocation time in the city is 12.5 years.

[16] In an additional descriptive exercise, we find that the probability of having any active mafia family in a

conclusive evidence regarding the effect of the policy on mafia activity, the observed reduction in active mafia families in a street experiencing re-allocations may signal that at least part of the regeneration effect of the re-allocation policy is obtained through the reduction of the mafia presence in treated areas. This may be due to a combination of factors, such as stronger law enforcement in the aftermath of re-allocations, especially if confiscated assets have been converted into police stations. 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 is made (Riccardi and Soriani, 2016).

6 Conclusions

This paper assesses the extent to which confiscation of mafia real estate assets and their re-allocation to new uses produce spillover on neighbouring buildings, modifying their monetary value. Our estimates, obtained by making use of unique micro-level data, unveil a short-term and highly localised impact of confiscation/re-allocation events on house prices. Confiscations have a negative effect on local prices, while re-allocations benefit local communities acting as positive local amenities, particularly in certain areas. Our estimates stipulate that each confiscated asset decreases the monetary value of properties located within 250-350 metres from the asset by 0.2-0.7%. Any additional re-allocated asset is associated with a 0.2-0.5% increase in housing prices.

street is lower after re-allocations.

The negative effect recorded in the aftermath of the confiscation is consistent with the findings of qualitative analyses on the policy (Dalla Chiesa, 2016), and the fact that confiscations are often followed by construction or restoration work that may result in noise pollution or other disturbances. Conversely, the positive effect of re-allocations can be interpreted either as the capitalisation of an increase in local amenities or as the result of a reduction in the disamenities associated with the presence of criminal organisations.

The policy effect is characterised by a rapid spatial decay. The recorded effect is no longer visible beyond 400m from confiscated/re-allocated assets and, consistently, tends to disappear when local housing markets are used as units of analysis. The social stigma associated with the presence of mafia organisation in a neighbourhood, the risks associated with an empty property, as well as the provision of local services and public amenities all produce their effects only within walking distance from target asset.

The effects of the policy on housing markets are found to be short-lived and tend to disappear within 4 years. This pattern, previously recorded for other very localised urban policies (Gobillon et al., 2012), can have different explanations. The negative shock produced by the confiscation, when driven by the 'bad press' of the event or by the need of local businesses to adjust to a new equilibrium, could naturally disappear in a relatively short period. The rapid decay of the positive shock following re-allocations can be attributed to the quick adjustment of local housing markets to the higher demand recorded in the area. Italian cities are characterised by a particularly high number of empty properties.[17] A positive price shock could convince some owners to put their property on the

[17] In 2019, the country recorded almost 10 million empty properties, mostly concentrated in Southern regions and urban areas (ISTAT).

market, fostering an increase in supply capable of absorbing the shock even in the absence of new developments. A second explanation has to do with the possibility that, in the period following re-allocations, local administrators choose to redirect local services out of the areas that have benefited from the re-allocations, towards excluded areas. From this perspective, the policy effect could be 'diluted' across the whole municipality.

We have investigated the effect of the policy in areas characterised by a stronger or lower presence of criminal organisations. Mafia-controlled real estate assets exhibit varying uses in places with differing levels of mafia influence. In mafia-rigged territories, a large number of mafia assets are used for both operational and economic purposes, while in locations with less mafia influence real-estate assets are more likely investments used by criminal organisations for money laundering (Operti, 2018). Residents may be more aware of confiscations in neighbourhoods where former operational mafia assets are no longer operational post-confiscation. If this is the case, it should not be surprising to observe a negative effect of confiscations where mafia organisations have the means to 'strike back'. At the same time, the reductions of property prices induced by confiscations in areas characterised by lower mafia presence may be due to the fact that confiscation events signal the presence of criminal investments in places where they are less expected, producing resonance within the local community.

The effects of re-allocations are particularly visible in areas with stronger presence of criminal organisations. This result can be explained by the expected returns of a policy in neighbourhoods which are generally less socio-economically prosperous. In mafia-rigged areas, re-allocation procedures signal the presence of the State through social amenities and institutions which are overall less present. In these cases, the creation of additional local amenities could naturally lead to higher welfare effects or engagement devices for local communities (Falcone et al., 2016), contributing to the revitalisation of the targeted areas. From a policy perspective, applying the policy in mafia-rigged territories could be seen as strategic due to the sub-optimal supply of public services. Although 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 is exclusively an amenity effect, our street-level exercise on Naples suggests that at least a part of it could be associated with a reduction of intensity of mafia activities in the locations where re-allocations occur.

The analysis has important policy implications, both for Italy as well as for all countries adopting measures of asset confiscation as a means to tackle criminal activity. Overall, what emerges 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 surrounding buildings, particularly in mafia-rigged territories. However, the negative effect recorded in the aftermath of the confiscation together with the extreme length of the re-allocation procedure highlights the need for a profound restructuring of the policy. A key recommendation would be to reduce the number of years between confiscation and re-allocation. The timing of re-allocations varies sharply across the country and may depend on local courts and our results indicate that efforts should be made in speeding up the re-allocation procedures. Moreover, the legislator could consider ways to temporally allocate the assets to the benefit of local communities even during the period between confiscation and final re-allocation. Finally, the introduction of case-by-case assessment procedures would help determining whether the assets have any value for the local community. In many cases, the resources obtained by the disposal of the asset could be used to finance other types of regeneration policies, with higher expected benefit for the neighbourhood.

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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).[18]

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,

[18] 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

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 et al., 2016). This is because real estate properties have a strong symbolic meaning for criminal groups as they are a physical representation of their power 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.

A.2 Location and timing of re-allocations

The implementation of law 109/96 and the creation of the ANBSC in 2010 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 182 properties in total being re-allocated within three years after the confiscation, as visible in Table A1. The average length of the re-allocation procedure varies sharply across the national territory, as illustrated in Figure A1a, with no clear identifiable geographical pattern. Figure A1b illustrates that there is no clear relationship between confiscated mafia assets and the number of confiscations per capita recorded in each local court.

Table A1: Timing of re-allocations

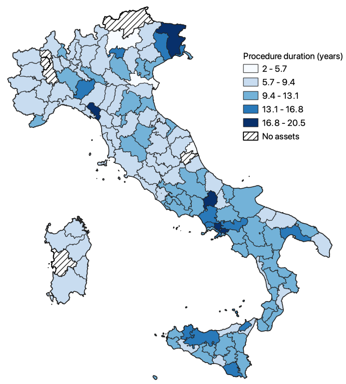
	Years between confiscation and re-allocation					
	0-1	2-3	4-5	6-7	8-9	10+
	All re-allocations					
Nr re-allocated real estate properties	8	174	885	2,470	2,796	9,454
% of total (15,787)	0.05	1.1	5.6	15.6	17.7	59.9
	Sale points in cities sample 2011-2018					
Nr re-allocated real estate properties	2	75	175	576	549	2,554
% of total (3,931)	0.05	1.9	4.4	14.6	14	65

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

Table A2, reporting the count and share of re-allocations by political colour of local governments over the 1998-2017 period, suggests that the length of the re-allocation procedures is unrelated with the political colour of the municipal government where the asset is located. The proportion of assets 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 A2, it also appears that re-allocations occur less than proportionally under governments run by civic lists - i.e. politicians with no clear ideological affiliation - than in governments ruled by left-wing, right-wing, or centre governments. As a consequence, it

Figure A1: Re-allocation duration by Court

(a) Geographic distribution



(b) Re-allocation duration and confiscation per capita

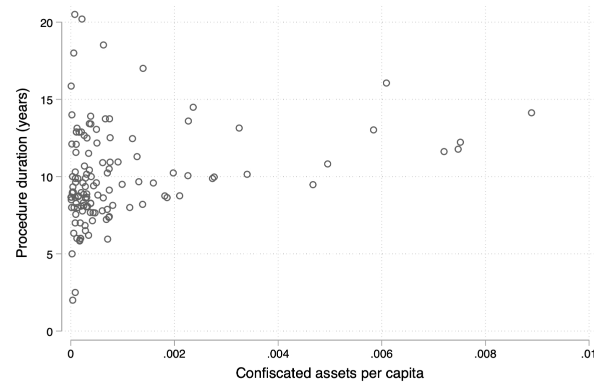


Figure A1a shows the average time required for local cohorts to re-allocate confiscated mafia assets. Figure A1b shows the relationship between the time between confiscation and reallocation and the number of confiscation per capita recorded in each local court area.

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.

Table A2: Local governments and re-allocations

	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.

B Confiscations, re-allocations, and local characteristics

B.1 Balancing tests

We examine how the length of confiscation and re-allocation procedures correlates with the characteristics of local areas. Panel A, Table B1, focuses on the duration of confiscation procedures, computed as the difference between the year of confiscation of an asset and the first confiscation recorded for the relative mafia family. Since a judge can dispose the final confiscation of all assets after the final conviction of a mafia member, any difference between the time of confiscations of assets belonging to the same individual could potentially be associated with strategic considerations about the potential for re-use of different asset types. The results show a negative and significant relationship between length of the procedure and share of migrants. However, no significant difference is recorded within-OMI.

Panel B, Table B1, focuses instead on the length of re-allocation procedures, computed as the time between confiscation and re-allocation. As explained in the previous section, different actors are involved in the management of the asset and in its allocation to a new use. Even in this case, the urgency assigned to different procedures could depend on the assessment of its potential benefits for the local community. Once again, we find a negative and significant relationship with the share of 1st generation migrants. However, the effect becomes non-significant once we include OMI-fixed effects.

In Table B2, we run a standard balancing test, where our main explanatory variable - the number of confiscated assets recorded within a certain radius from each sale point - is regressed on a set of Census characteristics aggregated at the buffer-level. Panel A shows that the number of re-allocated assets recorded within 150m from a sale point is positively correlated with the share of buildings in bad condition and the share of population aged 15-64. These results are consistent with an effort of local policymakers to free strategic resources in areas where there is more demand for local services. However, once we include OMI-fixed effects, the results disappear, suggesting that assets located in the same

OMI area are subject to a similar treatment. In Panel B, we run the same exercise, this time focusing on assets confiscated within a radius of 350 metres. All characteristics are insignificant when OMI fixed effects are included, with the exception of activity rate.

In Table B3 we repeat the same balancing test for re-allocated assets. Not surprisingly, the results closely mimic what we find for confiscated assets: the presence of migrants is negatively correlated with the number of re-allocated assets, while a higher share of buildings in bad condition and a relevant share of population aged 15-64 are associated with a higher number of re-allocated assets. The results disappear once we include OMI fixed effects.

Overall, based on our findings, the spatial distribution of confiscated and re-allocated assets does not seem correlated with relevant socioeconomic characteristics of the surrounding environment, within OMI areas.

Table B1: Confiscation and re-allocation timing

	Local area characteristics				
	1st gen. migrants	Buildings in bad condition	Active population	Education	Deprivation index
	(1)	(3)	(4)	(4)	(5)
Dep. variable: *Confiscation lag*	-3.415***	2.798	2.210	-0.205	0.00248
	(1.215)	(2.327)	(1.431)	(0.358)	(0.298)
OMI FE	No	No	No	No	No
Observations	39,304	39,754	39,304	38,891	38,747
R-squared	0.003	0.001	0.002	0.000	0.000
	-0.922	1.924	-0.934	0.350	0.00969
	(1.438)	(1.830)	(2.579)	(0.368)	(0.471)
OMI FE	Yes	Yes	Yes	Yes	Yes
Observations	38,679	39,131	38,679	38,263	38,122
R-squared	0.509	0.506	0.508	0.509	0.508
	1st gen. migrants	Buildings in bad condition	Active population	Education	Deprivation index
	(6)	(8)	(9)	(4)	(10)
Dep. variable: *re-allocation timing*	-5.329**	-1.556	1.082	-0.337	-0.702
	(2.156)	(1.582)	(2.518)	(0.320)	(0.588)
OMI FE	No	No	No	No	No
Observations	14,538	14,601	14,538	14,464	14,430
R-squared	0.008	0.001	0.000	0.002	0.002
	0.337	-2.190	1.693	-0.205	0.452
	(1.164)	(1.870)	(1.441)	(0.296)	(0.328)
OMI FE	Yes	Yes	Yes	Yes	Yes
Observations	14,125	14,186	14,125	14,051	14,017
R-squared	0.574	0.572	0.574	0.574	0.574

Notes. The table illustrates the relationship between the time required to confiscate and re-allocate an asset and the characteristics of the area where the confiscation took place. In the first panel, the dependent variable is the number of years between the time a convicted family - identified by the surname of the mafia family members - had its first asset confiscated and the moment in which a following confiscation took place. In the second panel, the dependent variable is the length of re-allocation procedure. Independent variable: share of 1st-generation formigrants, share of buildings in bad conditions, share of active population, percentage of residents with primary education or less, and general index of deprivation. 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.

Table B2: Confiscation and local characteristics: balancing test

Dep. variable: Nr of confiscation	Local area characteristics				
	1st gen. migrants	Buildings in bad condition	Active population	Education	Deprivation index
	(1)	(3)	(4)	(4)	(5)
Panel A: 150m					
	-0.0795	12.21***	6.209***	0.00538	0.216
	(0.934)	(2.403)	(1.511)	(0.109)	(0.180)
OMI FE	No	No	No	No	No
Observations	33,069	33,096	33,069	33,028	32,968
R-squared	0.000	0.023	0.007	0.000	0.001
	0.374	-0.584	0.185	0.0202	0.0240
	(1.046)	(1.645)	(0.659)	(0.0608)	(0.105)
OMI FE	Yes	Yes	Yes	Yes	Yes
Observations	32,978	33,006	32,978	32,937	32,877
R-squared	0.601	0.601	0.601	0.601	0.601
Panel B: 350m					
	0.466	18.58***	10.67***	0.0847	0.142
	(1.221)	(3.058)	(2.043)	(0.152)	(0.161)
OMI FE	No	No	No	No	No
Observations	47,480	47,526	47,480	47,469	47,435
R-squared	0.000	0.041	0.013	0.000	0.000
	1.935	-0.118	1.829**	-0.0104	0.142
	(1.281)	(2.197)	(0.808)	(0.0918)	(0.100)
OMI FE	Yes	Yes	Yes	Yes	Yes
Observations	47,387	47,434	47,387	47,376	47,341
R-squared	0.567	0.567	0.567	0.566	0.567

Notes. The table illustrates the relationship between the number of re-allocation around each sale point and characteristics of the area where the confiscation took place. Independent variable: share of 1st-generation formigrants, share of buildings in bad conditions, share of active population, percentage of residents with primary education or less, and general index of deprivation. 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.

Table B3: Re-allocations and local characteristics: balancing test

Dep. variable: Nr of re-allocations	Local area characteristics				
	1st gen. migrants	Buildings in bad condition	Active population	Education	Deprivation index
	(1)	(3)	(4)	(4)	(5)
Panel A: 150m					
	-3.130***	3.017***	4.714***	-0.0769	-0.0414
	(0.983)	(0.558)	(1.398)	(0.114)	(0.254)
OMI FE	No	No	No	No	No
Observations	33,069	33,096	33,069	33,028	32,968
R-squared	0.003	0.014	0.003	0.000	0.000
	0.0878	0.0213	0.162	-0.00755	0.135
	(0.626)	(0.286)	(0.497)	(0.0465)	(0.127)
OMI FE	Yes	Yes	Yes	Yes	Yes
Observations	52,416	52,314	52,327	52,346	52,342
R-squared	0.513	0.513	0.513	0.513	0.513
Panel B: 350m					
	-4.959***	12.82***	10.93***	0.0597	0.175
	(1.418)	(2.815)	(3.874)	(0.198)	(0.455)
OMI FE	No	No	No	No	No
Observations	47,480	47,526	47,480	47,469	47,435
R-squared	0.004	0.009	0.007	0.000	0.000
	1.619	2.286	3.506	-0.00676	0.468
	(1.277)	(2.801)	(2.988)	(0.0814)	(0.366)
OMI FE	Yes	Yes	Yes	Yes	Yes
Observations	47,387	47,434	47,387	47,376	47,341
R-squared	0.368	0.368	0.368	0.368	0.369

Notes. The table illustrates the relationship between the number of re-allocation around each sale points and characteristics of the area where the confiscation took place. Independent variable: share of 1st-generation formigrants, share of buildings in bad conditions, share of active population, percentage of residents with primary education or less, and general index of deprivation. 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.

B.2 Additional tests

In order to test the validity of the model, we perform an additional robustness exercise, which simultaneously the relationship between our main variables of interest and all the covariates used in the baseline model. Following Pei et al. (2019) (PPS), we implement both a ''balance' and a 'coefficient comparison' test. In the baseline model, log housing prices are a function of the treatment (s_i, confiscation or relocation over the previous 3 years) and a vector $kx1$ of added regressors, $x_i^{'}$:

$$y_i = \beta^l s_i + \boldsymbol{x_i'}\gamma + e_i \tag{B1}$$

As proposed by D. Lee and Lemieux, 2010, we regress k variables s_i on the covariates x_i in order to identify k separate equation and then compute the joint significance:

$$x_i = \boldsymbol{\delta} s_i + u_i \tag{B2}$$

PPS define it the 'right-hand-side' (RHS) balancing test. According to the authors, this test 'has a size distortion under the null hypothesis and tend to reject too often' when using robust standard errors. They also notice that the bias tends to get worse when a large number of covariates are included in the model. For all these reasons, the coefficient comparison test appears to me more appropriate for our empirical model. This approach consists in testing whether the regression parameter of interest, β^s, changes significantly when confounders x_i are added. In practice, we first estimate two different models:

$$y_i = \beta^s s_i + e_i y_i = \beta^l s_i + \boldsymbol{x_i'}\gamma + e_i \tag{B3}$$

Then, we measure the coefficient difference as:

$$\beta^l - \beta^s = \gamma^{'}\delta \tag{B4}$$

In table B4, we report the test results obtained implementing both the balancing (RHS) and the coefficient comparison test. The balancing test does not reject the hypothesis that re-allocations are significantly correlated with the covariates, while the same hypothesis cannot be rejected for confiscations. However, the coefficient comparison test, that is not subject to the distortions reported by PPS, rejects both hypotheses.

Table B4: PPS balancing tests

Variable	test	F	chi2	p>F, p>chi2
Confiscations	Coeff comparison		2.48	0.12
Re-allocations	Coeff comparison		1.17	0.28
Confiscations	Balancing	1.53		0.02
Re-allocations	Balancing	0.92		0.61

Note: This table report the result of two joint significance tests performed on the baseline model (Eq. 4.1). The number of observations is 50,485 in all regressions.

C OMI-level estimates

As a complementary analysis to our main sale-point estimates we investigate the relationship between re-allocations and property prices at the OMI (*Osservatorio del Mercato Immobiliare*) area level for the 2005-2018 period. OMI zones are smaller than neighbourhoods and correspond to functional local housing markets. The Italian Real Estate Agency defines OMIs 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.'* Almost all Italian 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 and each real estate asset typology, the dataset includes maximum and minimum selling prices of properties. In our analysis, we compute the average price to construct our dependent variable.[19,20] 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.

We investigate the relationship between confiscation/re-allocation and house prices at the OMI-level by estimating Two-Way-Fixed-Effects event studies. To do so, we create q leads and lags dummy variables referring to each year before and each year after the confiscation(s) or re-allocation(s). The first year before confiscations/re-allocations is used as reference category.[21] The models are:

$$\ln p_{jmt} = \sum_{\tau=2}^{q} \varphi_{-\tau} C_{jmt-\tau} + \sum_{\tau=1}^{q} \varphi_{+\tau} C_{jmt+\tau} + \delta_j + \tau_t + u_{jmt}, \tag{C1}$$

[19] As a robustness check, we have used the maximum market value per zone as dependent variable. The results (available upon request) are robust to this change.

[20] 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 (Budiakivska and Casolaro, 2018).

[21] Adopting the Sun and Abraham (2021) estimator, excluding late-treated from the control group and hence accounting for heterogeneous treatment effect produces qualitatively equivalent results (available upon request).

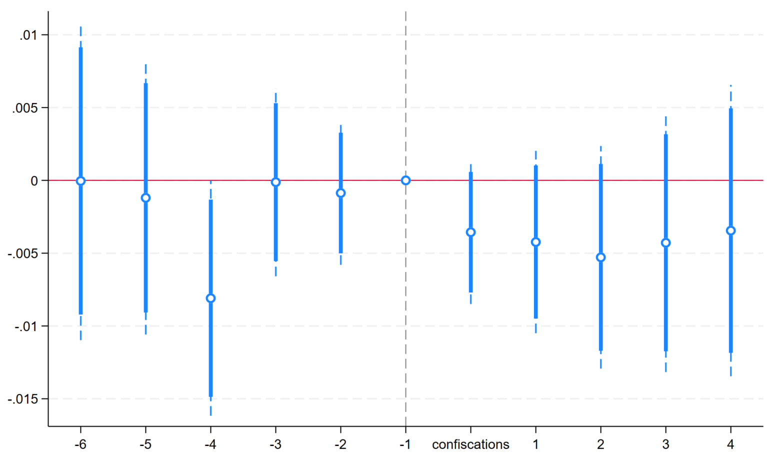
$$\ln p_{jmt} = \sum_{\tau=2}^{q} \varphi_{-\tau} R_{jmt-\tau} + \sum_{\tau=1}^{q} \varphi_{+\tau} R_{jmt+\tau} + \beta\, C_{jmt} + \delta_j + \tau_t + u_{jmt}, \tag{C2}$$

where $\ln p_{jt}$ is the natural logarithm of average housing prices per square meter in OMI j, municipality m and year t. In the first model, this is regressed on dummy variables for pre-confiscation $(C_{r,s,t-2}, ..., C_{r,s,t-q})$ and post-confiscation $(C_{r,s,t+1}, ..., C_{r,s,t+q})$ years; all re-allocation years are excluded. In the second model it is regressed on dummy variables for pre-re-allocation $(R_{r,s,t-2}, ..., R_{r,s,t-q})$ and post-re-allocation $(R_{r,s,t+1}, ..., R_{r,s,t+q})$ years, controlling for a dummy variable referring to the first three post-confiscation years C_{jt}. We include year (τ_t) and OMI (δ_j) fixed effects; standard errors are clustered at OMI level. All OMI zones having confiscations or re-allocations prior to the beginning of our sample period, 2005, are excluded from sample. For each model, to isolate the treatment effects we focus on OMI zones having experienced only one episode of confiscation(s) or re-allocation(s) during the sample period. We estimate the model for the full sample of OMI areas in Italy and the restricted sample of 55 cities adopted in the sale-point analysis.

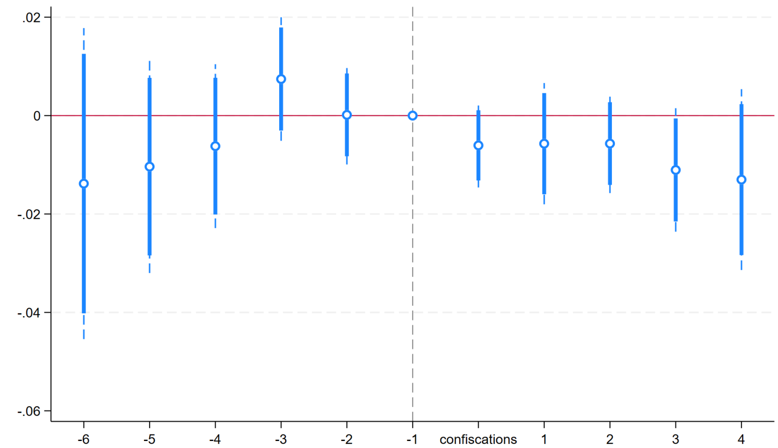
The results are displayed in Figure C1, showing coefficients around the policy event up to 6 years before and up to 4 full years following the confiscations/re-allocations. Both the full sample and the restricted sample show some evidence of a decrease in house prices following the confiscation(s) event (Figure C1a and b), while no clear effect of re-allocations on how prices are found (Figure C1c and d). These results, while interesting, represent only preliminary evidence of any impact of the policy on the average value of OMI buildings. Estimating the policy impact on aggregated units (OMI) implies aggregating multiple confiscation or re-allocation cases occurring in the same year in the same OMI, i.e. different kinds of assets. Furthermore, a wide number property-specific characteristics are unaccounted for in the estimates, thus potentially acting as omitted variables. We account for all these aspects in our sale-point analysis, zooming in *within* OMI areas to identify the asset-specific effects on surrounding buildings.

Figure C1: OMI estimates - event studies

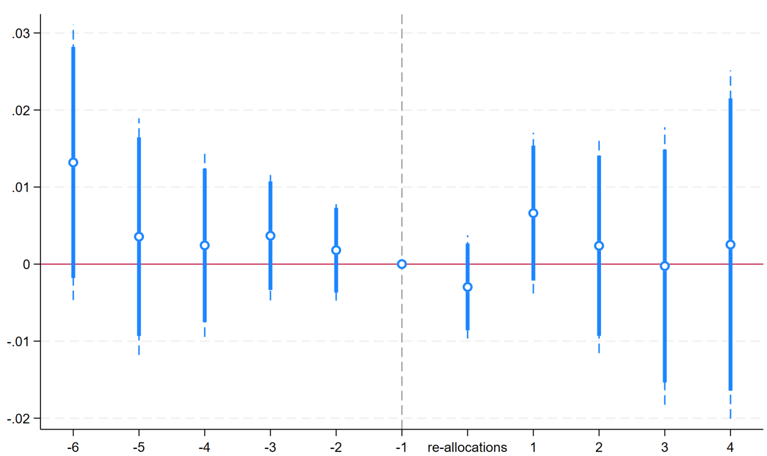
(a) Confiscations - all Italy



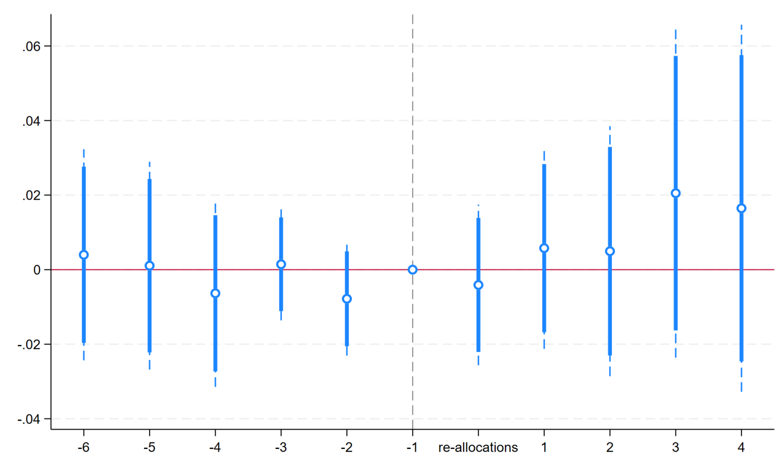
(b) Confiscations - 55 cities



(c) Re-allocations - all Italy



(d) Re-allocations - 55 cities



The figure shows the event study estimated at OMI-level and using log house prices as dependent variable. Continuous lines refer to 95% confidence intervals, dotted lines refer to 95% confidence intervals. Sample of single episodes of confiscations/re-allocations during 2005-2018; OMI with confiscations/re-allocations pre-2005 are excluded. Panels a, c refer to all Italian OMI, panels b, d refer to OMI within municipalities used in the sale-point analysis.

D Data

D.1 Descriptive Statistics

Variables collected from *Immobiliare.it* the biggest Italian real estate website are reported in Table D1. Descriptive statistics for treatment and control variables are reported in Table D2 .

Figure D1: Sale points across the sample cities

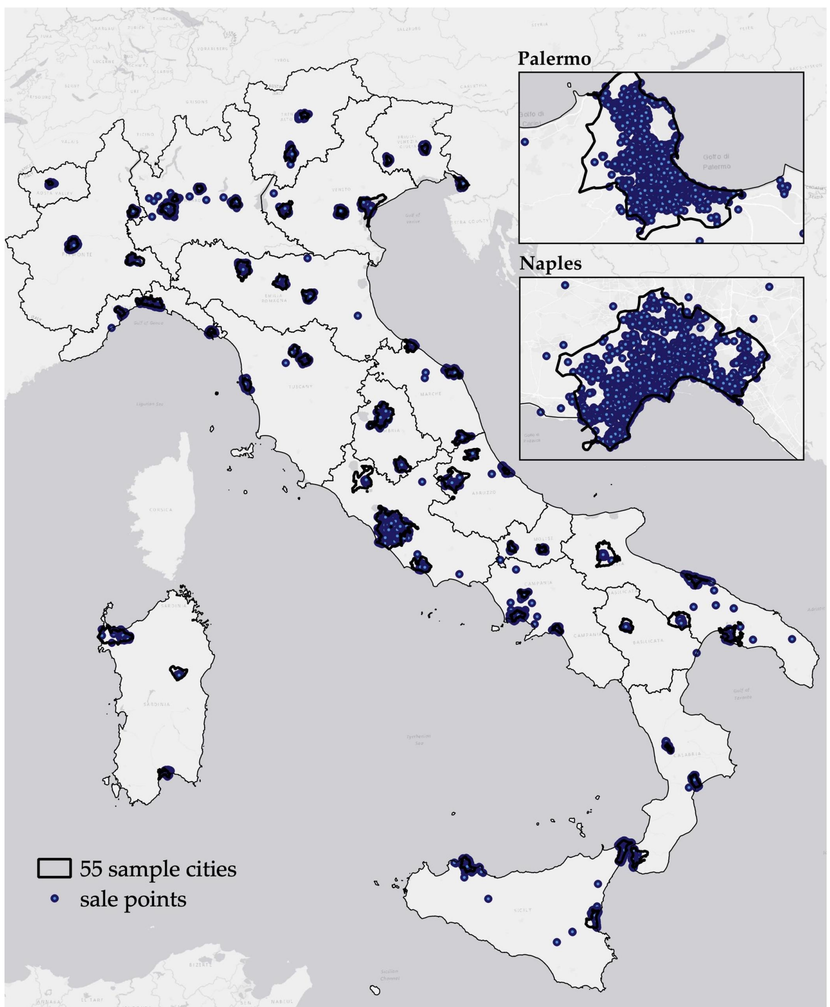


Table D1: Property characteristics

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 D2: Descriptive statistics: outcome, treatment variables and sale point characteristics

Variable	Obs	Mean	Std. Dev.
Sale points (buffer 250m):			
Ln price €/m2	52,161	7.619	0.574
Re-allocations	53,669	0.139	1.119
Confiscations	53,669	0.201	1.479
4^{th} year *before* re-allocations	52,215	0.056	0.655
3^{rd} year *before* re-allocations	52,219	0.048	0.497
2^{nd} year *before* re-allocations	52,219	0.071	0.733
1^{st} year *before* re-allocations	53,669	0.596	0.655
1^{st} year *after* re-allocations	53,669	0.060	0.649
2^{nd} year *after* re-allocations	53,669	0.044	0.511
3^{rd} year *after* re-allocations	53,669	0.035	0.565
4^{th} year *before* confiscations	52,215	0.029	0.386
3^{rd} year *before* confiscations	52,219	0.033	0.422
2^{nd} year *before* confiscations	52,219	0.044	0.520
1^{st} year *before* confiscations	53,669	0.053	0.621
1^{st} year *after* confiscations	53,669	0.056	0.65
2^{nd} year *after* confiscations	53,669	0.062	0.710
3^{rd} year *after* confiscations	53,669	0.081	1.075
Controls:			
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 table reports descriptive statistics for the sale-point-level variables used in the analysis.

E Results

E.1 Baseline Sale-point analysis

Table E1: Sale point analysis controls

Dep. variable: Log euro per m^2	Buffer radius: 150 metres	250 metres	350 metres	450 metres
	(1)	(2)	(3)	(4)
Confiscations	-0.00703***	-0.00289**	-0.00223**	-0.00219***
	(0.00226)	(0.00129)	(0.00101)	(0.000766)
Re-allocations	0.00515**	0.00350**	0.00221***	0.000702
	(0.00227)	(0.00170)	(0.000658)	(0.000836)
Property up for auction	-0.385***	-0.385***	-0.385***	-0.385***
	(0.0254)	(0.0254)	(0.0254)	(0.0254)
Box	-0.422***	-0.422***	-0.422***	-0.422***
	(0.0351)	(0.0352)	(0.0352)	(0.0352)
Attic	0.0986***	0.0985***	0.0985***	0.0985***
	(0.0151)	(0.0151)	(0.0151)	(0.0151)
Loft	-0.0829***	-0.0830***	-0.0828***	-0.0826***
	(0.0275)	(0.0274)	(0.0275)	(0.0275)
Appartment	0.0101	0.0101	0.0101	0.0102
	(0.0125)	(0.0125)	(0.0125)	(0.0125)
House	-0.0756***	-0.0756***	-0.0756***	-0.0755***
	(0.0180)	(0.0180)	(0.0181)	(0.0181)
Villa	-0.0136	-0.0137	-0.0137	-0.0136
	(0.0164)	(0.0164)	(0.0164)	(0.0164)
Building	-0.0874**	-0.0875**	-0.0880**	-0.0874**
	(0.0396)	(0.0396)	(0.0396)	(0.0395)
Number of rooms	-0.0144***	-0.0143***	-0.0143***	-0.0143***
	(0.00168)	(0.00168)	(0.00168)	(0.00168)
Number of bathrooms	0.0617***	0.0617***	0.0617***	0.0617***
	(0.00374)	(0.00374)	(0.00374)	(0.00374)
Type of kitchen	-0.0314***	-0.0314***	-0.0314***	-0.0314***
	(0.00373)	(0.00373)	(0.00373)	(0.00373)
Floor number	0.00600***	0.00600***	0.00602***	0.00602***
	(0.000788)	(0.000788)	(0.000788)	(0.000787)
Parking	0.0509***	0.0508***	0.0508***	0.0509***
	(0.00417)	(0.00417)	(0.00417)	(0.00417)
Lift	0.0806***	0.0806***	0.0807***	0.0807***
	(0.00450)	(0.00450)	(0.00450)	(0.00450)
Refurbished	0.195***	0.195***	0.195***	0.195***
	(0.0107)	(0.0107)	(0.0107)	(0.0107)
Heating	0.0330***	0.0331***	0.0330***	0.0330***
	(0.00431)	(0.00431)	(0.00432)	(0.00432)
Air conditioning	0.0374***	0.0373***	0.0373***	0.0374***

Continued on next page

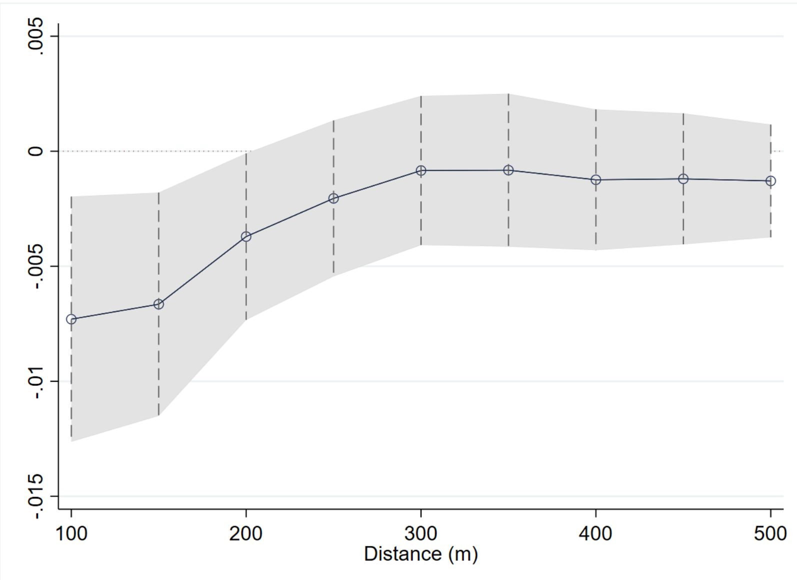
Table E1 – continued from previous page

Dep. variable: Log euro per m2	Buffer radius: 150 metres	250 metres	350 metres	450 metres
	(1)	(2)	(3)	(4)
	(0.00362)	(0.00362)	(0.00362)	(0.00362)
High energy efficiency	0.120***	0.120***	0.120***	0.120***
	(0.00953)	(0.00953)	(0.00953)	(0.00953)
Distance to green space	-3.16e-06	-3.17e-06	-3.12e-06	-3.11e-06
	(4.43e-06)	(4.42e-06)	(4.42e-06)	(4.42e-06)
Distance to water (5 km)	-9.48e-06*	-9.51e-06*	-9.59e-06*	-9.56e-06*
	(5.47e-06)	(5.47e-06)	(5.47e-06)	(5.47e-06)
Distance to beach	-1.45e-06	-1.44e-06	-1.45e-06	-1.46e-06
	(3.35e-06)	(3.35e-06)	(3.35e-06)	(3.34e-06)
Distance to a view	-1.24e-05***	-1.24e-05***	-1.24e-05***	-1.24e-05***
	(4.25e-06)	(4.25e-06)	(4.25e-06)	(4.24e-06)
Distance to bus or tube	1.39e-07	1.07e-07	5.05e-08	2.42e-07
	(8.54e-06)	(8.55e-06)	(8.56e-06)	(8.55e-06)
Distance to train or bus station	8.78e-06	8.81e-06	8.90e-06	8.84e-06
	(6.46e-06)	(6.46e-06)	(6.46e-06)	(6.47e-06)
Distance to airport	8.14e-06**	8.15e-06**	8.14e-06**	8.17e-06**
	(3.88e-06)	(3.88e-06)	(3.88e-06)	(3.88e-06)
Distance to commercial centre	2.80e-06	2.82e-06	2.79e-06	2.80e-06
	(4.32e-06)	(4.31e-06)	(4.31e-06)	(4.31e-06)
Distance to church	1.09e-06	1.16e-06	1.17e-06	1.03e-06
	(8.70e-06)	(8.70e-06)	(8.70e-06)	(8.69e-06)
Distance to state school	1.16e-07	1.68e-07	1.50e-07	-2.24e-08
	(1.20e-05)	(1.20e-05)	(1.20e-05)	(1.20e-05)
Noise (within 500m of a highway)	-0.00317	-0.00303	-0.00311	-0.00348
	(0.00904)	(0.00905)	(0.00906)	(0.00903)
Inside an industrial area	-0.0214*	-0.0214	-0.0214	-0.0214
	(0.0130)	(0.0130)	(0.0130)	(0.0130)
% of population with higher education	0.305***	0.305***	0.305***	0.304***
	(0.0197)	(0.0197)	(0.0197)	(0.0197)
% of migrant population	-0.188***	-0.189***	-0.188***	-0.189***
	(0.0237)	(0.0237)	(0.0237)	(0.0237)
Population density	-1.58e-06***	-1.59e-06***	-1.59e-06***	-1.59e-06***
	(2.37e-07)	(2.38e-07)	(2.37e-07)	(2.36e-07)
Year FE	Yes	Yes	Yes	Yes
OMI FE	Yes	Yes	Yes	Yes
Municipality-year FE	Yes	Yes	Yes	
Observations	50,485	50,485	50,485	50,485
R-squared	0.786	0.786	0.786	0.786

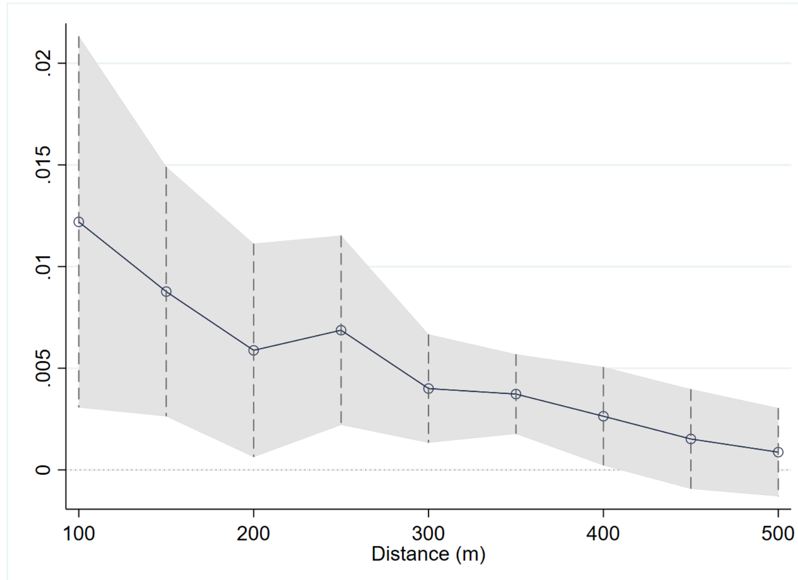
E.2 Distance decay

Figure E1: Distance decay effect - within municipalities

(a) Confiscations

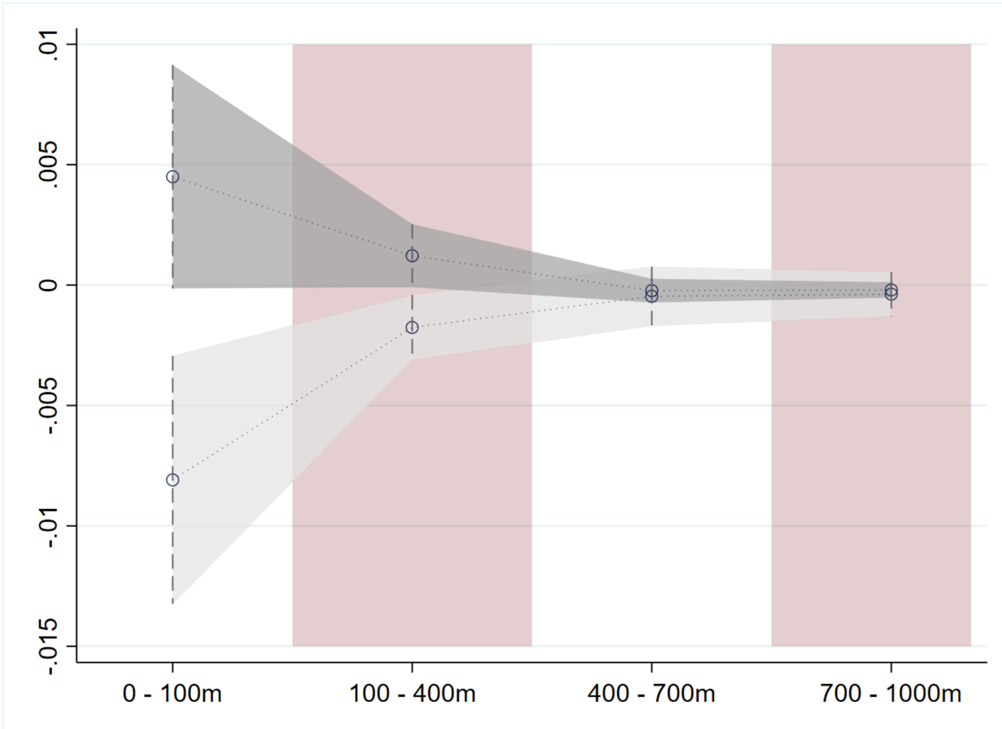


(b) Re-allocations



Estimated coefficients of the baseline model at different buffer distances. Relative to the coefficients shown in Figure 4, these estimates do not include OMI fixed effects but only municipality $\times$ year fixed effects.

Figure E2: Estimates by different rings of distance around confiscations/re-allocations

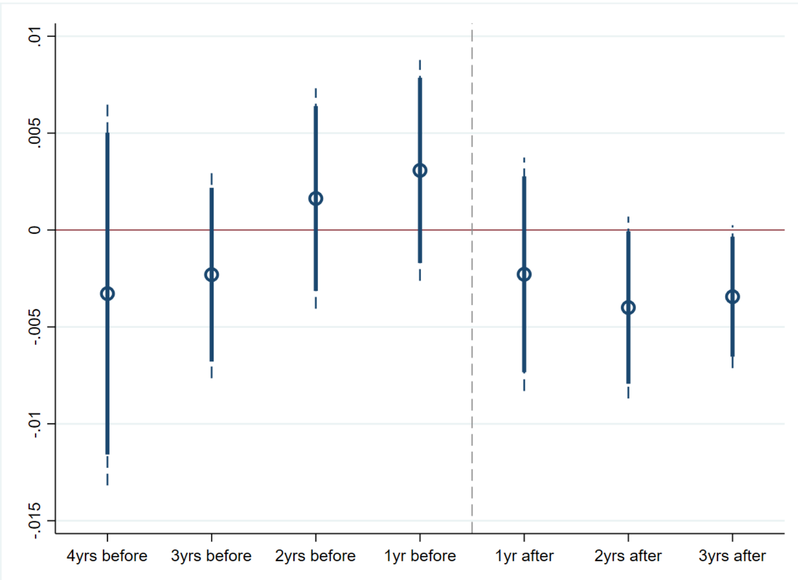


Estimated coefficients of the baseline model including a set of variables referring to different rings of distance from confiscations/re-allocations: 0-100 metres, 100-400 metres, 400-700 metres, 700-1000 metres. Dark grey area around point estimates (top): 90% CI of coefficients of re-allocations; light grey area around point estimates (bottom): 90% CI of coefficients of confiscations.

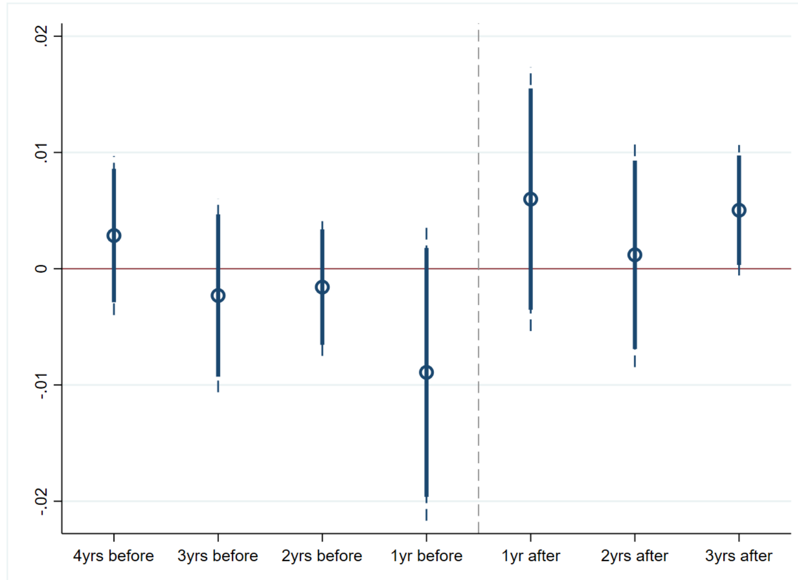
E.3 Event Studies

Figure E3: House values before/after confiscations and re-allocations (250m)

(a) Confiscation



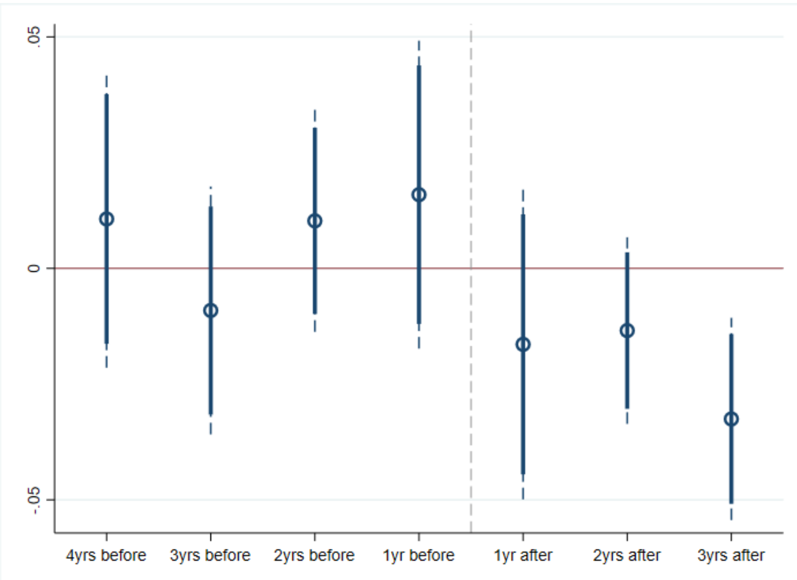
(b) Re-allocations



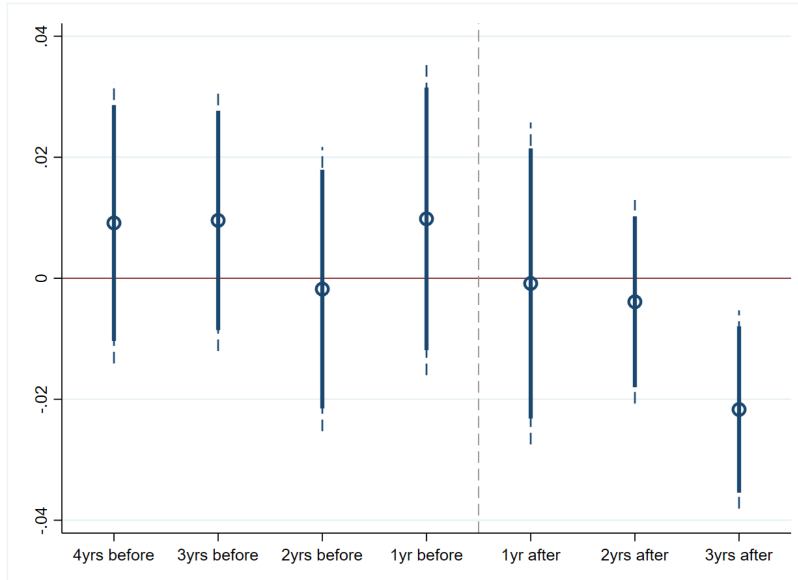
Coefficients of a model estimating year-by-year differences in house price for buildings located within 250m of confiscations/re-allocations and sold up to 4 years before and 3 years after confiscations/re-allocations. Continuous (dashed) lines around point estimates refer to 90% (95%) CIs. Treatment variable: number of confiscated/re-allocation assets within buffer.

Figure E4: House values before/after confiscations and re-allocations - dummy treatment (350m/250m)

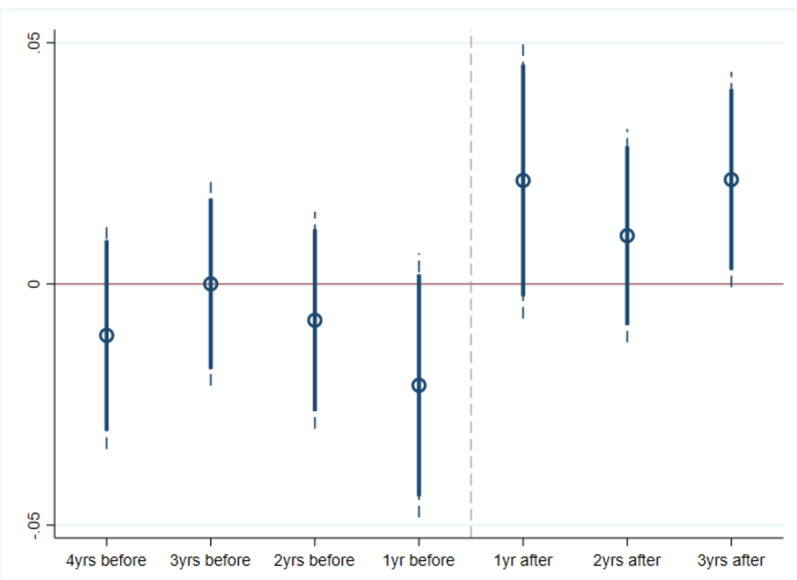
(a) Confiscation 250m



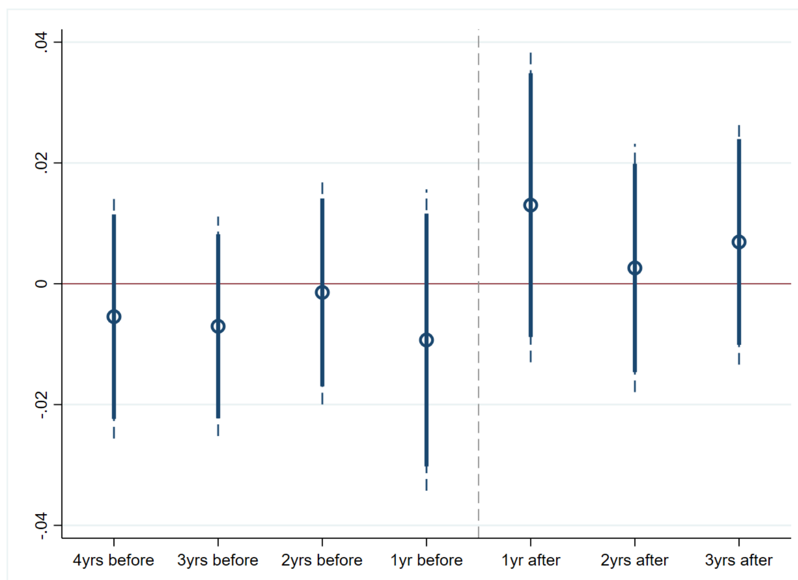
(b) Confiscation 350m



(c) Re-allocation 250m



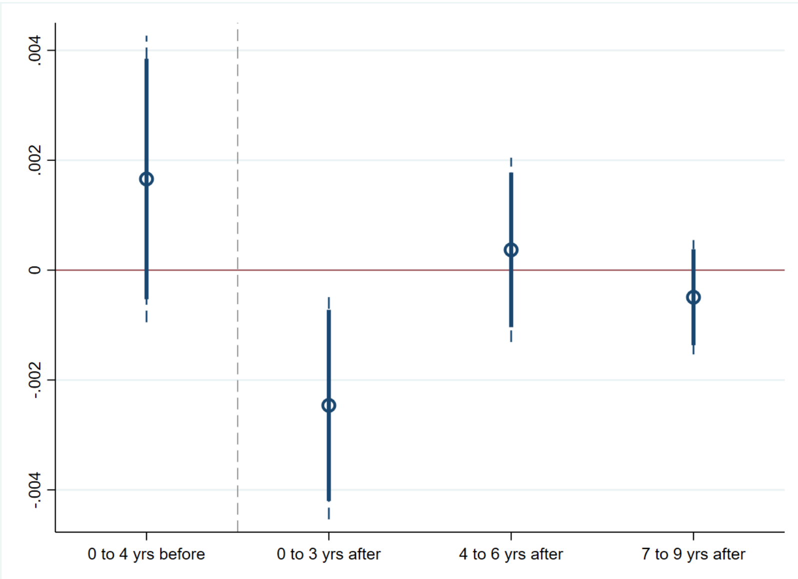
(d) Re-allocation 350m



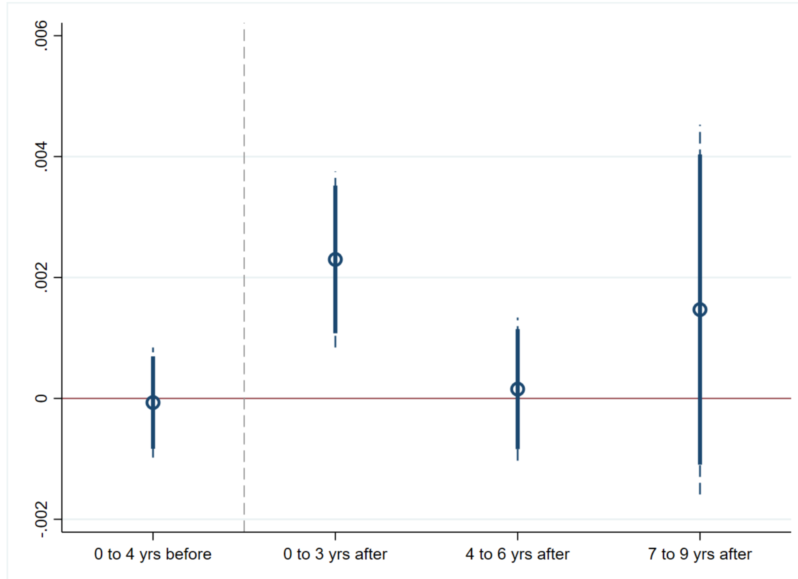
Coefficients of a model estimating year-by-year differences in house price for buildings located within 250m/350m of confiscations/re-allocations and sold up to 4 years before and 3 years after confiscations/re-allocations. Continuous (dashed) lines around point estimates refer to 90% (95%) CIs. Treatment variable: dummy = 1 if the sold building had confiscated/re-allocation assets within 250m/350m n years before/after its sale.

Figure E5: Long-term effect (350m)

(a) Confiscations



(b) Re-allocations

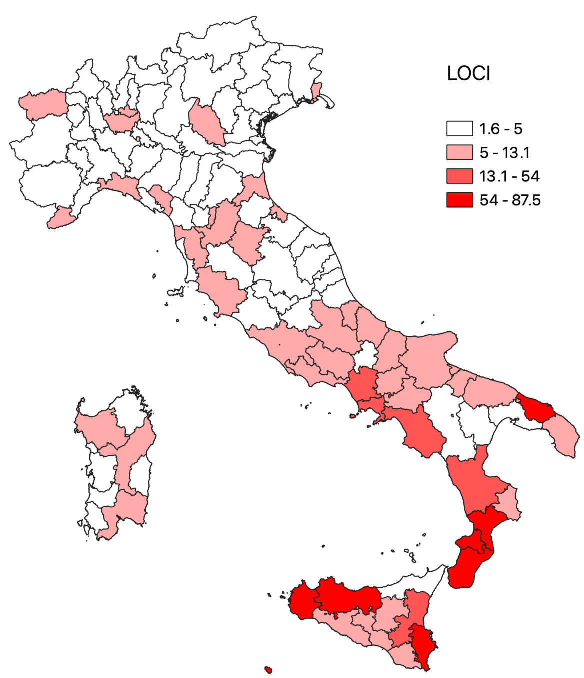


Coefficients of a model estimating differences in house price for buildings located within 350m of confiscations/re-allocations and sold up to 4 years before and 9 years after confiscations/re-allocations. Continuous (dashed) lines around point estimates refer to 90% (95%) CIs. Treatment variable: number of confiscated/re-allocation assets within buffer.

E.4 Mafia-intensity indicator

Mafia intensity is defined on the basis of an indicator developed by Bernardo et al. (2021), 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. 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. As illustrated on the map, the intensity of mafia presence varies as a continuous variable. To facilitate our heterogeneity analysis (Table 2), we have introduced a binary dummy variable at the median point, distinguishing areas with high mafia intensity from those with low mafia intensity.

Figure E6: Mafia intensity

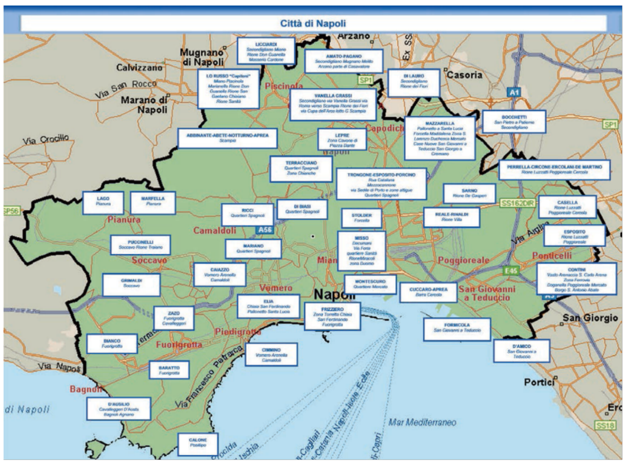


F Policy effect on organised crime activity

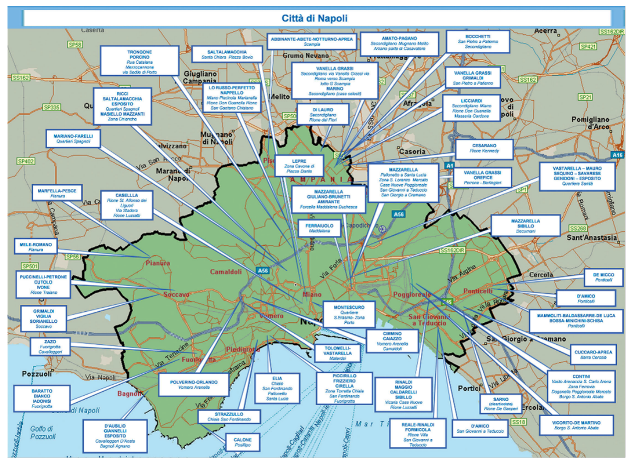
Anti-Mafia Directorate (DIA) maps illustrate the power exerted by each single mafia family on the territory. The DIA data are updated every year and make it possible to follow the evolution of mafia presence in small neighbourhoods and even in single streets. Figures F1a and F1b are retrieved from DIA reports shows the spatial distribution of mafia families in Naples in 2013 and 2018. Figure F1c shows the Naples road network and the buffer constructed within 100m from both sides of each road.

Figure F1: 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

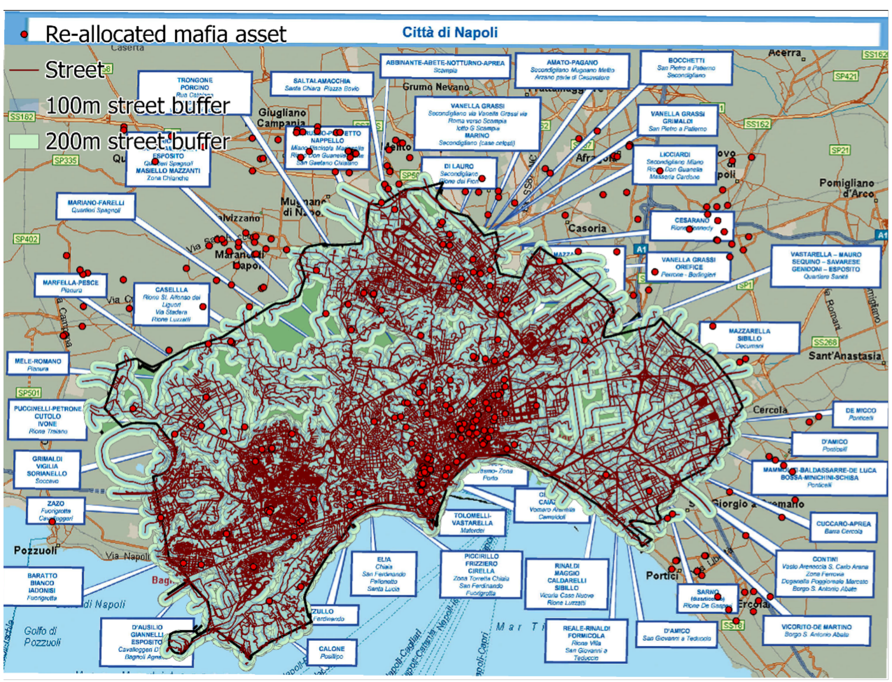
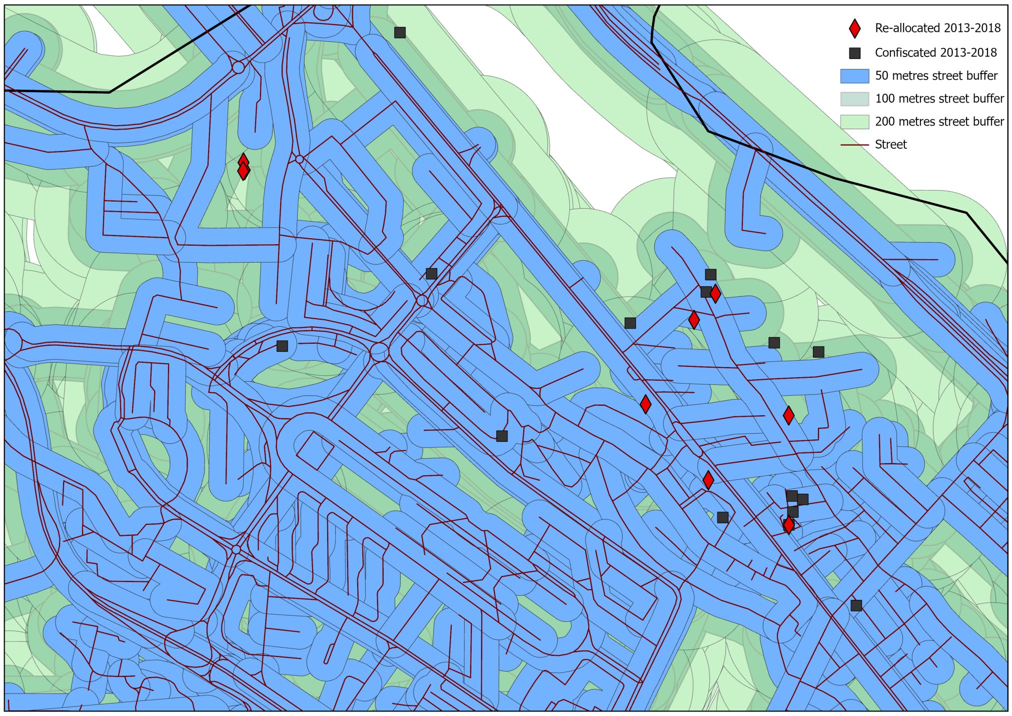


Figure F2: Buffer zones around streets in Naples



F.1 Difference-in-differences model

To investigate the effect of confiscations and re-allocations on mafia activity, we estimate:

$$Mafia\,families_{sjt} = \alpha C_{sjt} + \beta R_{sjt} + \sigma_s + \lambda_t + \delta_{jt} + \varepsilon_{sjt} \tag{F1}$$

where $Mafia\,families_{sjt}$ is the number of *Camorra* families active in street s, OMI zone j, year t. C_{sjt} is a dummy taking value 1 from the year confiscations take place in street s, R_{sjt} is a dummy switching on from the year of the first re-allocation episode takes place in street s. All streets having experienced policy events prior to 2013 are excluded from sample. The specification controls for time-invariant street-specific factors (σ_s), time shocks (λ_t) and OMI-year fixed effects (δ_{jt}). The model takes the form of a Two-Way-Fixed-Effects with variation in treatment timing. Period: 2013-2018. Results presented in Table F1.

Table F1: Street-level analysis on mafia activity

Dep. variable:		buffer:	
Nr of mafia families	50m	100m	200m
	(1)	(2)	(3)
Confiscations	-0.000893	0.0376	-0.0659
	(0.0942)	(0.0493)	(0.0434)
Re-allocations	-0.164	-0.124**	-0.241***
	(0.108)	(0.0606)	(0.0514)
Streets FE	Yes	Yes	Yes
OMI-year FE	Yes	Yes	Yes
Observations	71,808	71,808	71,808
R-squared	0.946	0.946	0.946

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Clustered standard errors at street level in parenthesis. Dep. variable: number of mafia families in each street of Naples. Confiscations: dummy variable = 1 from the first confiscation episode in a street until the end of the period (all buildings confiscated after 2013 have not been re-allocated before 2018). Re-allocations: dummy variable = 1 from the first re-allocation episode in a street until the end of the period. Column (1): 50 metres buffer around each street; (2): 100m buffer; (3): 200m buffer.

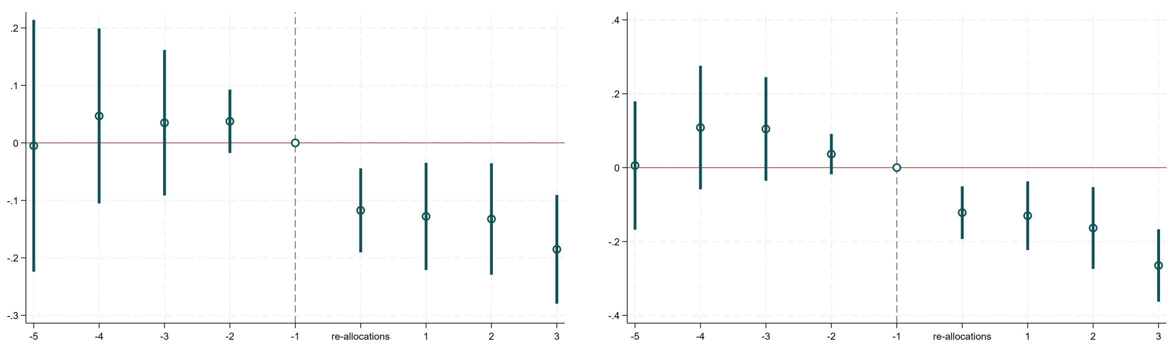
F.2 Event Study

We investigate the causal relationship between re-allocations and number of mafia families with event studies. We create q leads $(R_{r,s,t-2}, R_{r,s,t-3}, ..., R_{r,s,t-q})$ and lags $(R_{r,s,t+1}, R_{r,s,t+2}, ..., R_{r,s,t+q})$ dummy variables and include them in the model to check for anticipatory effects, using the first year before re-allocation as reference category, controlling for confiscations C_{st}. We estimate with Two-way Fixed Effects (TWFE) and Sun and Abraham (2021) estimators:

$$Mafia\,families_{st} = \sum_{\tau=2}^{q} \varphi_{-\tau} R_{s,t-\tau} + \sum_{\tau=1}^{q} \varphi_{+\tau} R_{s,t+\tau} + \beta C_{st} + \sigma_s + \lambda_t + \delta_{zt} + u_{st} \qquad \text{(F2)}$$

Figure F3: Event Study - re-allocation and mafia families (100m buffer)

(a) TWFE (b) Sun and Abraham (2021)



The figure shows the event study using nr of *Camorra* families in Naples' streets as dependent variable. Continuous lines refer to 95% confidence intervals.