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FULL ARTICLE

Shooting down the price: Evidence from Mafia homicides and housing prices

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Abstract

In this paper, we estimate the effect of the homicides by the *Camorra*, the Neapolitan Mafia, on housing prices in Naples. The study develops on a unique panel data set at the administrative district level for the period 2002–2018 of geo-localized homicides involving innocent victims (denoted as *IVH*), which are treated as exogenous shocks that negatively affect housing demand. We find that the occurrence of such homicides causes a decrease in housing prices in the range of 2.5–3.8 percentage points. This effect decreases with the distance from an *IVH* and over time. These results are robust to the utilization of different econometric specifications and to the considerations of possible confounding factors such as other types of textitCamorra homicides.

KEYWORDS
camorra, housing prices, organized crime, spatial econometrics

JEL CLASSIFICATION
C40, D01, O33

1 | INTRODUCTION

Criminal organizations such as the Italian Mafias pose a serious threat to economic development. A growing literature identified the detrimental effects that Mafias have, in particular, on GDP growth (Pinotti, 2015), foreign direct investments (Daniele & Marani, 2008), state capacity (Acemoglu et al., 2019), and the allocation of public funds (Di Cataldo & Mastrorocco, 2020).

This paper identifies another negative economic effect of Mafias, namely the one on housing prices. Specifically, in this article we estimate the effect of the homicides committed by *Camorra*, the Neapolitan Mafia, on housing prices in the city of Naples. This represents an interesting case study as in recent decades Naples has witnessed a remarkably high number of homicides involving the *Camorra*. The structural organization of *Camorra* likely explains this fact: the *Camorra* is a non-hierarchically coordinated criminal organization with many features of gangsterism, a widespread phenomenon in many different countries such as Brazil, Mexico, and the USA (Sciarrone & Storti, 2014). Its organizational structure, featuring a division in many small gangs competing to control the territory and the illegal activities taking place therein, often results in a more intense use of intimidation and violence compared to other organized criminal organizations, such as the Sicilian Mafia, which is characterized by a rigid vertical organization and established division of power over territories (see, e.g., Catino, 2014).

This study estimates the effect of *Camorra* homicides on the housing prices at the administrative district level in Naples for the period 2002–2018. The analysis develops around a unique panel data set of geo-localized *Camorra* homicides involving innocent victims (*IVH* henceforth). By innocent victim, we refer to individuals not affiliated with any *Camorra* clan who, in addition, did not consciously carry out actions that could have put them at risk of retaliation from the *Camorra*. An *IVH*, for example, can be the outcome of a random bullet during a bank assault or of a mistake, as in the case of Attilio Romanò, murdered in 2005 as he was mistaken for another person. Differently, there exist cases of non-affiliated individuals who, for their behavior, became nonetheless targets of the *Camorra*. These cases include, for example, the assassinations of Giancarlo Siani, a journalist investigating the *Camorra*, murdered in 1985, or Giuseppe Falanga, an entrepreneur murdered in 1980 for refusing to pay protection money to the *Camorra*. The latter type of homicides is not present in our data set.

The reasons to focus on *IVH* to study their relationship with housing prices are the following. First of all, *IVHs* can be treated as exogenous shocks, compared to the other *Camorra* homicides. In addition, from a behavioral perspective, these homicides are more likely to affect the residential choices of the population at large. In fact, given that they essentially involve ordinary citizens, any individual may perceive the increased risk of residing in a neighbor close to the location of their occurrence and of potentially being the next victim. As a consequence, these homicides are those likely to negatively impact on housing demand, reducing in this way housing prices in certain areas of the city.

We estimate the effects of *IVH* on housing prices through different econometric specifications. In particular, we consider a difference-in-difference framework and a generalized method of moments (GMM) setting to properly identify the effect of interest, by considering several concerns about endogeneity and confounding factors. In addition, we propose a robustness check based on a spatial econometric framework.

We find that *IVH* caused a reduction in housing prices in the range of 2.5–3.8 percentage points after their occurrence, depending on the econometric specification. The estimated effect decreases with the distance from the location of an *IVH* and with the elapsing of time after its occurrence. In the spatial econometric analysis, we also find that the housing prices increase in districts further away the location of an *IVH*, implying a relocation of the housing demand to areas perceived as safer, although the overall effect remains negative. These results are robust to the consideration of other types of *Camorra* homicides as well as other generic homicides.

This article contributes to the strand of literature investigating the socioeconomic outcomes of violent offenses by organized crime. Specifically, recent works studied how organized crime can strategically use murders and violent attacks to influence political outcomes, such as electoral participation and the capacity to govern effectively (Acemoglu et al., 2013; Alesina et al., 2019; Dal Bò et al., 2006; Daniele & Dipoppa, 2017). For example, Alesina et al. (2019), in a study of the Italian case, find that a sharp increase in violence against politicians before the electoral period reduces "anti-Mafia" efforts in the parliamentary debate.

In this context, some works investigated the direct effect of organized crime activities on the real estate market. For example, Schneider (2004), Nelen (2008), and Naheem (2017) show how the financial proceeds from illegal activities are laundered in housing markets, respectively, in Canada, the Netherlands, and China. From a criminal behavioral perspective, the recent work by Dugato et al. (2015) shows that Italian Mafias invest in real estate in areas where the control of the territory is particularly strong, and where the symbolic rewards are relevant.

Another set of studies addressed the question of the indirect impact of specific forms of violent crime on residential choices and housing prices. For example, Tita et al. (2006) find that crime affects the individual decisions of changing residential location and, in particular, that violent attacks generate the greatest cost in terms of loss of property value. Using geo-referenced data for the city of Sydney, Klimova and Lee (2014) show that murders negatively affect housing prices, with an average drop of 3.9% with respect to their initial value. Linden and Rockoff (2008) find a similar impact for within-neighborhood variation in property values (−4%), before and after the arrival of a sex offender in the neighborhood. Similarly, Pope (2008) finds a price reduction of around 2% in a Florida county when sex offenders move into a neighborhood, while in a study of Korea, Kim and Lee (2018) find higher effects from the presence of sex offenders, but with a higher time heterogeneity (i.e., the negative effects on housing prices disappears in few months). Finally, with respect to the case of Italy, Boeri et al. (2019) analyze the effect on housing prices exerted by the confiscation and re-allocation of real estate assets belonging to criminal organizations. Interestingly, they find that when the state reallocates such assets, housing prices in the surrounding area increase.

With respect to these strands of literature, the present work fills a gap by studying how the violence perpetrated by organized crime may impact on housing prices, by focusing on the Neapolitan *Camorra*. Moreover, in this way it identifies another channel through which organized crime may exert a negative effect on the economy.

The rest of the paper is organized as follows. Section 2 describes the features of Naples and of the *Camorra* activity over the city territory relevant for our analysis; Section 3 describes the data set; Section 4 contains the results of the empirical analysis; Section 5 presents the results of the spatial econometric analysis; and Section 6 contains the concluding remarks and indications for further research.

2 | BACKGROUND ANALYSIS OF NAPLES AND OF THE *CAMORRA*

According to recent statistics, Naples is the third most populated municipality in Italy. It hosts one of the biggest commercial ports in the southern Europe, and its population earns an average net income slightly above the regional average (ISTAT, 2015).

The city of Naples is divided into 30 administrative districts (see Figure A1), characterized by wide disparities in socioeconomic conditions. Figure A2, in particular, shows the level of the “Social Distress Index” (IDS, *Indice di disagio sociale*) in 2001 presented in Comune di Napoli -Servizio Statistica (2017), a publication by the statistical office of the Naples' municipality based on Census data.[1]

Figure A2 in the Appendix A highlights that the worse socioeconomic conditions are found in the northern districts of Scampia, Piscinola, Miano, Secondigliano, and San Pietro a Patierno, in the eastern districts of Ponticelli, Barra, and San Giovanni a Teduccio, in the south-central districts of Porto and Pendino, and in the western district of Pianura. On the contrary, the best socioeconomic conditions in Naples are found in the western-central districts of Arenella, Vomero, Chiaia, Posillipo, Fuorigrotta, and Montecalvario. These conditions appear very stable in time: the correlation of the IDS across districts in 2001 and 2011 is 0.98 (see Comune di Napoli-Servizio Statistica, 2017).

The activity of the *Camorra* in the city of Naples is characterized by a pervasive presence over the whole territory. The recent analysis of DIA - Ministero dell'Interno (2019) points out that there are no areas of the city that are

[1] The IDS is given by a weighted average of the discrepancies between the values of indicators of socioeconomic development and the national averages. The indicators considered for the computation of the index are: the unemployment rate, the employment rate, the youth concentration rate (i.e., the share of population aged 15 or less), and the education rate (i.e., the share of population with at least a high school degree). See Comune di Napoli -Servizio Statistica (2017), Appendix A1, for details. Higher values of the index correspond to higher levels of social distress.

immune from the presence of *Camorra* gangs.[2] Figure A3, from DIA - Ministero dell'Interno (2019), highlights the number of clans/families operating in the Naples' districts as of 2018.[3] As pointed out by DIA - Ministero dell'Interno (2019), in particular, the dynamics of the *Camorra* is characterized by a permanent state of change, as new coalitions are formed and old ones break down, new clashes take place for the turf or for the control of economic activities, both legal (e.g., restaurants and supermarkets) and illegal (e.g., drugs and counterfeiting), old *feuds* are revitalized, some groups are disrupted by police operations, etc. The clashes among rival gangs, in particular, can take place to reaffirm their own control over an area, or to extend control over other areas.

Following EUROPOL (2013), this permanent state of instability derives from *Camorra*'s horizontal structure, which differentiates this organization from vertically organized groups such as *'Ndrangheta* and *Cosa Nostra*, who originated in the Italian regions of Calabria and Sicily. All of these organizations appeared in the nineteenth century in similar conditions of development, geography (the South of Italy), and institutions (under the Bourbon Kingdom), and subsequently turned into transnational organizations with multiple businesses in several countries (see, e.g., Sciarrone & Storti, 2014).

Despite these similarities, Catino (2014) points out that, as a consequence of *Camorra*'s lower capacity of internal coordination with respect to other criminal organizations, the presence of the *Camorra* is associated with a high occurrence of homicides on the territory. In this respect, *Camorra* clans hold many of the typical features of gangsterism (Sciarrone & Storti, 2014), such as the use of intimidation and violence among rival gangs to control turf and illicit trades. These actions, oftentimes poorly planned, can occur during the daytime and in areas out of a gang's control. In this situation, homicides, in particular *IVH*, are more likely to occur.

Indeed, the city of Naples is characterized by a remarkably high number of homicides. While Italy unquestionably remains one of the safest countries worldwide, with a rate of 0.7 homicides per 100,000 inhabitants in 2015, Naples emerges as an outlier in terms of violence. The city of Naples observed 36 reported intentional homicides only in 2015, with a ratio of 3.7 homicides per 100,000 inhabitants in the same year. The average homicide rate in Naples from 2010 to 2015 was stable over time and equal to approximately 3 per 100,000 inhabitants, a value significantly higher than OECD countries' average for 2015 (see Table 1). As pointed out by Brancaccio (2009, p. 73), however, a large fraction of the total number of homicides in Naples is actually imputable to the *Camorra*.[4]

As mentioned in Section 1, to investigate the relationship between *Camorra* homicides and housing prices, this paper considers only the homicides of innocent victims (*IVH*). In the next section, we describe our data set in detail and provide more intuition on the occurrence of *IVH* with respect to the activity of the *Camorra* in Naples and to the socioeconomic conditions of the city.

3 | DATA

The data set used in this paper is obtained by merging housing price data and a unique set of self-collected data on *Camorra* homicides. Namely, we refer to *IVH*, which represents the crucial variable for our analysis, and other homicides imputable to the *Camorra*, different from *IVH*, denoted by *CH*, which will serve for robustness tests.[5]

Data on real estate prices come from (*Osservatorio del Mercato Immobiliare* (OMI), see OMI, 2019), an agency delivering half-yearly records on average maximum/minimum sale and rent price for micro-areas of the Italian cities.

[2]The report in DIA - Ministero dell'Interno (2019) is published by *Direzione Investigativa Antimafia* (DIA), a law enforcement institution specialized in combating organized crime.

[3]Similar figures presented in earlier reports by DIA (downloadable at: https://direzioneinvestigativaantimafia.interno.gov.it/page/relazioni_semestrali.html) confirm the same qualitative pattern: many clans/families operating in basically all the districts of Naples. The area of operations of each clan/family in Figure A3 is sometimes defined at a more detailed level than the administrative district.

[4]The evidence of Brancaccio (2009) refers to the province of Naples. The province is the smallest territorial unit for which data on crime are publicly available in Italy. Data on crime at city level (including their geo-localization) are not public in Italy and can be obtained only by specific agreements with law enforcement agencies. See Section 3 for details on our data set.

[5]We will also consider other generic homicides, denoted as *OH*.

TABLE 1 Intentional homicides in 2015 per 100,000 inhabitants

Country/Region	Mean
Italy	**0.70**
OECD	1.14
MENA	1.58
E_ASIA	2.74
EEC	2.96
Naples	**3.70**
SSA	9.71
LAC	12.26
CAC	29.46

Notes: Data on intentional homicide victims.
CAC: Central American countries; E_ASIA: East Asian countries; EEC: East European countries; LAC: Latin American countries; MENA: Middle East and North Africa region; SSA: Sub-Saharan Africa.
Sources: UNODC (2018) and ISTAT (2018).

The present study restricts its focus on four types of estates, those defined as "residential houses": civil housing, cheap civil housing, luxury civil housing, and villas, as these types of estates are the typical residential estates bought or rented by ordinary citizens. Figure 1 compares the boundaries of Naples' administrative districts with the OMI micro-zones defined for 2018.

In this work, we aggregated the housing prices from OMI micro-zones at the district level as the definition of the OMI zones is not stable over time. For this reason, we manually imputed in each semester the OMI housing prices for each micro-zone to the corresponding districts, and computed district-averaged housing prices for each semester for each type of estate considered.

We consider all *IVH* occurred in the period 2002h2–2018h1 in Naples. In this period, the city witnessed several blood feuds among rival families, such as the first Scampia's feud (started in 2004), with at least 100 murders among ex-affiliated and loyalist to the Di Lauro's clan, the feud between the Aprea and Celeste-Guarino families, and many others.[6]

Data on *IVH* are not reported in official Italian statistics and thus have been extracted, coded, and geo-localized from: https://www.vittimemafia.it/, a portal collecting the list of all the civilians killed by the Italian Mafias from 1861 onwards, including links to news on each event. These pieces of news provide detailed information on the date of the murders, their precise location (street and number of the closest building), the background of the victims, and whether they were accidental victims of *Camorra*.[7]

For our analysis, it is important to exclude that the effect on housing prices derives from overall gangs' activities and territorial control, or from the general level of violence in an area, rather than from *IVH*.For this reason, an extended version of the baseline specification discussed in Section 4 also includes an indicator on the number of *CH* and on the number of *OH*, which, however, are available for a shorter time period, namely 2009h1–2018h1. In particular, *CH* and *OH* for this period were reconstructed through the information provided by the Naples' Prosecutor

[6]DIA (2012, p. 128) points out the persistency in the Northern districts of Scampia and Secondigliano of a conflict of *Camorra* gangs for the control of the drugs trade, originating from the feud of 2004. See also Brancaccio (2009) for a recent history of *Camorra* feuds.

[7]We verified the reliability of these data with the ones available from alternative sources (e.g., https://www.wikimafia.it/), and from the official data we obtained from the Naples' Prosecutor Office (*Procura della Repubblica di Napoli*) which, however, include records for the period 2009h1–2018h1 only (see below). The data on *IVH* fully coincide with those in these alternative sources, so there was no need to integrate them.

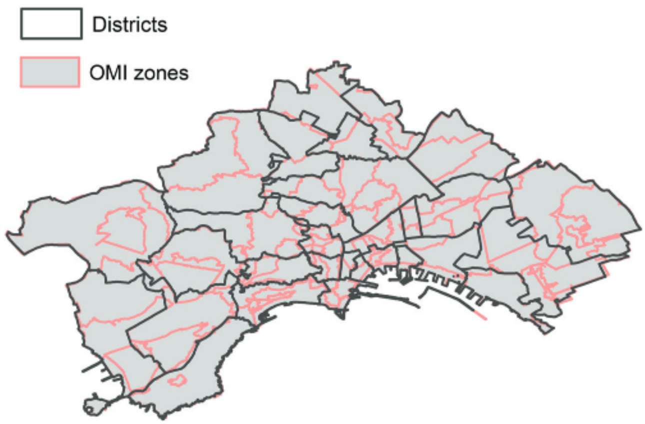


FIGURE 1 Districts' boundaries and OMI micro-zones

Office. We extended this data set to include the period 2007h2–2008h2 by matching raw data on homicides from the same office with evidence from the press.[8] Our robustness tests will consider the data from the Naples' Prosecutor office alone, as well as an extended data set on *CH* including data from 2007 and 2008.

Using the location of each *Camorra* homicide (both *IVH* and *CH*), we extracted its precise latitude and longitude. This allowed the computation of the total number of homicides that occurred within specified distances from the district borders for each semester. Figure A4 illustrates this procedure. In particular, for each district and semester, we calculated the number of homicides occurring at different distances of *n* meters ($n = 200, 500, 700, 1000$) from the district.[9]

The working hypothesis of this article is that a spatial linkage exists between housing prices in a district and the location of *IVH*. If the hypothesis holds, estate buyers will be more likely to respond to an *IVH* taking place near the estate, independently of whether it occurred within or outside the administrative boundaries of the district where the house is located. The distance of the district from an *IVH* becomes an important indicator for the perceived level of security of the area where the real estate of interest is located. This is the reason why we study the effect of the *IVH* taking place at different distances from a district, rather than just focusing on the ones occurring within the district. The procedure also allows us to test whether the expected negative effect of an *IVH* on housing prices decreases with the distance from a district. In a robustness test based on a spatial econometric approach, we will also check whether an *IVH* has a *positive* effect on housing prices in districts located further away from the location of the event, under the assumption that demand for housing may shift toward areas perceived as safer.

The top panel of Table 2 presents the descriptive statistics of *IVH*, while, for comparison, the bottom panel introduces the numbers of *CH* occurred during the shorter period of time for which we collected the data. As shown in Table 2, *IVH* amount, in mean terms, to approximately 10% of recorded *CH* at the different distance thresholds.

The econometric analysis will be conducted at a frequency period, i.e., semesters, which may prevent the inclusion of further controls due to lack of data at such frequency. For example, ISTAT conducts a detailed census on the Italian population, which can include data at a small territorial level as a city district, but at a much lower frequency, i.e., 10 years. We address this limitation in three ways. First, we will consider an indicator of nightlight obtained from

[8]For the years 2007 and 2008, we matched the raw data from Naples' Prosecutor Office containing total numbers of homicides with information from secondary sources as the press, allowing us to classify homicides as *CH* for approximately 60% of the raw number of homicides.
[9]This procedure is similar to the one adopted, for example, by Linden and Rockoff (2008) e Boeri et al. (2019).

TABLE 2 Summary statistics of *IVH* and *CH* in the district/semester panel

Variables	Observations	Mean	Std. dev.	Min	Max
Innocent victims homicides, IVH (2002h2–2018h1)					
IVH within a district	960	0.03	0.17	0	1
IVH within 200 m	960	0.05	0.25	0	3
IVH within 500 m	960	0.09	0.33	0	3
IVH within 700 m	960	0.11	0.36	0	3
IVH within 1000 m	960	0.17	0.44	0	3
Camorra homicides, CH (2009h1–2018h1)					
CH within a district	510	0.30	0.70	0	5
CH within 200 m	510	0.44	1.11	0	8
CH within 500 m	510	0.68	1.77	0	13
CH within 700 m	510	0.87	2.30	0	17
CH within 1000 m	510	1.18	3.	0	22

Notes: The table shows the summary statistics for total murders' variables in the panel of district/semester observations.

the National Oceanic and Atmospheric Administration (NOAA) (see Cecil et al., 2014), which is often considered a proxy of local income levels, and may proxy for time-varying socioeconomic characteristics of a district. These data are locally interpolated to generate half-yearly observations, while we linearly predict nighttime light value at local level for the missing years. Second, we include both district/estate fixed effects in the specification, to account for unobserved, persistent characteristics, such as those indicated in Figure A2, and a time trend. Third, we adopt a dynamic specification accounting for the lagged level of prices, which includes all the latent time-varying information up to the time period $t-1$.

Figure 2 allows us to conduct a preliminary check on the existence of possible spatial patterns in the relationship between the key variables: housing prices, divided by quantiles, and geo-localized homicides (both *IVH* and *CH*). Figure 2 shows that a clear pattern exists in housing prices, as higher prices generally characterize the districts with the better socioeconomic conditions, while the lowest prices are found in the districts with the worst socioeconomic conditions (compare Figure 2 with Figure A2).

On the contrary, while *CH* appear mostly, but not exclusively, concentrated in the districts with the lowest levels of socioeconomic development, *IVH* do not follow the same pattern. In particular, from Figure 2 it seems that *IVH* cannot be considered a mere by-product of *CH*, which can represent a proxy of *Camorra* violence at the district level.[10]

In addition, as *IVH* do not seem to characterize the districts with the lowest levels of socioeconomic development and the lowest levels of housing prices, it seems unlikely that causation runs from housing prices to *IVH*. Interestingly, the recent work of Dugato et al. (2020) aiming at predicting *Camorra* homicides in the city of Naples (without, however, distinguishing between *IVH* and *CH* as in this paper), finds that housing prices have a nonsignificant effect in predicting these homicides.[11]

The remarks on Figure 2 suggest that there does not seem to be clear patterns among socioeconomic development and housing prices on one hand, and *Camorra* homicides and *IVH* on the other hand, as well as between the two types of homicides. The econometric analysis of Section will provide a rigorous analysis of the relationship between *IVH* and housing prices considering the possible confounding role of districts' characteristics and of *CH*.

[10]Obtaining a more precise definition of *Camorra* penetration at district level along the lines, for example, of Calderoni (2011), is made difficult by the unavailability of geo-localized crime data at that geographical level. This represents another reason to use district dummies and a time trend in the econometric analysis.

[11]The work of Dugato et al. (2020) uses data from 2011 to predict geo-localized *Camorra* homicides in 2012.

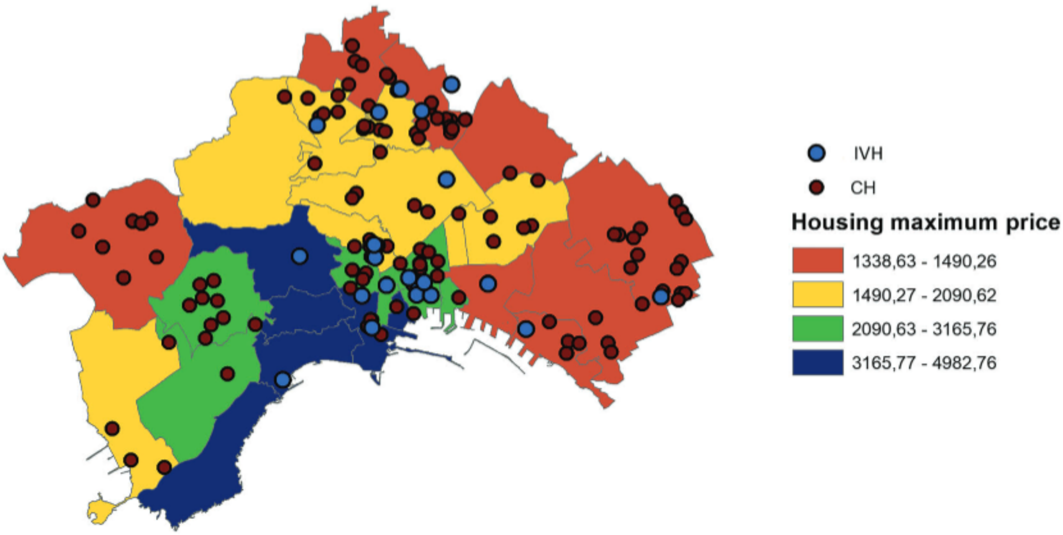


FIGURE 2 Average maximum price (in Euros) for square meter (2002–2018) of residential houses, CH (2009–2018) and IVH (2002–2018)

4 | EMPIRICAL STRATEGY AND RESULTS

As mentioned in Section 3, data on *IVH* include the latitude, longitude, and exact date of the event, making possible an identification strategy that exploits both space and time variation. An *IVH* is hereby considered as an exogenous shock affecting individual preferences for at least one period, and the panel structure allows capturing the change in housing prices after the shock.

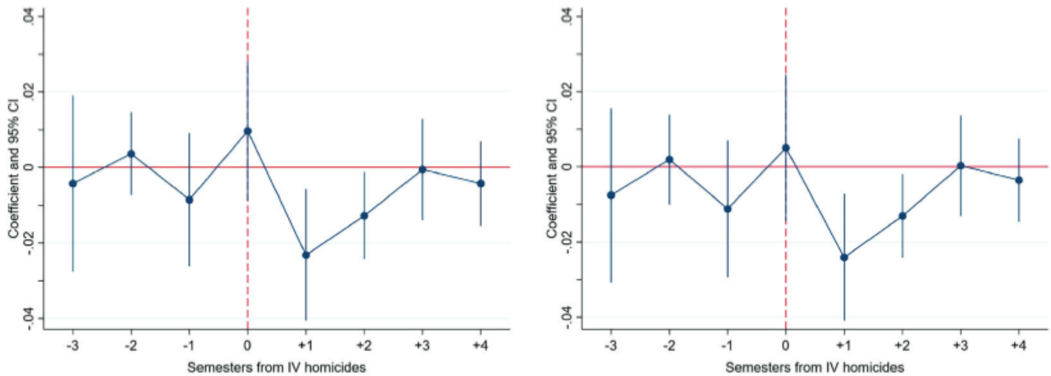
To investigate whether the occurrence of *IVH* may affect housing prices, we first implement a staggered difference-in-difference identification strategy, in which one or more *IVH* are considered as an exogenous treatment received by different districts within a given distance of the *IVH* location at different times (see, e.g., Stevenson & Wolfers, 2006, for a similar approach). Formally, we estimate the following equation:

$$lnP_{ij,t} = \delta lnP_{ij,t-1} + \sum_{\lambda=1}^{p} \beta_{-\lambda} IVH_{i,t-\lambda} + \sum_{\lambda=1}^{q} \beta_{+\lambda} IVH_{i,t+\lambda} + \phi DE_{ij} + \psi T_t + \alpha X_{i,t-1} + \mu_{it}, \quad (1)$$

where $lnP_{ij,t}$ is the natural log of the (average) price of estate type j in district i in period t (a semester), $lnP_{ij,t-1}$ is its lagged value, and $IVH_{i,t}$ is a dummy variable denoting the occurrence of one or more *IVH* within a given distance from district i at time t. The indices q and p represent, respectively, the post-homicide and the anticipatory effect of an *IVH*. The term $X_{i,t-1}$ denotes the district's nighttime light indicator, which is lagged to reduce the likelihood of reverse causality between this and the housing price indicator.[12] In addition, DE_{ij} denotes specific fixed effects for the panel unit (i.e., an estate type in a given district), capturing the joint effect of the district and the estate type; T_t is a time trend variable, included to account for possible common trends in prices, while $\mu_{i,t}$ is an error term clustered at district-estate level.

Figure 3 displays the lag and lead coefficients measuring the effect of the occurrence of one or more *IVH* on housing prices (respectively, the maximum and minimum sale prices). In the estimation of Equation (1), we

[12]The results are consistent when considering the contemporaneous measure of nighttime lights (results available upon request).



(a) Maximun sale price (b) Minimum sale price

FIGURE 3 Price dynamics before and after an *IVH*

included dummies covering from three pre-treatment periods up to four post-treatment periods, where the treatment is the occurrence of at least one *IVH*. Figure 3 also reports the 95% confidence interval of these point estimates.

Figure 3 suggests that housing prices display an evident break after the occurrence of an *IVH*. In particular, both minimum and maximum prices observe a remarkable reduction two periods after the treatment (i.e., 1 year). After this, the occurrence of an IVH does not appear to affect prices. Figure 3 also shows that the parallel trend assumption appears to be met, as the three pre-treatment coefficients are not significantly different from zero, indicating that treated and control areas did not observe differences in housing prices before the occurrence of an *IVH*. The full results of the estimation of Equation (1) are reported in Table A1 in Appendix A1, where we also tested its robustness to the inclusion of an interaction term between district dummies and the time trend to control for possible confounders (Models 3 and 7) and to the clustering of the errors at an higher level of geographical aggregation, i.e., district level (Models 4 and 8).

While these results quite clearly highlight a connection between the *IVH* and housing prices, it is well recognized that the estimation of a model with fixed effects and a lagged dependent variable may generate inconsistent estimates when the number of panel observations increases (Nickell, 1981). Furthermore, in the specific D-i-D context Bertrand et al. (2004) pointed out that concerns in terms of reliability of estimates and mis-specification may arise, leading to bias and inconsistent standard errors when the time series is short.

To overcome these limitations, we estimate the above relationship between *IVH* and housing prices following the Arellano–Bond GMM estimation methodology. This approach is based on the first differences of the time-varying variables, a procedure that cancels out the unobserved fixed effects. The coefficients are estimated using the second lag of the explanatory variables as instrument, whose adoption is supported by the results of a second-order autocorrelation test.

The baseline specification in this case takes the following form:

$$lnP_{ij,t} = \delta lnP_{ij,t-1} + \lambda D\_IVH_{i,t-1} + \phi DE_{ij} + \psi T_t + \alpha X_{i,t-1} + \mu_{i,t}, \tag{2}$$

where D_IVH_i denotes the number of *IVH* at $t-1$ within a given distance from district *i*. To further test the robustness of this approach, we also estimate Equation (2) using the Blundell–Bond level specification and the bias-corrected LSDV dynamic panel data model (see, e.g., Bruno, 2005). In the case of highly persistent data, as housing prices in our case, Blundell and Bond (2000) show that the level-GMM estimator has a far lower bias than the other

TABLE 3 *IVH* and housing prices in a dynamic panel framework (2003h1–2018h1)

Variables	Max sale (log) (1)	Min sale (log) (2)	Max sale (log) (3)	Min sale (log) (4)	Max sale (log) (5)	Min sale (log) (6)	Max sale (log) (7)
# D_IVH within 200 m	−0.033***	−0.030***	−0.037***	−0.038***	−0.025***	−0.025***	−0.043**
	(0.011)	(0.011)	(0.008)	(0.008)	(0.006)	(0.006)	(0.022)
Max sale price (log, lag)	0.895***		0.979***		0.906***		0.446***
	(0.035)		(0.006)		(0.011)		(0.113)
Min sale price (log, lag)		0.980***		0.946***		0.856***	
		(0.032)		(0.006)		(0.013)	
Nightlights index (lag)	0.093*	0.081*	−0.006	−0.010	0.043	0.025	−0.025
	(0.052)	(0.046)	(0.058)	(0.027)	(0.027)	(0.029)	(0.115)
Time trend	−0.002***	−0.002***	−0.003***	−0.003***	−0.003***	−0.002***	−0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
AR(1) *Pr* > *z*	0.000	0.000	0.000	0.000	-	-	0.008
AR(2) *Pr* > *z*	0.900	0.770	0.977	0.842	-	-	
Hansen/Sargan Over-Id test *Pr* > *z*	0.10	0.16	0.878	0.868	-	-	0.771
Dynamic model	Arellano–Bond	Arellano–Bond	Blundell–Bond	Blundell–Bond	Kiviet	Kiviet	Blundell–Bond
Observations	2557	2557	2557	2557	2557	2557	930
Number of groups	103	103	103	103	103	103	30

Notes: The table reports estimates obtained from a first-difference GMM Arellano–Bond estimation. The estates in the sample are civil housing, cheap civil housing, luxury civil housing, and villas. The dependent variables are the natural log of the maximum sale price (Model 1), the natural log of the minimum sale price (Model 2), the natural log of the maximum sale price (Model 3), and the natural log of the minimum sale price (Model 4). The instruments are limited to one lag to keep the number of instruments lower than the number of groups. All specifications control for the *IVH* within 200 m from the district (lag), nightlight index (lag), and the lag of the dependent variable. Only the first lag is added as instrument. Fixed effect at district-estate level. Robust standard errors clustered at district-estate level in parentheses. Level of significance is *$p < 10\%$; **$p < 5\%$; ***$p < 1\%$.

alternatives.[13] Table 3 presents the results of the estimation of Equation (2) as a dynamic panel following the mentioned approaches.

The coefficient on the number of *IVH* is negative and significant for all specifications, supporting the main hypothesis that the fear deriving from this particular type of homicides reduces the individual willingness to pay (Bayer et al., 2016; Pope, 2008), having a negative effect on housing prices. The magnitude of the coefficients suggests that the impact on housing prices of an additional *IVH* is between −2.5% and −3.8%. The bottom part of the table shows the results of the tests on the models, which allow to exclude both over-identification when the instruments are collapsed in a vector (Models 1 and 2) and the presence of second-order autocorrelation.[14] Model 7 in Table 3 reports the results obtained when focusing on the within-district average of the four residential types of housing considered in Models 1–6, to assess if the consideration of different estate types within the same district

[13]For this reason we will consider the Blundell–Bond specification as our preferred specification in some extensions that follows.

[14]To collapse the instruments in a vector, we used the command *xtabond2* in Stata. The estimated coefficients are consistent when considering *IVH* committed at a distance of 500, 700, and 1000 m (results available upon request).

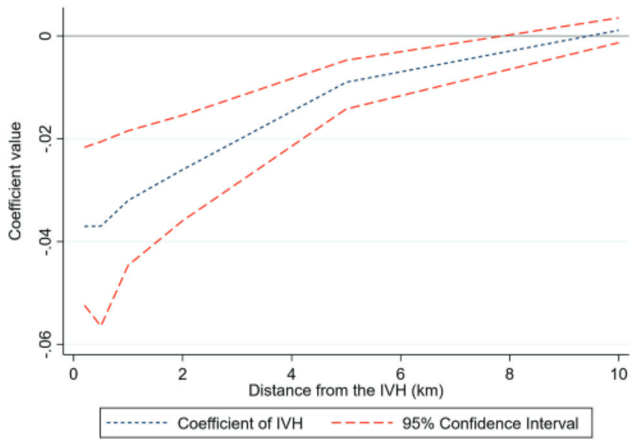


FIGURE 4 Effect of *IVH* at different distances from the district using Blundell–Bond and a panel of real estates (2002–2018)

could have introduced spurious variability.[15] The coefficient reported in Model 7 is consistent with the other models, being even higher.[16]

An implication of the theoretical framework is that the absolute value of the coefficient of an *IVH* on housing prices should decrease with the distance of the *IVH* from a district, as long as the perception of risk is stronger the closer is the location of an *IVH*. To this purpose, Equation (2) is estimated considering increasing distances from the *IVH*. Figure 4 summarizes the results on the magnitude of the coefficient of the effect of *IVH* using the Blundell–Bond specification. The absolute value of the coefficient decreases when the distance increases to more than 200 m. The effect remains negative and significant but decays with the distance, up to a value of approximately 8 km, where it becomes nonsignificant.

A potential criticism to the above approach refers to possible sudden changes in *Camorra* activity, which could undermine the direct link of causation between *IVH* and housing prices. It could be argued, indeed, that even if the adopted model is able to account for the level of prices during the preceding semester, and to some extent to a set of observed and unobserved characteristics, it could fail to control for a sudden change in the level of *Camorra* activity. The hypothesis behind this criticism could be that *Camorra* activities, such as extortions, usury, and homicides of *Camorra* affiliates, could suddenly change across semesters, affecting in this way housing prices. The model, therefore, would fail to consider this sudden change and would impute the effect of the increased *Camorra* activity to the *IVH*, which would therefore appear as a by-product of the variation in *Camorra* activity.

We have pointed out in Section 2 that this does not seem to be the case. However, to provide a more rigorous support to this claim, we extend the baseline specification to consider the number of *CH* and the number of other homicides (*OH*), different from *Camorra* homicides, as a proxy for the general level of violence in an area. As pointed out in Section 3, however, this implies focusing on a reduced sample because of limited data availability. Controlling for *CH* can also be considered a good placebo test as these homicides should not affect housing prices if the hypotheses made in this paper are correct. In addition, *CH* represent a good proxy of the level of violent *Camorra*

[15]Considering one average price per district is also relevant for the spatial econometric analysis, a robustness test presented in Section 5 as that type of analysis does not allow to keep the district/type dimension. In fact, in a spatial framework, the blocks of elements of the distance matrices would have zero distance (e.g., cheap and luxury estates in the same district have zero distance), implying a non-meaningful sparse block-stacked distance matrix (Lam & Souza, 2016).

[16]As robustness check, we have run two specifications including (i) time dummies and (ii) time × district dummies. In both cases, the coefficients are consistent with that presented in the main part of the analysis. However, the number of instrument increases substantially, and this makes the resulting value of the Hansen/Sargan test unreliable. In addition, results remain significant when controlling for the economic crisis using a dummy assuming value 1 for the period 2008h1–2011h2.

TABLE 4 *IVH*, *CH*, *OH*, and housing prices

Variables	Max sale (log) 2009–2018 (1)	Min sale (log) 2009–2018 (2)	Max sale (log) 2007–2018 (3)	Min sale (log) 2007–2018 (4)	Max sale (log) 2009–2018 (5)
# D_IVH within 200 m	−0.037**	−0.027*	−0.016**	−0.016**	−0.036**
	(0.018)	(0.016)	(0.007)	(0.008)	(0.017)
# D_CH within 200 m	0.001	0.002	0.001	0.002	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
# D_OH within 200 m					−0.002
					(0.001)
Max sale price (log, lag)	0.987***		0.983***		0.987***
	(0.004)		(0.003)		(0.003)
Min sale price (log, lag)		0.989***		0.984***	
		(0.004)		(0.003)	
Nightlights index (lag)	−0.027	−0.028	−0.007	−0.009	−0.027
	(0.029)	(0.029)	(0.016)	(0.012)	(0.030)
Time trend	Yes	Yes	Yes	Yes	Yes
AR(1) *Pr* > *z*	0.009	0.009	0.004	0.003	0.009
AR(2) *Pr* > *z*	0.019	0.025	0.013	0.016	0.018
AR(3) *Pr* > *z*	0.063	0.073	0.042	0.052	0.059
AR(4) *Pr* > *z*	0.114	0.129	0.079	0.094	0.112
Sargan Over-Id test *Pr* > *z*	0.509	0.205	0.524	0.157	0.722
Observations	1136	1136	1963	1963	1136
Number of groups	93	93	93	93	93

Notes: The table reports estimates obtained from system-GMM estimations (Blundell & Bond, 2000) on housing prices. The estates in the sample are civil housing, cheap civil housing, luxury civil housing, and villas. The dependent variables are the natural log of the maximum sale price (Models 1 and 3) and the natural log of the minimum sale price (Models 2 and 4). The instruments vary from 2 to 4 lags to keep the number of instruments lower than the number of groups and avoid autocorrelation issues. All specifications control for the total number of Mafia murders within 200 m from the district (lag), nightlight index (lag), and the lag of the dependent variable. Fixed effect at district-estate level. Robust standard errors clustered at district-estate level in parentheses. Level of significance is *p < 10%; **p < 5%; ***p < 1%.

activities in a given neighborhood. If the coefficient of *IVH* remains consistent to the inclusion of these additional controls, we could argue that *IVH* have an impact on housing prices even when accounting for other relevant *Camorra* violent actions.

Following this line of reasoning, we estimated Equation (2), using the Blundell–Bond approach, including the numbers of geo-localized *CH* and *OH*. Table 4 contains the results.

Models 1 and 2 in Table 4 contain results obtained when using exclusively data on *CH* from Naples Prosecutor's Office (i.e., for the period 2009–2018), while Models 3 and 4 report the results with the larger sample of *CH* (i.e., for the period 2007–2018) (see Section 3 for details). Results in Table 4 show that the effect of *IVH* remains negative and significant and that, differently, the impact of *CH* is not significant.[17] The magnitude and the significance of *IVH*

[17]Table 3 reports only SYS-GMM estimates as with a smaller sample and a smaller number of *IVH* the bias implied by difference-GMM estimations such as those based on the Arellano–Bond approach, in the case of autoregressive roots higher than 0.8 is much higher than level-GMM estimations, such as those based on the Blundell–Bond approach (see Blundell & Bond, 2000). With the alternative estimators of Table 3, we still find a negative coefficient for *IVH*, but nonsignificant (results are available upon request).

are, however, lower than those of Table 4. A likely explanation for this result is that the number of *IVH* in this shorter period is quite low, especially for Models 1 and 2. Finally, Model 5 adds to the regressors the number of geo-localized *OH*. The estimated coefficient of *IVH* is still negative and significant, while the coefficient of *OH* is nonsignificant.

Taken together, the results presented in Table 4 support the hypothesis that the occurrence of *IVH*, different from other types of *Camorra* homicides or to the general level of violence in an area, proxied by geo-localized *OH*, is a significant driver of housing prices. In the next section, we present the results of a robustness check based on a spatial econometric analysis of the effect of *IVH* on housing prices.

5 | ROBUSTNESS CHECKS: A SPATIAL ECONOMETRICS ANALYSIS

The existence of local negative effect deriving from *IVH*, and the contemporaneous occurrence of these crimes affecting different neighbors at the same time, may raise two reasons of concern. From an econometric perspective, despite the strategy in Equation (1) and (2) may reduce the bias deriving from multiple unobserved time-invariant confounders, when spatial correlation exists in the explanatory variables the estimation will yield biased coefficients.[18] In addition, Equation (2) is unable to capture whether *IVH* have a heterogeneous spatial effect when interacting with individual preferences. Third, it is natural to expect that house-seekers make the decision of buying a new house according to a set of constraints, such as the closeness to the workplace, family, friends, and services. Even after an *IVH*, these constraints are likely to play a key role in the decision to relocate, and therefore the impact on prices of housing estates located in the districts away from the location *IVH* may observe an unexpected upward turn. In other words, as found for example by Bayer et al. (2016), people might be willing to pay to live in safer neighborhoods; i.e., the housing prices may increase in districts further away from the locations of *IVH*.

For these reasons, in this section we propose as an additional test of our results a spatial econometric model. In particular we will initially consider the following alternatives. The first possible specification is the Spatial Autoregressive Model (SAR) that assumes a spatial effect on housing prices only through neighboring districts' prices. The second specification is the Spatial Error Model (SEM), where spatial influence is a nuisance disturbance parameter. Finally, the third specification is the Spatial Durbin Model (SDM) where spatial effects also come from independent variables measured in neighboring districts.

This analysis proceeds in two steps. First, we leave aside any assumption about what type of spatial dependence matters and estimate the three alternative models on a simplified, first-differenced version of Equation (2). Specifically, we estimate the following equation:

$$\Delta lnP_{i,t} = \rho \mathbf{W} lnP_{i,t} + \beta \mathbf{X}_{i,t} + \gamma \mathbf{W} \mathbf{X}_{i,t} + \upsilon_{i,t}, \tag{3}$$

where, in case of spatial dependence through the error terms, the idiosyncratic error term $\upsilon_{i,t}$ would be expressed as:

$$\upsilon_{it} = \lambda \mathbf{W} + \epsilon_{i,t}. \tag{4}$$

In Equations (3) and (4), $\mathbf{W}$ indicates the spatial distance matrix, while vector $\mathbf{X}_{i,t}$ contains the nightlight index and the numbers of *IVH*.[19] Once the main channel of spatial influence on housing prices is identified, we will estimate the full model with the complete dynamic specification.

[18] A general presentation of the spatial econometric analysis of crime spillovers is in Anselin et al. (2000).

[19] For this type of analysis, we considered only one type of estate for every district by averaging the housing prices for the four different estate types. This is necessary as, otherwise, the distance matrix cannot be properly constructed as it would contain rows of zeros for different estate types belonging to the same district.

TABLE 5 *IVH* and real estate prices (in first differences) in a spatial framework

Variables	Max sale (FD) (SEM) (1)	Max sale (FD) (SAR) (2)	Max sale (FD) (SDM) (3)	Max sale (FD) (SEM) (4)	Max sale (FD) (SAR) (5)	Max sale (FD) (SDM) (6)
# D_IVH within 200 m	−0.026***	−0.025**	−0.025**			
	(0.010)	(0.010)	(0.010)			
# D_IVH within 1000 m				−0.017***	−0.017***	−0.017***
				(0.000)	(0.006)	(0.006)
Nightlights index (lag)	0.076	0.075	0.074	0.074	0.074	0.074
	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)
γX						
# D_IVH within 200 m			−0.116*			
			(0.064)			
# D_IVH within 1000 m						−0.026
						(0.044)
Nightlights index (lag)			0.093			0.066
			(0.341)			(0.341)
Spatial						
$\hat{\rho}$		−0.624***	−0.657***		−0.612***	−0.619***
		(0.142)	(0.144)		(0.141)	(0.142)
$\hat{\lambda}$	−0.626***			−0.602***		
	(0.141)			(0.139)		
Spatial effects (short run)						
Direct						
# D_IVH within 200 m		−0.025**	−0.022**			
# D_IVH within 1000 m					−0.017***	−0.017***
Nightlights index (lag)		0.074	0.074		0.073	0.071*
Indirect						
# D_IVH within 200 m		0.010**	−0.059			
# D_IVH within 1000 m					0.006**	−0.007
Nightlights index (lag)		0.03	0.027		−0.028	0.011
Total						
# D_IVH within 200 m		−0.015**	−0.081**			
# D_IVH within 1000 m					−0.010***	−0.024
Nightlights index (lag)		0.045	0.097		0.045	0.082
Observations	930	930	930	930	930	930
Number of groups	30	30	30	30	30	30

Notes: The table reports estimates obtained from spatial panel model on the house prices panel sample. The dependent variable is the natural log of the maximum sale price. All specifications control for *IVH* within 200 m and 1000 m (lag) and their spatial lag, nightlight index (lag), and its spatial lag, the lag of the dependent variable. Robust standard errors in parentheses. Level of significance is *p < 10%; **p < 5%; ***p < 1%.

TABLE 6 *IVH* and housing prices in a spatial framework (levels)

Variables	Max sale (log) (SAR) (1)	Min sale (log) (SAR) (2)	Max sale (log) (SAR) (3)	Min sale (log) (SAR) (4)
Max sale (log, lag)	0.844***	0.839***		
	(0.017)	(0.018)		
Min sale (log, lag)			0.848***	0.842***
			(0.017)	(0.018)
# D_IVH within 200 m	−0.023**	−0.023**		
	(0.010)	(0.010)		
# D_IVH within 1000 m			−0.014**	−0.014**
			(0.006)	(0.006)
Nightlights index (lag)	0.038	0.036	0.037	0.035
	(0.053)	(0.053)	(0.053)	(0.053)
$\hat{\rho}$	−0.563***	−0.557***	−0.573***	−0.566***
	(0.106)	(0.109)	(0.107)	(0.000)
Spatial effect (short run)				
Direct - #D_IVH within 200 m and 1000 m	−0.024**	−0.024**	−0.014**	−0.014**
Direct - Nightlights index (lag)	0.044	0.042	0.044	0.042
Indirect - # D_IVH within 200 m and 1000 m	0.009**	0.009**	0.005**	0.005**
Indirect - Nightlights index (lag)	−0.016	−0.015	−0.016	−0.015
Total - # D_IVH within 200 m and 1000 m	−0.015**	−0.015**	−0.009**	−0.009**
Total - Nightlights index (lag)	0.028	0.025	0.028	0.027
Spatial effect (long run)				
Direct - # D_IVH within 200 m	−0.214**	−0.200**	−0.137**	−0.127**
Direct - Nightlights index (lag)	0.399	0.335	0.415	0.367
Indirect - # D_IVH within 200 m	0.181**	0.167**	0.118**	0.107**
Indirect - Nightlights index	−0.335	−0.294	−0.353	−0.307
Total - # D_IVH within 200 m	−0.033**	−0.033**	−0.020**	−0.020**
Total - Nightlights index (lag)	0.064	0.061	0.062	0.059
Observations	930	930	930	930
Number of groups	30	30	30	30

Notes: The table reports estimates obtained from spatial panel model on the house prices panel sample. The dependent variable is the natural log of the maximum sale price. All specifications control for *IVH* within 200 m and 1000 m (lag) and their spatial lag, nightlight index (lag), and its spatial lag, the lag of the dependent variable. Robust standard errors in parentheses. Level of significance is *p < 10%; **p < 5%; ***p < 1%.

The spatial estimation relies on a spatial matrix **W** constructed using a minimum threshold truncated approach, based on the districts' centroids.[20] This corresponds to assume that the weight of the effect on housing prices of district *i* from district *j* decays as the distance between *i* and *j* increases.[21] Table 5 reports the results of SAR, SEM, and SDM specifications of Equation (3), considering *IVH* within 200 and 1000 m from a district.

[20]For the estimation of the spatial models, we used the Stata *xsmle* code.

[21]Stetzer (1982) and Stakhovych and Bijmolt (2009) point out that the weight matrix definition is a crucial choice in applied spatial econometrics, so that the coefficients of interest may remarkably change with different matrix definitions. For this reason, we also considered different distance matrices (i.e., based on rook and queen contiguity), but results (available upon request) were not affected.

Results in Table 5 show that the effect of *IVH* on housing prices is negative and significant for all the specifications considered. In terms of absolute magnitude, the effect is consistent with the range of values presented in Section 4. In particular, the magnitude of the coefficient of *IVH* decreases with the distance of an *IVH* from a district and varies from −2.6%, when considering *IVH* within 200 m, to −1.8%, for *IVH* within 1000 m.[22] The spatial effects appear relevant: the SEM model identifies a spatial dependence in the error terms, and both the SAR and SDM models show that a relevant channel of spatial dependence resides in changes in housing prices in neighboring districts (see the significant value of ρ in Models 2, 3, 5, and 6).

In addition, the SAR model is the only one reporting a significant indirect effect of *IVH*. The indirect effect associated with the occurrence of an additional *IVH* within, respectively, 200 and 1000 m from a district, amounts to 1% and 0.6%. This points toward the presence of spillover effects of *IVH* across housing prices in different districts. The total overall effect remains, however, negative. The SAR model suggests that this effect ranges between −1.5% and −1%, depending on the distance from an *IVH*. The effect arises exclusively from the SAR model, and this suggests that the relevant spatial linkage is among housing prices. In Equation (3), the γ terms of the more general SDM contained in Models 3 and 6 of Table 5 are not always significantly different from 0, suggesting that the SAR specification is better able to capture the relevant spatial effects.

For these reasons, we argue that the SAR specification is the one better able to capture spatial effects, in particular it highlights the direct and indirect effects of *IVH* on housing prices. In what follows, therefore, we select the SAR specification for the estimation of the fully specified dynamic spatial model. Table 6 presents the results of estimation of the dynamic SAR model.

Table 6 shows that adding the time-lagged housing price levels does not substantially impact on the magnitude and on the statistical significance of the coefficients of *IVH*: the occurrence of a *IVH* is associated with a variation in price of about −2.4% for the *IVH* within 200 m, while its effect decreases to −1.4% for *IVH* within 1000 m.

The estimation of a dynamic model also allows for the computation of long-run direct and indirect effects, besides the short-run effects.[23] The bottom panel of Table 6 contains the results. Interestingly, the long-run magnitude of the total effects is higher than the short-run impact, although it remains close to the range of values estimated so far. In the next section, we derive the main conclusions of our analysis and discuss some directions for further research.

6 | CONCLUDING REMARKS

In this paper we identified a novel negative economic effect of organized crime. We showed that violent organized crime's actions such as homicides have a negative effect on housing prices. To support this claim, we focused on the city of Naples where the criminal organization named *Camorra* is rampant, and on a specific type of homicide, that we denoted as *Innocent Victim Homicide*.

The empirical evidence we presented proved to be robust to different econometric specifications and to the inclusion of a number of potentially confounding factors, referred to time-invariant district characteristics, as well as to time-varying factors such as other types of homicides, attributable to the *Camorra* or not.

These results suggest that house-seekers adjust their choices when observing a *IVH* in a certain area of the city, while they do not modify them when observing other types of homicides, such as *CH*. A potential explanation could be that these two types of violent actions play a different role on expectations and risk perceptions in the population. For example, as *CH* relate to homicides of *Camorra* affiliates or individuals engaged in contrasting *Camorra* activities, house-seekers could consider the occurrence of a *CH* as an expected event not changing their risk exposure. In contrast, the occurrence of *IVH* may have a strong effect on their risk attitude, as they can assume to be a potential target.

[22]Consider, for example, that the average district area is about 4 km^2; thus the Euclidean distance from the centroids of two districts would be at least 2 km.

[23]The long-run effects can be computed by considering the housing prices in the dynamic specification at their equilibrium level. See, e.g., LeSage and Pace (2014).

On the contrary, if an *IVH* is an exogenous, unpredictable event, why should ordinary citizens be actually affected? Strictly speaking, the fact that one *IVH* occurred at a certain time in a certain place does not imply that it will happen again. We conjecture that a possible explanation resides in the different media exposure that *IVH* and *CH* receive. In Appendix B1 we show that, indeed, an *IVH* receives a much greater media exposure than an *CH*. Dugato et al. (2020) report cases of *IVH* that were even covered by international media, such as the BBC. If this is the case, it can happen that *IVHs* remain more strongly imprinted in the collective memory, and are able to affect the housing demand of population at large, at least for some periods after their occurrence, as the evidence in Figure 3 and Table 3 suggests. The relationship between Mafia violence, its amplification through the media, and its economic effects remains an interesting area for further research.

Finally, the spatial econometric analysis suggests that *IVHs* not only reduce housing prices in areas near the locations of their occurrence, but they are associated with increases in housing prices in areas further away. This result points to the possibility that Mafia violence in an urban context can increase the dispersion of housing prices within a city. As long as this is an important component of inequality, as pointed out for example by Glaeser and Gottlieb (2009, p. 43), organized crime activities can have another relevant negative economic effect, namely an increase in inequality. Preliminary evidence in Appendix C1 shows that, indeed, in a cross-section of Italian provinces the presence of *horizontal* criminal organizations is associated with higher within-city housing price dispersion. A thorough examination of this issue goes beyond the scope of this paper and remains another topic for further research.

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APPENDIX A: OTHER FIGURES AND TABLES

Figure A1 shows the map of Naples, with its 30 administrative districts.

Figure A2 shows the level of the Social Distress Index as measured in 2001 for each district of Naples. Higher levels of the index are associated with higher distress.

Figure A3 is from DIA - Ministero dell'Interno (2019) and shows the spatial distribution of *Camorra* Clans in the city of Naples as of 2018.

Figure A4 provides an example of the approach adopted to geo-localize the *IVH* in our analysis. For example, for a specified distance from homicide X, given by the ray of the circumference around its location, the housing prices of Districts 1 and 2 are expected to be affected. Homicide Y, instead, will be assumed to affect housing prices in Districts 7, 8, and 9. Clearly, more districts can be considered as affected when the threshold distance from the homicides increases.

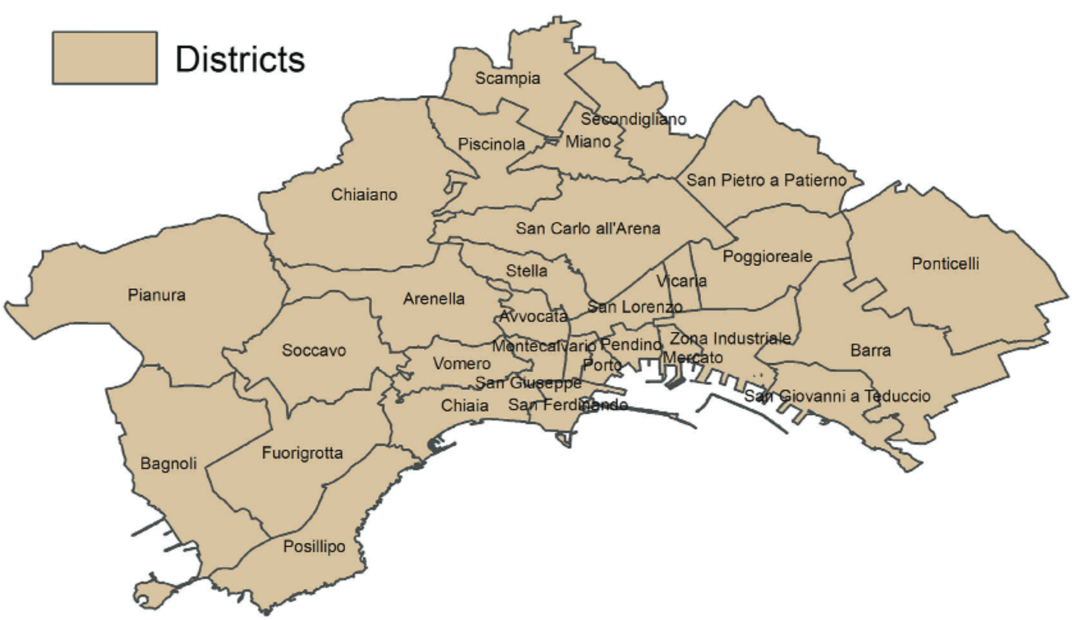

FIGURE A1 The 30 administrative districts of Naples

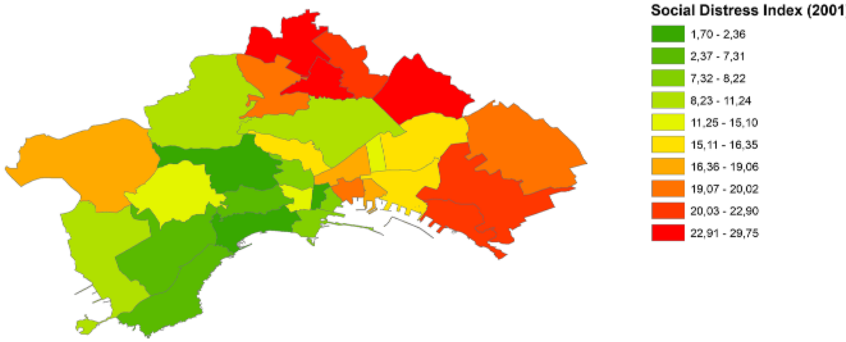

FIGURE A2 Social Distress Index in 2001 in the 30 administrative districts of Naples. *Source*: Comune di Napoli -Servizio Statistica (2017)

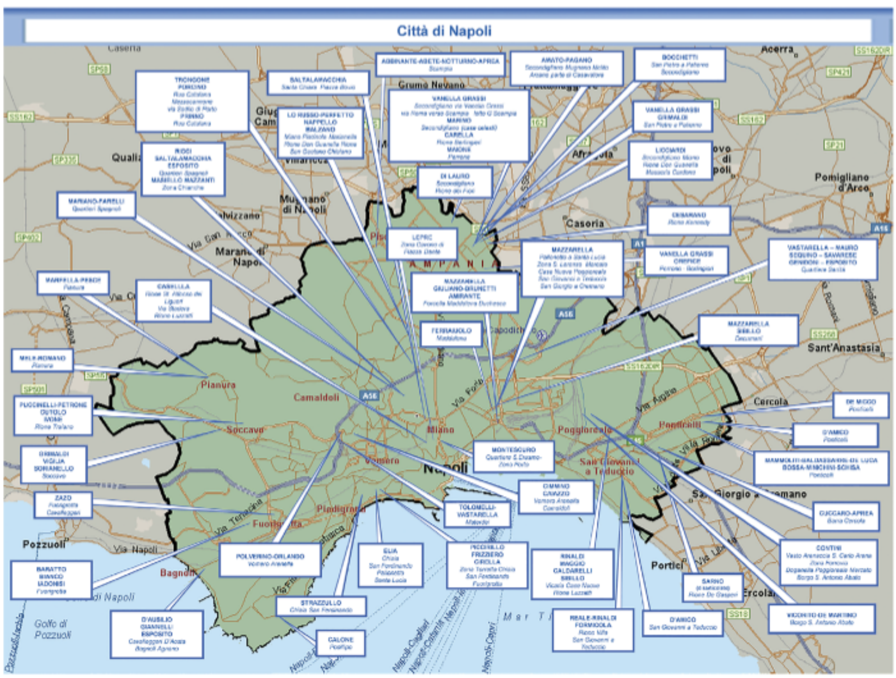

FIGURE A3 *Camorra* clans in Naples. *Source*: DIA - Ministero dell'Interno (2019)

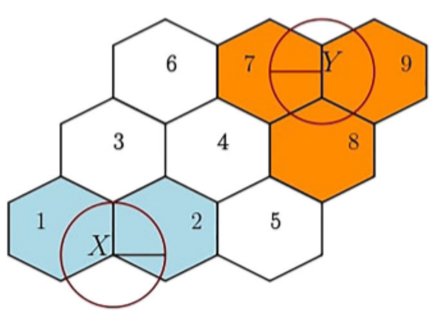

FIGURE A4 Geo-localization of homicides and their effects on housing prices

TABLE A1 IVH and housing prices in a difference in difference framework (2003h1–2018h1)

Variables	(1) Max sale (log)	(2) Max sale (log)	(3) Max sale (log)	(4) Max sale (log)	(5) Min sale (log)	(6) Min sale (log)	(7) Min sale (log)	(8) Min sale (log)
# D_IVH within 200 m (lag 3)		−0.004	−0.017	−0.004		−0.008	−0.020*	−0.008
		(0.012)	(0.012)	(0.016)		(0.012)	(0.012)	(0.016)
# D_IVH within 200 m (lag 2)		0.004	−0.005	0.004		0.002	−0.007	0.002
		(0.006)	(0.007)	(0.008)		(0.006)	(0.008)	(0.008)
# D_IVH within 200 m (lag 1)		−0.009	−0.020*	−0.009		−0.011	−0.023*	−0.011
		(0.009)	(0.011)	(0.011)		(0.009)	(0.012)	(0.011)
# D_IVH within 200 m		0.010	0.002	0.010		0.005	−0.002	0.005
		(0.009)	(0.009)	(0.011)		(0.010)	(0.009)	(0.011)
# D_IVH within 200 m (lead 1)	−0.028***	−0.023***	−0.034***	−0.023*	−0.028***	−0.024***	−0.035***	−0.024*
	(0.009)	(0.009)	(0.011)	(0.013)	(0.009)	(0.008)	(0.010)	(0.012)
# D_IVH within 200 m (lead 2)		−0.013**	−0.019***	−0.013*		−0.013**	−0.019***	−0.013*
		(0.006)	(0.006)	(0.007)		(0.006)	(0.006)	(0.007)
# D_IVH within 200 m (lead 3)		−0.001	−0.008	−0.001		0.000	−0.007	0.000
		(0.007)	(0.006)	(0.011)		(0.007)	(0.006)	(0.011)
# D_IVH within 200 m (lead 4)		−0.004	−0.012*	−0.004		−0.004	−0.011*	−0.004
		(0.006)	(0.007)	(0.009)		(0.006)	(0.006)	(0.009)
Max sale price (log, lag)	0.817***	0.827***	0.742***	0.827***	0.817***			
	(0.011)	(0.018)	(0.020)	(0.020)	(0.011)			
Min sale price (log, lag)						0.827***	0.737***	0.827***
						(0.019)	(0.022)	(0.020)
Nightlights index (lag)	0.006	0.032	0.039	0.032	0.006	0.025	0.031	0.025
	(0.012)	(0.035)	(0.031)	(0.045)	(0.012)	(0.036)	(0.032)	(0.046)
Constant	1.532***	1.723***	2.464***	1.723***	1.532***	1.670***	2.419***	1.670***
	(0.086)	(0.168)	(0.176)	(0.205)	(0.086)	(0.165)	(0.183)	(0.196)

(Continues)

TABLE A1 (Continued)

Variables	(1) Max sale (log)	(2) Max sale (log)	(3) Max sale (log)	(4) Max sale (log)	(5) Min sale (log)	(6) Min sale (log)	(7) Min sale (log)	(8) Min sale (log)
Time trend	YES	YES		YES	YES	YES		YES
Interaction District Dummies*Time trend			YES				YES	
Cluster standard errors	ID	ID	ID	District	ID	ID	ID	District
Observations	2557	1934	1934	1934	2557	1934	1934	1934
R^2	0.864	0.822	0.844	0.822	0.864	0.823	0.844	0.823
Number of id	103	102	102	102	103	102	102	102

Notes: The table reports estimates obtained from a difference-in-difference design. The estates in the sample are civil housing, cheap civil housing, luxury civil housing, and villas. The dependent variables are the natural log of the maximum and minimum sale price (Models 1–8). Fixed effect at district/estate level and time trend is considered in Models 1, 2, 4, 5, 6, and 8, while Models 3 and 7 contain an interaction between fixed effects and the time trend. Robust standard errors clustered at district/estate level in parentheses in Models 1, 2, 3, 5, 6, and 7, while Models 4 and 8 present standard errors clustered at the district level. Level of significance is *$p < 10\%$; **$p < 5\%$; ***$p < 1\%$.

APPENDIX B: NEWS AND *CAMORRA* Homicides

In this appendix, we present measures of media coverage of *IVH* and *CH*. We use two measures to this purpose. The first one is the number of news about a homicide. Specifically, for two matched couples of *IVH* and *CH* occurring in the same day in Naples, we consider the variable *LexisNexis*, which accounts for the number of articles that include the victim's name published by the main media and newspapers in Italian language. In this case, we consider the news in the 3 months following the events. The second measure is the value of the *Google Trend Index* for the names of the victims in the days following the homicide, which may account for the interest in the event expressed by the population.

Table A2 shows that *IVH*s receive much greater attention by the media than *CH*s as the *LexisNexis* variable is much higher for an IVH. In particular, the *LexisNexis* variable highlights that in the 3 months after the events the coverage is much higher for an *IVH*. On the contrary, the *Google Trends Index* shows that an *IVH* generates much more searches on victim's name both on the day of the tragic event and in the subsequent days: searches on *CH* are so low that Google Trends Index does not even report it in its public platform. This suggests that the interest of the public in an *IVH* is much higher than for a *CH*, supporting the hypothesis that an *IVH* impacts on the collective memory much more than a *CH*.

TABLE A2 News dissemination in the media: Random vs Camorra homicides

		Google Trends						
	LexisNexis[24]	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
20/10/2010								
Innocent victim homicide	96	100	19	46	28	38	13	27
Camorra homicide	0	0	0	0	0	0	0	0
6/9/2015								
Innocent victim homicide	44	75	100	72	56	29	74	17
Camorra homicide	16	0	0	0	0	0	0	0

Notes: The table compares two innocent victims' homicides with two cases of Camorra homicides occurred on the same day (details available upon request). The value assumed by the variable *Google Trends* indicates a relative frequency of a given search term, the victim's name in this specific case, into Google's search engine divided by the total searches conducted in the geographical area under consideration. The value of *LexisNexis* provides information on the number of articles including the name of the victim over a given period of time. In this case, the span of time considered is 3 months after the murder, and the search is restricted to news in Italian.

APPENDIX C: ORGANIZED CRIME AND HOUSING PRICES' DISPERSION

In this appendix, we provide descriptive evidence on the relationship between the presence of criminal organizations, classified according to their organizational structure, and housing prices' dispersion in a cross-section of Italian provinces.

Table A3 reports the type of criminal organization (horizontal/vertical) operating in the provinces where organized crime is pervasive (i.e., in the regions of Apulia, Campania, Calabria, and Sicily), according to EUROPOL (2013), as well as an indicator of Mafia presence from Calderoni (2011) in these provinces.

Figure A5 reports the values of housing prices' variances in different groups of Italian provinces, partitioned according to the pervasive presence of organized crime and to the type of criminal organization operating in their territories.[25]

[25]These variances are computed across the administrative districts of a city and are based on the four types of housing considered in the main text.

TABLE A3 Mafia types by organization model

Province	Mafia index (rank)	Region	OC	Type of OC
Reggio Calabria	98.32	Calabria	'Ndrangheta	VC
Napoli	87.03	Campania	Camorra	HC
Caserta	84.73	Campania	Camorra	HC
Palermo	83.22	Sicily	Sicilian Mafia	VC
Catania	82.5	Sicily	Sicilian Mafia	VC
Crotone	81.22	Calabria	'Ndrangheta	VC
Trapani	77.86	Sicily	Sicilian Mafia	VC
Catanzaro	76.97	Calabria	'Ndrangheta	VC
Vibo Valentia	74.13	Calabria	'Ndrangheta	VC
Agrigento	71.75	Sicily	Sicilian Mafia	VC
Ragusa	61.82	Sicily	Sicilian Mafia	VC
Messina	60.82	Sicily	Sicilian Mafia	VC
Enna	57.74	Sicily	Sicilian Mafia	VC
Salerno	57.65	Campania	Camorra	HC
Bari	55.72	Apulia	Camorra Barese	HC
Siracusa	50.71	Sicily	Sicilian Mafia	VC
Lecce	48.76	Apulia	Sacra Corona Unita	VC
Brindisi	47.11	Apulia	Sacra Corona Unita	VC
Avellino	46.29	Campania	Camorra	HC
Cosenza	44.1	Calabria	'Ndrangheta	VC
Foggia	36.64	Apulia	Società Foggiana	VC

Notes: Classification of provinces of the Italian regions of Apulia, Campania, Calabria, and Sicily, Mafia Index from Calderoni (2011), and type of organized crime from EUROPOL (2013).

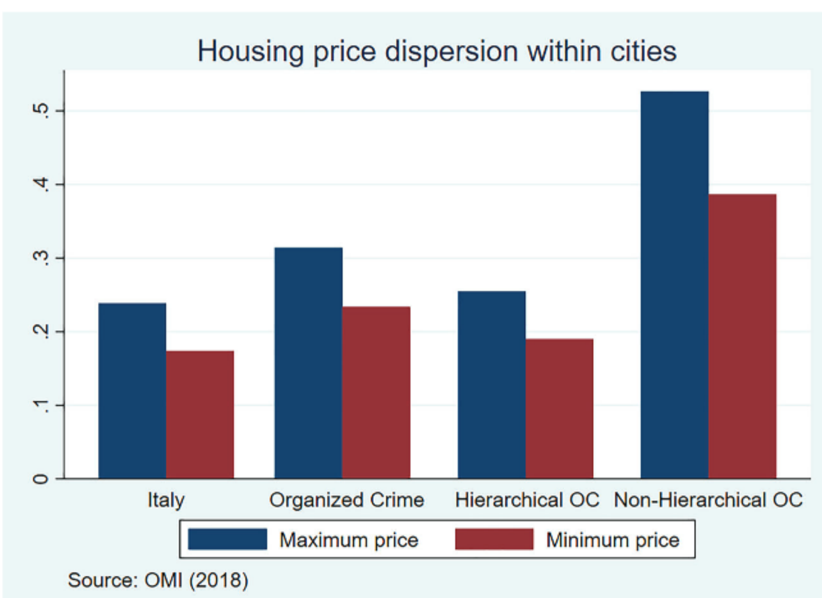

FIGURE A5 Variance of max and min prices in Italian Provinces in 2011

TABLE A4 Housing price variances and OC variables

Variables	Max sale (ln) (1)	Min sale (ln) (2)	Max sale (ln) (3)	Min sale (ln) (4)	Max sale (ln) (5)	Min sale (ln) (6)
Mafia index (rank)	0.002***	0.002***				
	(0.00)	(0.00)				
Mafia homicides			0.011**	0.007**		
			(0.01)	(0.00)		
Vertical hierarchical Org. (1=yes)					0.044*	0.039**
					(0.03)	(0.02)
Horizontal hierarchical Org. (1=yes)					0.297**	0.228***
					(0.11)	(0.09)
Constant	0.216***	0.154***	0.251***	0.183***	0.238***	0.171***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Obs.	100	100	99	99	100	100
R^2	0.119	0.145	0.177	0.166	0.234	0.273

Notes: The dependent variable is the within-city variance of housing prices for residential houses. Bootstrapped standard errors, with 100 replications, in parentheses. Level of significance is *p < 10%; **p < 5%; ***p < 1%.

To further characterize the correlation between Mafia presence, its organizational structure, and housing prices' dispersion, we estimate the following equation:

$$Var P_c = \beta_0 + \lambda OC_c + \mu_c, \tag{C1}$$

where $Var\ P_c$ denotes the within-city variance of (the natural log of) maximum and minimum prices in the capital of province c in 2011, OC_c is an indicator of Mafia in province c, which will be measured, alternatively, by: (i) the indicator of Mafia presence by Calderoni (2011); (ii) the raw number of Mafia homicides in 2011, from ISTAT (2018), a component of the index of Calderoni (2011) which is related to our measure of *IVH*; (iii) dummy variables for the type of criminal organization characterizing the province: horizontal/vertical; μ_c is the error term. Table A4 presents the results of the estimation of Equation (C1).

Results in Table A4 show that all the organized crime variables are positively correlated with the within-city variance of housing prices. The coefficient for the dummy for the presence of a "horizontal" Mafia is, however, particularly high. Further results, available upon request, show that the dummy for the presence of an horizontal structure of organized crime is still significant and positive after controlling for other possible correlates of housing price variance, such as within-city variance of education, unemployment, and indicators of housing quality, such as housing density and the share of historical buildings per district.