Shooting down the price: evidence from mafia homicides and housing market volatility

Michele Battisti* **Giovanni Bernardo†** **Andrea Mario Lavezzi‡** **Giuseppe Maggio§**

This Draft: September 11, 2019

Abstract

In this paper we estimate the effect of homicides by the *Camorra*, the Neapolitan Mafia, on housing price dispersion, an important component of inequality. To this purpose, we geo-localize homicides involving innocent victims, that we denote as *random homicides*, in the city of Naples for the period 2002-2018, and estimate their effects on housing prices at district level. By means of panel analyses we show that random homicides decrease by approximately 2% housing prices in districts close to the occurrence of such murders. In addition, by a spatial econometric analysis we show that the effects of a random homicide spill over to districts far from the occurrence of such murders, exerting a *positive* effect on housing prices of approximately 1%. These results are consistent with a theory according to which random homicides by the Camorra affect residential choices, reducing the demand for housing in districts close to random homicides, and increasing it in district far away from such crimes.

Keywords: Organized crime, housing prices, spatial econometrics.

JEL Classification Code: C40, D01, O33

*Dipartimento di Giurisprudenza, Universita' degli Studi di Palermo, Piazza Bologni 8, 90134 Palermo (PA), Italy, email: michele.battisti@unipa.it

†Dipartimento di Giurisprudenza, Universita' degli Studi di Palermo, Piazza Bologni 8, 90134 Palermo (PA), Italy, email: giovanni.bernardo@unipa.it

‡Dipartimento di Giurisprudenza, Universita' degli Studi di Palermo, Piazza Bologni 8, 90134 Palermo (PA), Italy, email: mario.lavezzi@unipa.it

§Department of Geography, University of Sussex, Sussex House, Falmer, Brighton, BN1 9RH, UK, email: g.maggio@sussex.ac.uk

1 Introduction

Criminal organizations such as the Italian Mafias pose a serious threat to economic development. In particular, there is a growing literature describing the detrimental effects that Mafias has on several dimensions of economy such as foreign direct investments (Daniele and Marani, 2011), GDP growth (Pinotti, 2015) and state capacity (Acemoglu et al., 2017). The nexus between organized crime and inequality, on the contrary, is a topic so far overlooked in the literature with the exception of Battisti et al. (2019). To investigate this relationship, we analyze the effect that Mafia violence can exert on housing prices' dispersion, an important component of inequality (see e.g. Maclennan and Miao, 2017).

This paper speaks to two different strands of literature. First, it contributes to the literature on crime and residential choice. From a general perspective, Zenou (2003) discussed the spatial determinants of crime underlining that social interactions and distance to jobs can induces individuals to commit more crime. Tita et al. (2006) find that crime affects the individual decisions on changing residential location and, in particular, that violent attacks generate the greatest cost in terms of loss of property value. Using geo-referenced data on the city of Sydney, Klimova and Lee (2014) find that murders negatively affect housing prices, with an average drop of 3.9% with respect to their initial value. Linden et al. (2008) find a similar impact for within-neighborhood variation in property values (-4%) before and after the arrival in the neighborhood of a sex offender. None of these works, however, considered violent offenses from a criminal organization, as we do in the present article. Also, they do not take into account the spillover effects on housing prices across different district as we do in this work.

Secondly, this work contributes to the strand of literature investigating the socio-economic outcomes of violent offenses by organized crime. Specifically, recent works ask whether organized crime can strategically use murders and violent attacks to influence political outcomes, such as electoral participation and the capacity to govern effectively (Dal Bo' et al., 2006; Acemoglu et al., 2013; Daniele and Dipoppa, 2017; Alesina et al., 2018). For example, Alesina et al. (2018) focus on the Italian case and find that a sharp increase in violence against politicians before the electoral period reduces "anti-Mafia" efforts in the parliamentary debate. Our work is the first providing evidence that organized crime violence is able to impact on housing prices, affecting in this way inequality.

In this paper we estimate the effect on housing prices of murders committed in the city of Naples by the *Camorra*, the Neapolitan Mafia. We focus on this case study since the city of Naples in the last few decades observed a huge number of homicides, most of which involving *Camorra* affiliates. The reason for such numbers relies on the functional structure of the Camorra, which is typical a non-hierarchically coordinated criminal organization with many of the typical features of gangsterism (Sciarrone and Storti, 2014), a widespread phenomenon in many different countries such as USA and Brazil that implies a massive use of intimidation and violence than other criminal organizations of mafia-type. In order to ensure the exogenous nature of murders we build a dataset of geo-localized *random homicides*, i.e. involving victims not affiliated to a Camorra gang or engaged in activities contrasting it (e.g. policemen, judges, or journalists), and estimate the effect of such homicides on district-level housing prices' in Naples for the period 2002-2018. Our insight is the following: random homicides are those more likely to affect the residential choice of the largest part of the population, as any individual in principle can be affected, even in cities plagued by the presence of organized crime.

Our main finding is that random homicides lead to higher dispersion in housing prices across districts. Specifically, we provide a first correlational evidence about the fact that the presence of *horizontal organized crime* and the higher number of homicides that it implies are associated to higher house price dispersion both across Italian cities and within the city of Naples. Secondly, we show that, in a panel data framework, random homicides are related to a decrease of around 2% in housing prices at district level in the city of Naples. This result is robust to potential identification confounding elements due to total Camorra homicides in the area. Third, in a spatial panel framework we estimate a net decrease of 1.5% in housing prices in the period following a homicide, which stems from a price variation in the district where the murder occurred of -2.5% and an increase in price in a neighboring district of 1%. Finally, we find that the long-run effects estimated in the spatial analysis amount to more than 3% and are therefore bigger than the short-run effects of 1.5%.

The rest of the paper is organized as follows. In Section 2 we offer some preliminary evidence on the relation between the organizational form of organized crime and housing price inequality; Section 3 describes the dataset, the territory under examination and the variables we use; Section 4 presents the results of the empirical analysis; Section 5 reports robustness checks related to identification issues and different distances and neighboring effects settings. Section 6 contains concluding remarks.

2 Background Analysis and Research Hypothesis

While Italy appears as one of the safest countries worldwide with a rate in 2015 of 0.7 homicides per 100,000 inhabitants, in the same year 36 intentional homicide have been reported in Naples with a ratio of 3.7/100.000. The average homicide rate from 2010 to 2015 was also quite stable over time with a value of 3 for each 100,000 inhabitants, a value significantly higher than OECD countries' average for 2015 (see Table 1).

As highlighted in a report made by EUROPOL (2013), the excessive use of violence and the high number of homicides by the Neapolitan *Camorra* can be explained by

Table 1: Intentional homicides in 2015 per 100,000 inhabitants

Country	Mean
Italy	**0.7**
OECD	1.14
MENA	1.58
E_ASIA	2.74
EEC	2.96
Naples	**3.7**
SSA	9.71
LAC	12.26
CAC	29.46

Notes: Data on intentional homicide victims from World Bank (UNODC, 2018) and Istat (ISTAT, 2018). Note that: MENA is an acronym referring to the Middle East and North Africa region;E_ASIA;EEC;SSA;LAC is an acronym referring to the Latin American countries; CAC is an acronym referring to the Central American countries.

its horizontal structure, which differentiates it from vertically organized groups such as *'Ndrangheta* and Cosa Nostra, whose main territories are the regions of Calabria and Sicily. All 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[1]. Despite these similarities, Catino (2014) shows that the Camorra organization implies a higher number of homicides, but a lower capacity to plan and carry out crucial homicides such as those of politicians, policemen and judges, due to its lower coordination. Camorra clans, especially in the Naples' metropolitan, are more fragmented in structure with many of the typical features of gangsterism (Sciarrone and Storti, 2014) such as an extensive use of intimidation and violence among rival gangs or families to control turf and illicit trades which implies that both camorra and random homicides are more likely to occur.

[1]See for instance Sciarrone and Storti (2014)

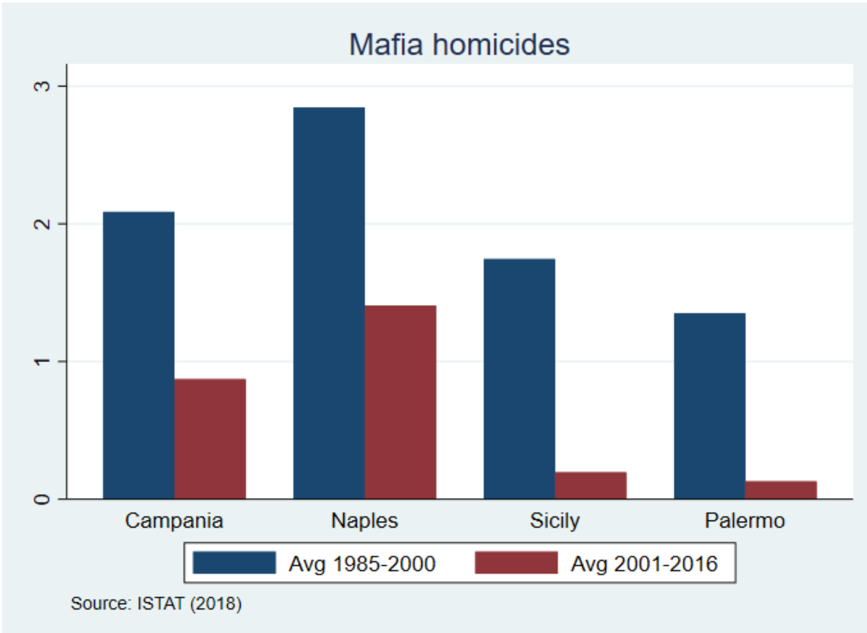

Figure 1: Mafia homicides for 100k persons

Figure 1 compares the values of per-capita Mafia homicides[2] in the province of Naples and in Campania, i.e. the region having Naples as capital, with those of Palermo and Sicily, where the historically powerful *Cosa Nostra* is located.[3] We see that the values for Naples in recent periods are remarkably high. This suggests that even in comparison with a region or a regional capital where organized crime is pervasive, the uncertain control of the territory by a *horizontal* organization such as the Camorra, makes it much unsafer.

In Figure 2 we compare the variance of maximum and minimum housing prices across administrative districts for each Italian provincial capital to the average variance across provincial capitals of the three regions characterized by the strong presence of Organized Crime, and to the two distinct sub-groups of cities where the predominant organization has a "vertical" or an "horizontal" structure for 2011, the year of the last Italian census.[4] Figure

[2]Murders committed by Mafias reported by the police forces to the judicial authority (*Omicidi per motivi di mafia or camorra*) from ISTAT (2018).

[3]Italian official statistics on crime do not report data beyond the provincial level.

[4]Table A1 in Appendix A reports the type of organization characterizing provincial capitals based on the

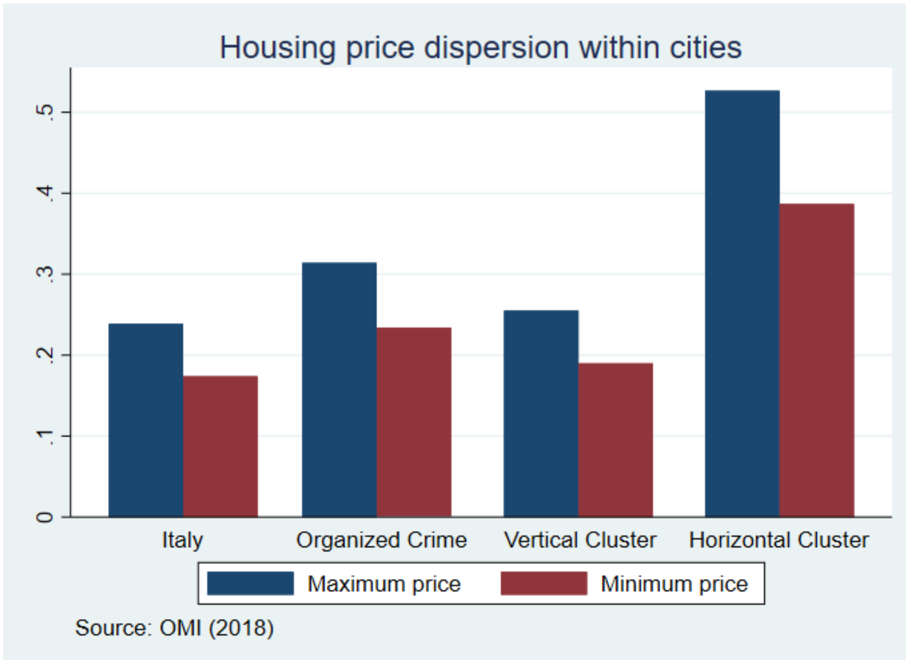

Figure 2: Variance of Maximum and Minimum house prices for: i) *Italy*: average of Italian provincial capitals; ii) *Organized Crime*: average of provincial capitals in which Organized Crime is widespread; iii) *Vertical Cluster*: average of provincial capitals in which *vertical* Organized Crime is widespread; iv) *Horizontal Cluster*: average of provincial capitals in which *horizontal* Organized Crime is widespread. For lists of provincial capitals at ii)-iv) see Table A1.

2 clearly shows that the dispersion of housing prices is much higher in cities where organized crime is strong and, in particular, where it has a horizontal structure. From a more general perspective, if we perform a variance decomposition of housing prices across and within Italian provincial capitals we see that the within-component of the dispersion accounts for 45% of the total housing price variance, pointing out that the within component is an important factor of inequality among households.

To investigate the relationship with Mafia violence, we do not utilize the crude number of mafia homicides previously showed in this section, but consider those that, following the insights presented in Section 1, implied people non-affiliated with the *Camorra*. Specifically,

EUROPOL (2013) classification. Data on housing prices are from OMI (2018), and are described in Section 3.

we define *random homicides* as homicides committed by a Camorra mobster implying individuals not affiliated with a Camorra gang, or in occupations that may put an individual at risk, i.e. of judges, policemen or journalists. In the rest of analysis we will term as RH the homicides caused by Camorra, regarding non-affiliated and CH as the homicides regarding affiliated.

The insight is the following: RH are those more likely to affect the residential choice of the largest part of the population, as any individual in principle can be affected, even in cities plagued by the presence of organized crime. This type of homicides, therefore, are those expected to have a sizeable effect on the demand for houses of the population at large. In particular, we expect that the effect of a RH has an effect in the area close to the location of the homicide, reducing the demand for housing, but also spills over to different areas further away, where it increases the demand for housing, as long as these areas are considered safer. These effects, therefore, introduce a wedge between housing prices in different districts, increasing within-city housing price dispersion. Moreover, focusing on the homicides of civilians not affiliated to the Camorra also guarantees to exclude any causality from being a Camorra member or a potential Camorra target to the occurrence of the murder.

In order to strengthen our hypothesis, empirical evidence suggests that RH receive a great deal of attention by the media, so that the spread of news about them should influence public opinion and residential choices more than news about camorra homicides. In particular, Table 2 shows evidence on the dissemination of news of a typical Camorra murder, i.e. involving an affiliate to a Camorra clan, compared to a random homicide occurred on the same day. The variable called *LexisNexis* (Weaver and Bimer , 2008) accounts for the number of articles that include the victim's name published by the main media and newspapers in Italian language during the three months following the tragic event. Homicides that involve individuals not affiliated with Camorra gangs are widely disseminated through traditional

Table 2: News dissemination in the media: Random vs Camorra homicides

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

Notes: the table compare two random homicides with two case 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 taken into consideration is three months after the murder, and the search is restricted to news in Italian.

media, while other Camorra homicides do not attract the same level of attention. Moving the attention on data from Google Trends, we can see that random homicides remarkably capture the interest of public opinion, generating a peak of searches on victim's name during the day of the tragic event and high interest even in the subsequent days, while searches on Camorra homicides are so low that they are not even reported by Google Trends.

For a preliminary check of whether the key variables, housing prices and homicides[6], display any geographical pattern, we use quantile spatial maps at district level to show respectively the maximum housing prices of transactions and the time-averaged percentage difference between maximum and minimum price and homicides within districts, together with the geo-localized Camorra homicides, both random and total. Fig. 3 shows that there exists a clear pattern in housing prices, with higher prices in the South-West of Naples.[7]

[6]Data on housing prices are from OMI (2018) while data on Random and Camorra homicides are respectively from `http://www.vittimemafia.it/` and the Naples' Prosecutor Office. Data are described in Section 3.

[7]Considering minimum prices returns a similar map, not reported.

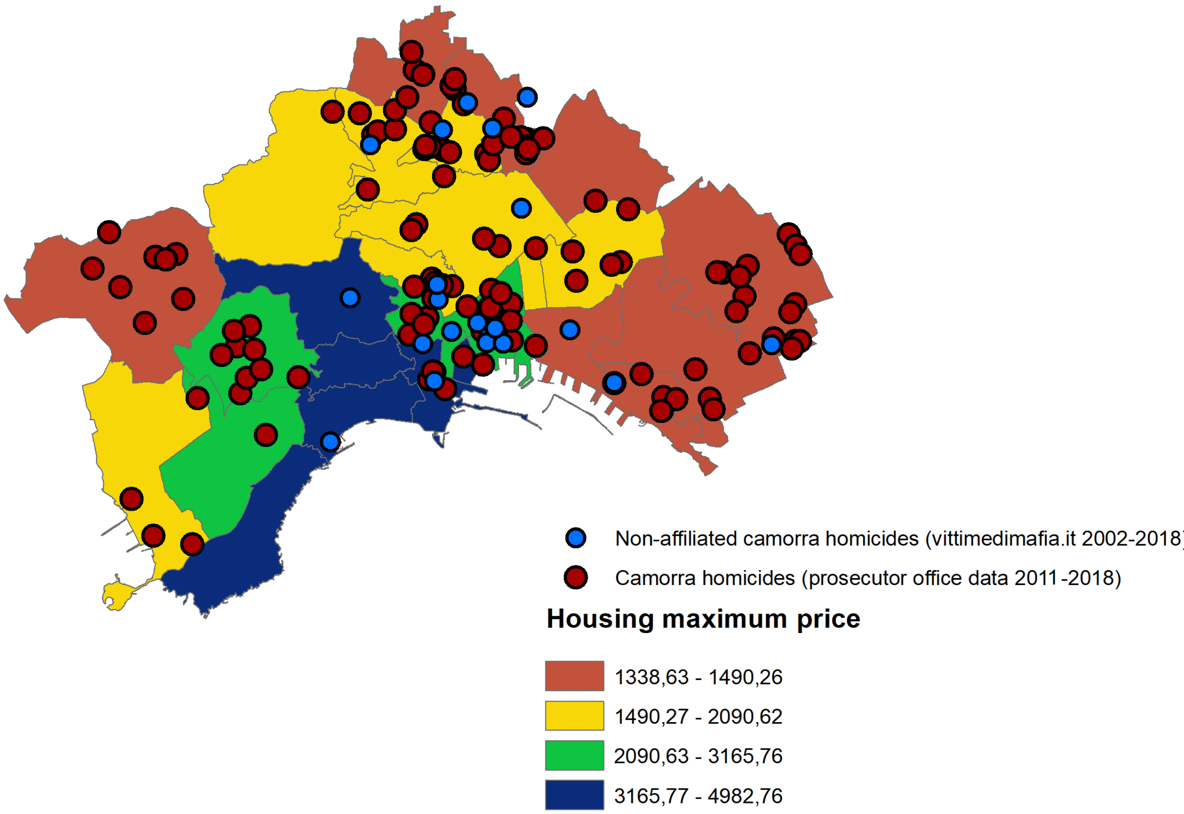

Figure 3: Homicides of Camorra affiliates (2011-2018), innocent victims (2002-2018) and Average maximum price for sq mt (2002-2018), civic houses

The geo-localized random homicides do not seem spatially correlated across districts with district-level housing prices, while the Camorra homicides concentrate in the districts of Scampia in the Northern part of the city, and in Stella, Montecalvario, San Lorenzo, Zona Industriale, in the Southern part. Figure 3 highlights a spatial pattern of random homicides, which cluster in two areas. The spatial distribution of random homicides is in line with the risk map built by Dugato et al. (2017),[8] in which the probability of a Camorra

[8]Dugato et al. (2017) consider Camorra homicides, without distinguishing between random and non-

homicide in 2012 has been predicted using variables such as past homicides, intensity of drug dealing, confiscated assets, and rivalries among groups. From Figures 3 we draw the following conclusions: the spatial pattern of prices' levels and of random homicides do not seem correlated. In addition, the spatial pattern of within-district price dispersion does not seem correlated to homicides either. Overall, this makes very unlikely the possibility that causality runs from housing prices to (random) homicides. Therefore, taking into account the structural characteristics captured by the fixed effects, we may consider the random homicides as exogenous and not expected.

In the next sections we fully describe our dataset and provide an econometric analysis aiming at identifying the effects of random homicides on housing price dispersion, including the spillover effects that we expect to characterize this relationship.

3 Data

In our econometric analysis we will adopt a cross-sectional approach to assess the correlation between the organisational structure of criminal groups, violence and dispersion of housing prices at national level, while panel and spatial approaches to address the case study of Naples. Data on real estate prices are from the *Osservatorio del Mercato Immobiliare* (OMI, 2018), an agency delivering half-yearly records on average maximum/minimum sale and rent price for micro-areas of Italian cities. We consider the prices of only what are defined "residential houses[9]", to focus on the typical estates bought or rented by the inhabitants of the city.[10]

random homicides, between 2004 and 2010, our sample of random homicides covers a longer period (2002-2018) while our sample for total Camorra homicides is more recent (2011-2018).

[9]The types of real estate considered are: civil housing, cheap civil housing, luxury civil housing and villas.

[10]A comparison among and within cities of housing prices implies two issues: prices are nominal, but on a single year as 2011 this is not a concern. Most importantly, Italy has a high variance across regions in the price levels, but we do not have PPP deflators to make prices homogeneous across cities. To tackle this issue,

The final sample, as noted, includes all the random homicides occurred in the period 2002h2-2018h1 in Naples. Such data are not reported in official Italian statistics, so we extracted them from `http://www.vittimemafia.it/`, a portal collecting information and news articles on all the civilians killed by the Italian mafias from 1861 onwards. For the purpose of controlling for an important possible confounding factor, we integrated these data with *Camorra homicides* and *other homicides* occurred within the municipal boundaries. In particular, the shorten period 2009h1-2018h1 has been reconstructed using data provided by the Naples' Prosecutor Office[11] while the period **2007h2-2008h2** using secondary data sources[12]. In this period the city witnessed several blood feuds among rival families, such as the first Scampia's feud, with at least 100 affiliated killed among ex-affiliated and loyalist to the Di Lauro's clan, the feud between Aprea's and Celeste-Guarino families, and many others. Using the press articles reporting the relevant information, we geo-localized each random homicide by the latitude and the longitude of the location where it occurred, and then merged those belonging to each administrative district, obtaining district-level numbers of homicides.

Figure 4 shows in a simple way how *RH* have been defined. In particular, for each district we computed the number of homicides occurred within a distance of n meters from each point of its border, ($n = 200, 500, 700, 1000$) - e.g. looking at figure 4 we can see that homicides X will be accounted for district 1 and 2 while homicides Y for district 7, 8 and 9. This approach is justified by the spatial linkage that we expect between housing prices in a district and the location where homicides occurred. Estate buyers, indeed, are likely to respond to murders taking place near the estate, independently of whether they occurred

to compute average housing prices, we use as weight the real GDP per capita by province from Cambridge Econometrics (2016).

[11] *Procura della Repubblica di Napoli*

[12] **We found newspaper evidences that matched a ratio with respect to total homicides of province around 60%.**

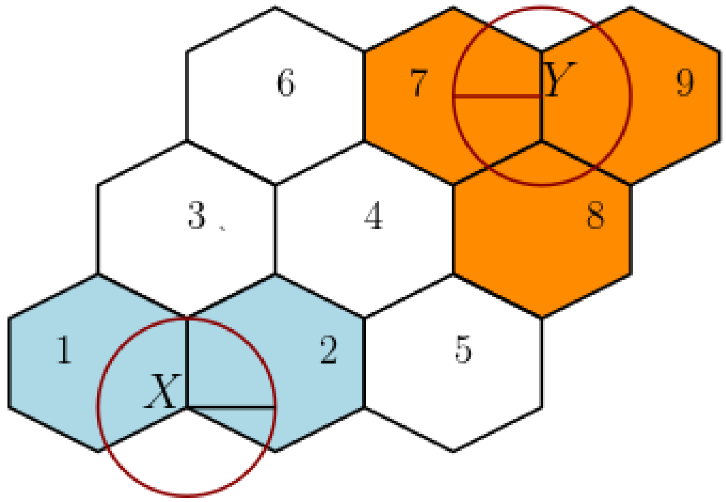

Figure 4: Geo-localization of random homicides

within or outside the administrative boundaries of the district. In this sense, we assume that the effect of a murder is not location-specific. The distance of the district from a murder, therefore, becomes an important indicator for the level of security of the area. This is the reason why we attempt to capture the effect of random homicides at different thresholds of distance form a district. The top panel of Table 3 contains the descriptive statistics of the random homicides (RH).

AGGIUNGERE in tab 3 CH 2009-10

For a comparison, the bottom panel of Table 3 presents the numbers of total Camorra homicides (CH) for the shorter period in which they are available. It can be observed that random homicides amount, in mean terms, to approximately 10% of recorded Camorra homicides at the different thresholds.

The set of controls we use for cross-sectional analysis include indicators of the census areas characteristics, such as the share of buildings in the district built before 1950, proxying for the distance from the center of the city,[13] as well as other indicators of socio-economic

[13]As a consequence of the WWII reconstruction a large part of Italian cities experienced a housing boom and sustained population growth after this period, which determined an expansion of urban peripheries and

Table 3: Summary statistics on random homicides and Camorra homicides in the district/semester panel (2002h1-2018h2)

Random Homicides, RH (2002h2-2018h1)					
Variables	Observations	Mean	Std. Dev.	Min	Max
RH within a district	960	0.03	0.17	0	1
RH within 200m	960	0.05	0.25	0	3
RH within 500m	960	0.09	0.33	0	3
RH within 700m	960	0.11	0.36	0	3
RH within 1000m	960	0.17	0.44	0	3
Camorra Homicides, CH (2010h1-2018h1)					
Variables	Observations	Mean	Std. Dev.	Min	Max
CH within a district	510	0.30	0.70	0	5
CH within 200m	510	0.44	1.11	0	8
CH within 500m	510	0.68	1.77	0	13
CH within 700m	510	0.87	2.30	0	17
CH within 1000m	510	1.18	3.	0	22

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

characteristics, such as the share of population with tertiary education level, unemployment rates and housing density.[14]. Taken together, these variables aim at proxing for the quality of life in a census area and they are computed as within-city variances to capture the level of dispersion. In the panel analysis, we control for the lagged value of the housing price and for the nightlight data from the National Oceanic and Athmospheric Administration (NOAA) (Cecil et al., 2014) as proxy of local income levels. Since these data are available at year level, we compute their value at semester level using the local between year growth rate.

the use on large scale of cement for the new housing.

[14]Table A2 in Appendix A reports data sources, explanation and coverage of the data.

4 Econometric Analysis

In this section we describe our econometric strategy. We start by a simple cross-section analysis, showing effects of indicators of Mafia on the variance of maximum and minimum prices across Italian cities. Then, we take into account the dynamics by a panel analysis on data from Naples. Finally, we consider the asymmetric spatial dynamics of homicides the districts where homicides occurred and neighboring districts, estimating short- and long-run effects by a spatial econometrics analysis.

4.1 Italian cities: cross-sectional analysis

The first of our aims is to assess the correlation between indicators of Mafia pervasiveness and of its characteristics (horizontal or vertical) on the dispersion of housing prices within a city. We study this issue in across Italian provincial capitals. In the cross-section analysis on Italian provincial capitals, in particular, we correlate the variance of log prices of residential house across census areas (both minimum and maximum sale prices), to indicators of Mafia and other controls.[15] For the estimation we consider the following specification:

$$VarPrice_c = \beta_0 + \lambda MI_c + \alpha X_c + \mu_c \qquad (1)$$

where $VarPrice_c$ denotes the within-city variance of (the natural log of) maximum and minimum prices in city c, β_0 is the intercept, MI_c is an indicator of Mafia in the city, λ is the

[15]In addition to the controls introduced in Section 3, we include a variable counting the census areas (ACE) included in each districts. ACE are sub-municipal areas with autonomous administrative function at the date of the census. This territorial subdivision is available just for municipalities with a population greater than 20,000 inhabitants. It takes into account the dimension of the city that is one of the potential determinants of different housing prices in a city.

corresponding coefficient. We will consider for this purposes the mafia index at provincial level provided by Calderoni (2011), the number of mafia homicides,[16] and dummies indicating the presence of a horizontal or vertical criminal organization. Finally, X_c is a vector of controls, discussed in Section 3, α the vector of coefficients, and μ_i is the i.i.d. error term.

Table 4 presents the results of the estimation of Equation (1) without the controls X_c.

Table 4: Housing price variances and OC variables

Variables	Max sale (ln)	Min sale (ln)	Max sale (ln)	Min sale (ln)	Max sale (ln)	Min sale (ln)
	(1)	(2)	(3)	(4)	(5)	(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-squared	0.119	0.145	0.177	0.166	0.234	0.273

Notes: Dependent variable is variance of house prices. Bootstrapped standard errors, with 100 replications, in parentheses. Level of significance are *p<10%; ** p<5%; *** p<1%.

Table 4 shows that while all the organized crime variables are positively related to the within-city variance of housing prices, the coefficient for the dummy on horizontal structure appears particularly high.[17]

In Table 5 we add to Models 5 and 6 of Table 4 the control variables on district characteristics to check if the coefficients of interest remain significant (these covariates are expressed, for each city, as variances across city districts).

[16] In this case we refer to the homicides imputed to a criminal organization of Mafia-type. Unfortunately, it is not possible to identify random homicides by criminal organizations in other cities.

[17] A regression including both indicators of Mafia intensity, i.e. Mafia index and Mafia homicides, returns positive coefficients for both with a lower level of significance, respectively 5% and 10%.

Table 5: Housing price variances, OC and control variables

Variables	Max sale (ln)	Min sale (ln)	Max sale (ln)	Min sale (ln)
	(1)	(2)	(3)	(4)
Vertical Hierarchical Org. (1=yes)	0.036	0.035	0.015	0.020
	(0.03)	(0.02)	(0.03)	(0.02)
Horizontal Hierarchical Org. (1=yes)	0.249**	0.198**	0.243**	0.194***
	(0.10)	(0.08)	(0.11)	(0.08)
Share of pop. with tertiary education	0.892**	0.519**	0.952**	0.565*
	(0.36)	(0.27)	(0.51)	(0.30)
Unemployment rate	0.321	0.172	0.202	0.097
	(0.60)	(0.41)	(0.78)	(0.41)
Housing density (area of inhabited houses/population)			0.010	0.003
			(0.10)	(0.07)
Share of historical building			1.114*	0.748
			(0.68)	(0.41)
Constant	0.179***	0.135***	0.176***	0.132***
	(0.02)	(0.01)	(0.02)	(0.01)
Census Areas (ACE)	Yes	Yes	Yes	Yes
Obs.	100	100	100	100
R-squared	0.376	0.390	0.403	0.414

Notes: Dependent variable is variance of housing prices, computed across city districts. Bootstrapped standard errors, with 100 replications, in parentheses. Level of significance are *p<10%; ** p<5%; *** p<1%.

Results in Table 5 show that the strong positive correlation between the dummy for organized crime's horizontal structure and housing price dispersion is robust. Among the other explanatory variables, variance in districts' education and in the quality of houses seems to play a role, as expected. In particular the variance of education within city may have an important relationship with inequality as shown for example by Berry and Glaeser (2005) and Glaeser et al. (2009).

4.2 Naples: panel approach

Data on RH in the municipality of Naples include the latitude, the longitude and the exact date of the event, making possible an identification strategy that exploits both space and time variation. This framework considers the murder as an external shock affecting individual preferences for at least one period, and the panel structure allows capturing the change in prices after the shock. This approach is more efficient and less affected by omitted variable bias, as it controls for a set of time invariant district unobserved characteristics, such as local geographical, institutional, and cultural features. The specification includes also time period dummies capturing, for example, the effect of common shocks in all the zones, such as the impact of 2008 economic crisis, or for example changes in the State budget allocated to law enforcement agencies controlling the territory, etc. Finally, the effect on the prices of the occurrence of one or more murders in a district is better identified by the addition of the lagged value of the prices at time $t-1$.

In a first step we consider a specification such as Equation (2):

$$lnPrice_{ij,t} = \beta_0 + \delta lnPrice_{ij,t-1} + \lambda MK_{i,t-1} + \phi DistrictEstate_{ij} + \psi T_t + \alpha X_{i,t-1} + \mu_{i,t} \quad (2)$$

where $lnPrice_{ijt-1}$ is the lagged natural log of the average price of the estate j in district i at time t; $MK_{i,t-1}$ is a variable capturing the number of murders at time $t-1$ within a given distance from district i; $DistrictEstate_{ij}$ are a fixed effects specific for the panel observation; T_t is a set of time dummies (half-year), μ is an error term clustered at district-estate level. The matrix $X_{i,t-1}$ contains the lag of the districts' nighttime lights,[18] a proxy for local

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

economic development, interpolated half-yearly. We take the lag of this variable to reduce any reverse causality in the estimation. Finally, $\mu_{i,t}$ is the error term.

As pointed out by Nickell (1981), the estimation of this model with fixed effects may generate inconsistent estimates when the number of panel observations increases[19]. One strategy to overcome this limitation is to estimate the above equation using the Arellano-Bond GMM estimation. This approach takes first differences of the time-varying variables, a procedure that cancels out the unobserved fixed effect. To maintain the number of instruments lower than the number of groups, the coefficients are estimated using the second lag of the explanatory variables as instrument, and substituting the year fixed effects with a trend variable. As alternative specifications, we also estimate the Blundell-Bond level specification, and the bias-corrected LSDV dynamic panel data model (Bruno, 2005). In our case of highly persistent data, (Berry and Glaeser, 2005) show how the level GMM estimator has a far lower bias than the difference GMM.

Table 10 displays the results to the the estimation of Eq. (2) as a dynamic panel. According to our estimates, the coefficient on the number of murders is negative and significant for all specifications and supports the hypothesis that the fear of crime reduces the individual willingness to pay (Pope, 2008; Bayer et al., 2016). The estimated coefficient suggest an impact of an additional homicide ranges between -2.5% and -3.8% of the housing price.

[19]We estimate equation 2 using OLS with fixed effects. Results, available upon request, show that coefficient is significant across all specifications with an impact of an additional homicide ranging between -2.2% and -3.3%

Table 6: Random homicide and housing prices in a dynamic panel framework (2003h1-2018h1)

Variables	Max Sale (log)	Min Sale (log)	Max Sale (log)	Min Sale (log)	Max Sale (log)	Min Sale (log)	Max Sale (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
# RH within 200m (lag)	-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	Blundell	Kiviet	Kiviet	Blundell
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 an first-difference GMM Arellano-bond on the house prices panel sub-sample. The estates in the sample are civil housing, cheap civil housing, luxury civil housing. The dependent variables are the natural log of the maximum sale price (column 1), the natural log of the minimum sale price (column 2); the natural log of the maximum rent price (column 3); the natural log of the minimum rent price (column 4). The instrument are limited to one lag to keep the number of instrument lower than the number of groups. All specifications control for the RH within 200m from the district (lag), nightlight index (lag), and the lag of the dependent variable. Only the first lag is added as instrument. Robust standard errors in parentheses. Results remain significant when controlling for the economics crisis using a dummy assuming value 1 for the period 2008h1-2011h2. Level of significance are *p<10%; ** p<5%; *** p<1%.

The bottom part of the table shows the result of the tests on the model, whose results suggest the absence of over-identification when the instrument are collapsed in a vector (columns 1-2), and of second-order correlation.[20] In Model 7 in Table 10 we consider only one type of housing, computed as the average of the four residential types of housing considered in Models 1-6. This is relevant for the spatial econometric analysis of Section 4.3. In such type of analysis, in fact, we cannot consider the district/type of house dimension. In a spatial framework we would have that blocks of elements of the distance matrices would have zero distance (e.g. cheap and luxury estates in the same district have zero distances), implying a non meaningful sparse block-stacked distance matrix (Lam and Souza, 2016). As we can see, in Model 7 the effects of RH remain consistent with the other models.

To conclude this section, Table **??** present results of random homicides computed at different distance thresholds[21] on prices. The main result is that coefficients of random homicides are still negative and strongly significant with magnitude that has a decreasing decay on longer distances by the geo-localization of homicides. An additional mafia killing in a district is associated to a decrease in maximum sale prices by 1.5%. This effect remains significant, but decreases in magnitude, when the threshold increase up to 1000m, where the point estimates is equal to -1.3 percent. The value of the coefficient decreases with the distance but remains significant. This result allows to derive two implications: first, the transactions in a district are influenced by the occurrence of murders outside the administrative boundary, but this effect is decreasing in the distance from the event. Individuals, therefore, likely discount for this distance when concluding an estate transaction. As we will see later, this implies that effects on price dynamics within a district are quite

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

[21] Table **??** in Appendix A reports the cross section equivalent. Results for other prices than maximum and dynamic panels are similar and are available upon request

different by those on price dynamics within the city.

The above finding is consistent when accounting for the killings at different threshold of distance from the neighborhood focusing on the Blundell-Bond and the panel of real estate types. Figure 4 report the results. The estimated coefficient decreases in absolute value when moving from 200 meters to 1 kilometre (km), 2 km and 5 km, but remains negative and significant, suggesting that the captured effect is decaying with the distance from the homicides, while it become non-significant once passed the threshold of 8 km.

To sum up, in this section we showed that the random homicides by the Camorra negatively impact on house prices levels with GMM. Our next point is that these murders might create a wedge in prices between districts depending on the location of the murders: as they reduces prices in a district affected by the murder, they should increase it in districts not (or less) affected by them. However, such effect cannot be estimated by the empirical approaches used so far. In the next section we resort to the estimation of spatial models, to test whether our hypothesis is supported by the data.

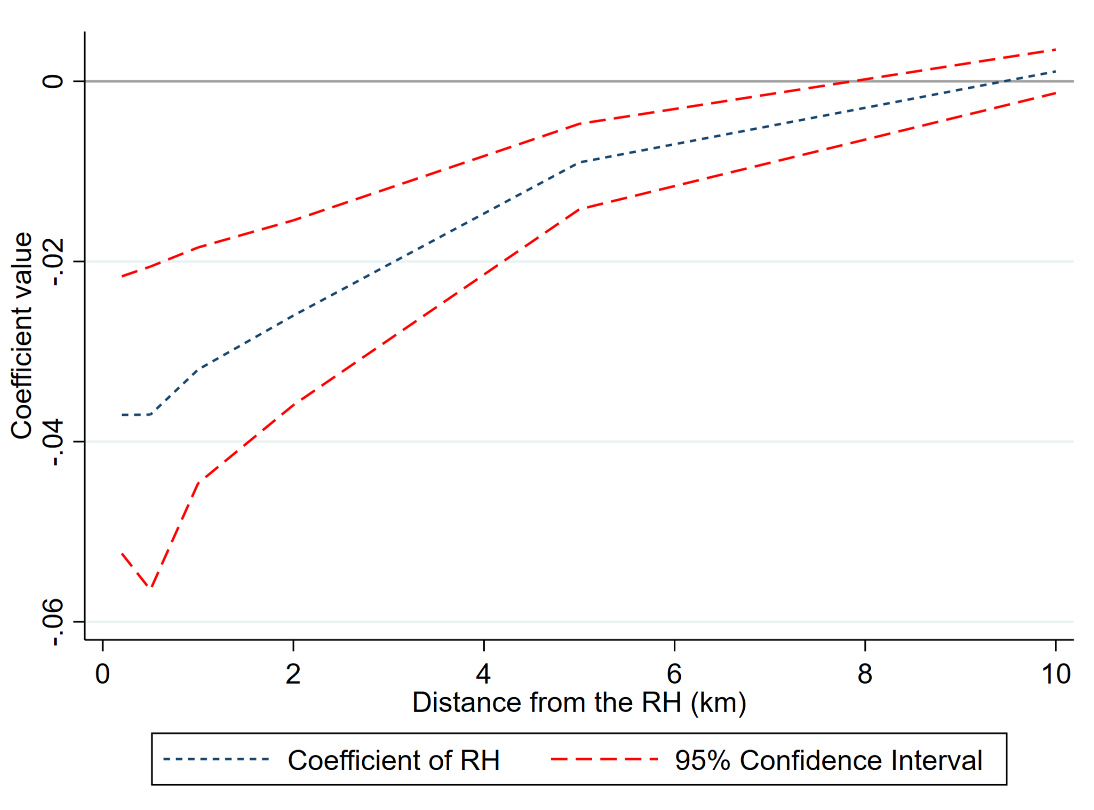

Figure 5: Effect of RH at different distances from the district using Blundell-Bond and a panel of real estates (2002-2018)

4.3 Naples: Spatial Dynamics of the Effect of Random Homicides

While previous sections highlighted the negative effects of random homicides in the district or nearby on districts' housing prices, evidence presented in Section 2 suggested a more general effects of organized crime violence on within-city housing price dispersion. In addition, we highlight that the negative effect of murders decays with distance: murders occurred far away from a district have a smaller impact on district's housing prices. This suggests heterogeneous dynamics of these effects across the city, as in Bayer et al. (2016), showing that people are willing to pay to live in safer neighborhoods. In this section we perform

Table 7: Housing price variances and random homicides

Variables	Max sale (1)	Min sale (2)	Max rent (3)	Min rent (4)
# RH within 200m	0.020**	0.020**	0.029**	0.030**
	(0.009)	(0.008)	(0.013)	(0.012)
Variance Nightlight	1.623**	1.646**	1.130	1.139
	(0.826)	(0.800)	(0.924)	(0.962)
Constant	0.634	0.602	1.197	1.152
	(0.978)	(0.943)	(1.071)	(1.112)
Obs.	30	30	30	30
R-squared	0.23	0.23	0.20	0.21

Notes: Dependent variable is variance of house prices. Bootstrapped standard errors, with 500 replications, in parentheses. Levels of significance are *p<10%; ** p<5%; *** p<1%.

a spatial analysis of the effects of mafia murders on prices, aimed at identifying spillover effects, if any.

Just to gain some preliminary intuition we show the overall effects of random homicides on the price house variance for the city of Naples. That is, for every half-year we compute the variance of housing prices and the number of random homicides across the Naples' districts, and examine their correlation across the period of observation. Table 7 shows that the coefficient of the variance of murders is positive with respect to the cross-district variance of house prices, independently whether we take into account rent or sale contract.[22]

From an econometric point of view, despite the strategy in Eq. (2) is able to reduce the bias caused by multiple unobserved time-invariant co-founders, there can be still concerns about biases in the coefficients. For example, in case of spatial correlation in the explanatory variables, the estimation will yield biased coefficients.[23] Another possibility is that murders may have an heterogeneous spatial effect when interacting with individual preferences. The

[22]To have a proxy of district amenities we keep the index of nightlight in the regressions. As we show section 2, the coefficients of murders decline when the distance from homicides increase.

[23]A general presentation of the spatial impact of crime is in Anselin et al. (2000).

purchase or the rent of a house, undeniably, is driven by a set of local determinants, such as the distance from working place, the level of public goods locally available, the distance from other relatives or friends, etc. These determinants are not varying with the occurrence of a murder and may play a role of geographical constraints for the individual choice on where to reside. We hypothesize, therefore, that when a mafia murders occurs in a district, the demand for real estate in that district decreases, but the one for real estate in a close neighborhood increases. According to this interpretation, we expect that a murder happening in a district or close to it will decrease the average price of the estates sold in that district, but will increase the housing prices in the other districts, where the demand for houses is diverted.

To account for this and other spatial effects, we focus only on the prices of housing estates at district level and assume a framework similar to the general dynamic Cliff-Ord model (Cliff and Ord , 1981), as follows:

$$lnPrice_{i,t} = \tau lnPrice_{i,t-1} + \rho W_t lnPrice_{i,t} + \psi W_{t-1} lnPrice_{i,t-1} + \beta \mathbf{X}_{i,t} + \gamma W_t \mathbf{X}_{i,t} + \upsilon_{it} \quad (3)$$

where:

$$\upsilon_{it} = \lambda W_{t-1} + \epsilon \quad (4)$$

In this specification, W indicates the spatial distance matrix, while vector $\mathbf{X}$ contains the nightlight index and random homicides numbers.

The generality of this approach allows to test different hypotheses on spatial dependence, obtained by setting to zero some of the coefficients in the model. In particular, the first possible specification is the Spatial Autoregressive model (SAR), derived from the Cliff-Ord model when $\rho \neq 0$, $\psi \neq 0$, $\gamma = 0$ $\lambda = 0$. The second specification is the Spatial Error Model

(SEM), obtained by setting $\rho = 0$, $\psi = 0$, $\gamma = 0$, $\lambda \neq 0$. Finally, the third specification is the Spatial Durbin Model (SDM), where $\rho \neq 0$, $\psi \neq 0$, $\gamma \neq 0$ and $\lambda = 0$. The advantage of the SAR and SDM models is that they allow the estimation of the (long-run) direct, indirect, and total effects of random homicides. This is a crucial issue for our hypothesis: to show that random homicides in neighboring districts $j \neq i$ have a *positive* effect on housing prices in district i.

The dynamic nature of the spatial model also allows comparing the short-run and long-run effect of mafia homicides on housing prices. The short run effect is simply the derivative of the dependent variable with to the covariate of interest (for instance RH), taking into account the spatial lag that is equivalent to OLS estimation, premultiplied by the Leontief inverse of the reduced collected spatial and non-spatial coefficients (Arbia et al., 2010):

$$\frac{\partial y_{i,t}}{\partial X_{i,t}^{RH}} = (I_n - \rho W_t)^{-1}[\beta_{i,t}^{RH} I_n] \tag{5}$$

The coefficients capturing the long-run effects are obtained by setting $y = y^*$, i.e. to its steady-state value, where in our case y is the housing price level. In the case of the SAR model (i.e. with $\gamma = 0$ and $\lambda = 0$) they take on a form such as:

$$\frac{\partial y_{i,t}}{\partial X_{i,t}^{RH}} = ((1-\tau)I_n - (\rho + \psi)W_t)^{-1}\,[\beta_{i,t}^{RH} I_n] \tag{6}$$

Since we have not a prior hypothesis on which type of spatial dependence matters, first of all we estimate all these alternative models on a static reduced form of Eq. (3) where we use first differences of prices to time lagged variables. Therefore, for instance in the case of SDM, we estimate:

$$\triangle lnPrice_{ij,t} = \rho W_t lnPrice_{i,t} + \beta \mathbf{X}_{i,t} + \gamma W_t \mathbf{X}_{i,t} + \upsilon_{i,t}. \tag{7}$$

Then, after identifying the main channel of spatial influence on prices, we estimate the full model with the complete time dynamics.

That means we start from the full SDM specification of (7) and see if the substantial dependence and nuisance spatial parameters are significant, otherwise we look to more parsimonious specifications as SAR or SEM.

For the estimation we use a spatial matrix constructed using a minimum threshold truncated approach, which treats districts as neighbors if they are within a distance that allows each district to have at least one neighbor.[24] Table 8 reports the results of the estimation of the reduced forms of SAR, SEM and SDM specifications, considering RH at both 200 and 1000 mt from a district.

Results in Table 8 show that: the effect of random homicides on prices is negative and significant for all the specifications considered. In particular, its magnitude decreases with the distance of a murder from a district: the magnitude varies from -2.9% when considering the murders occurring within 200 meters, to -1.8% for the murders occurred within 1000 meters.[25] Spatial effects appear relevant: the SEM specification reveals the presence of spatial autocorrelation of the shocks, while both the SAR and SDM models show that a relevant channel of spatial dependence could be in changes in housing prices in neighboring districts (see the significant value of ρ in Models 2,3,5,6). The negative value of spatial dependence confirms the visual insight of figure 3, where there is not a clear division of the cities in clusters of high prices very far from clusters of low prices in terms

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

[25] Consider, for example, that the average district area is about 4 km^2, thus the linear distance from the centroid of two squared districts would be at least 2 km.

Table 8: Random homicides 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)
# RH within 200m (lag)	-0.026***	-0.025**	-0.025**			
	(.010)	(.010)	(.010)			
# RH within 1000m (lag)				-.017***	-0.017***	-0.017***
				(.000)	(.006)	(.006)
Nightlights index (lag)	0.076	0.075	0.074	0.074	0.074	0.074
	(.056)	(.056)	(.056)	(.056)	(.056)	(.056)
γX						
# RH within 200m (lag)			-0.116*			
			(.064)			
# RH within 1000m (lag)						-.026
						(.044)
Nightlights index (lag)			0.093			0.066
			(0.341)			(.341)
Spatial						
$\hat{\rho}$		-0.624***	-0.657***		-0.612***	-0.619***
		(.142)	(.144)		(.141)	(.142)
$\hat{\lambda}$	-0.626***			-0.602***		
	(.141)			(.139)		
Spatial effects (short run)						
Direct						
# RH within 200m (lag)		-0.025**	-0.022**			
# RH within 1000m (lag)					-0.017***	-0.017***
Nightlights index (lag)		0.074	0.074		0.073	0.071*
Indirect						
# RH within 200m (lag)		0.010**	-0.059			
# RH within 1000m (lag)					0.006**	-0.007
Nightlights index (lag)		0.03	0.027		-0.028	0.011
Total						
# RH within 200m (lag)		-0.015**	-0.081**			
# RH within 1000m (lag)					-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 RH within 200m and 1000m (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 are *p<10%; ** p<5%; *** p<1%.

of geographical distance (remember that with minimum threshold criterion many districts have several neighbors). We later compare this result with matrix of neighbors based only on price distance and see that spatial dependence turns to be positive. As noted, with the SAR and SDM models it is possible to compute the long-run direct, indirect, and total effects of random homicides, as reported in the bottom part of Table 8.

The only significant indirect effect is obtained with the SAR model, for both distances of a random homicide. In particular, the indirect effect of random homicides within, respectively, 200 and 1000 mt from a district, amounts to 1% and 0.6%. This confirms our hypothesis of spillover effects of random homicides across housing prices in different districts. The total effect is however negative. In particular, for the SAR model the total effect is negative and significant and amounts to, respectively for random homicides within 200 and 1000 mt from a district, to -1.5% and -1%. The fact that these effects are captured by the SAR model only suggests that the relevant spatial linkage is among housing prices.

More specifically in terms of eq. (7) the γ terms of the more general SDM contained in columns 3 and 6 are not significantly different from 0, while the ρ terms (as in restricted models at columns 2-5) are strongly significant. It means that in the potential set of restrictions the SAR looks as the most reliable option.

The total effect, however, remains negative and significant, suggesting an overall decline of prices due to random homicides. The coefficient associated to the control variables reports the expected signs and magnitude. Nightlight are never significant in this specification. Finally, since prices are likely to depend substantially on their lagged realization, we estimate the model in Table 8 to a spatial dynamic framework by adding the lag of the housing prices into the specification.

Table 9 reports the results of this empirical exercise for the SAR model, that as we see in Table 8 appears to perform better than the other models in terms of the significance of the coefficients of interest. Adding the time-lagged prices does not impact substantially on the magnitude and on the statistical significance of the coefficients of the random homicides. The occurrence of a murder is still associated to a reduction in price of about -2.4% for the murders occurring within 200 mt from a district, while its effect decreases to -1.4% for murders within 1000 mt. The bottom panel of Table 9 shows the results. The direct effect is negative and significant both for the short and for the long run, whereas the estimated indirect effect appear again positive and significant. Interestingly enough, the short-run magnitude is much lower than the long-run impact, suggesting that the price effects (that may be due for instance to neighbor' reputation) hold even more in the long run).

5 Robustness Checks: adding total Camorra homicides and different spatial effects

In this section we take into account two potential problems of our estimations:

1. we did not consider Mafia homicides other than random homicides in our regressions.[26] The problem could consist in the fact that in locations where many Camorra homicides occur the probability of a random homicide is higher. If this is the case we could have an omitted variable problem ,that is: housing pricing are not affected by random homicides but by the overall presence of a high level of Camorra violence, measured in this case by the total number of Camorra homicides, that also increases the probability of random homicides.

2. The weight matrix we considered is based on pure distance so that the relevant

[26] As noted, the main source for such data only contains homicides involving non-affiliates to the Camorra.

Table 9: Random homicides and real estate 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***		
	(.017)	(.018)		
Min Sale (log, lag)			0.848***	0.842***
			(0.017)	(0.018)
# RH within 200m (lag)	-0.023**	-0.023**		
	(.010)	(.010)		
# RH within 1000m (lag)			-0.014**	-0.014**
			(.006)	(.006)
Nightlights index (lag)	0.038	0.036	0.037	0.035
	(.053)	(.053)	(.053)	(.053)
$\hat{\rho}$	-0.563***	-0.557***	-0.573***	-0.566***
	(0.106)	(.109)	(.107)	(.000)
Spatial effect (short run)				
Direct - # RH within 200m and 1000m (lag)	-0.024**	-0.024**	-0.014**	-0.014**
Direct - Nightlights index (lag)	0.044	0.042	0.044	0.042
Indirect - # RH within 200m and 1000m (lag)	0.009**	0.009**	0.005**	0.005**
Indirect - Nightlights index (lag)	-0.016	-0.015	-0.016	-0.015
Total - # RH within 200m and 1000m (lag)	-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 - # RH within 200m (lag)	-0.214**	-0.200**	-0.137**	-0.127**
Direct - Nightlights index (lag)	0.399	0.335	0.415	0.367
Indirect - # RH within 200m (lag)	0.181**	0.167**	0.118**	0.107**
Indirect - Nightlights index (lag)	-0.335	-0.294	-0.353	-0.307
Total - # RH within 200m (lag)	-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

neighbor district are the closest. Works such as Case (1991) and Arbia et al. (2010) highlight the role of socio-economic weighted distance, so that the relevant distance is a multidimensional concept, not restricted to geography.

In order to deal with the first problem we collected primary data on Camorra homicides from the prosecutor office for the period 2011-2018, and integrated these data with secondary data on Camorra homicides, obtained from newspaper news, for the period 2006-2010. We run, therefore, the Blundell-bond specification for the two periods to test whether our results are consistent to the inclusion of this Camorra homicides variable. The first two columns of Table 10 reports the results with the primary data (2011-2018) while the second two columns reports the finding when focusing on the sample the secondary data (2007-2018) As we see results are still robust to this problem and Camorra homicides are not significant. [27]

As for the consideration of different distance matrices, let us consider two different types of matrix: a simple contiguity matrix and a socio-economic distance matrix (see Case, 1991, Case et al., 1993, Arbia et al., 2010), where the nearest neighbor of a district is a district with the most similar housing price level. The insight in the latter case is that if an individual perceives a district as unsafe s/he can look for another district that is similar in terms of price, following a reasoning for instance similar to the one proposed by (Bayer et al., 2016). Following this hypothesis we built a standardized inverse matrix based on minimum threshold, in which the distance is based on the absolute difference with respect to the $-i$ district price,[28]

[27]Table 10 report only SYS-GMM estimates. This is justified as follows. With a smaller sample and a smaller number of RH homicides, the bias implied by difference-GMM estimations such as Arellano-Bond estimations, in the case of autoregressive roots higher than 0.8, is much higher than level-GMM estimations, such as those based on Blundell-Bond estimations (see Blundell and Bond, 2000). With the alternative estimators, we found the same expected signs for the coefficient of RH, but not significant (results ares available upon request).

[28]By computing the price averages over time for the districts, the distance of 301 euros allows to have at

Table 10: Different types of homicides and housing prices in a SYS-GMM (2011h1-2018h1)

Variables	Max Sale (log) 2011-2018	Min Sale (log) 2011-2018	Max Sale (log) 2007-2018	Min Sale (log) 2007r-2018
# RH within 200m (lag)	-0.037**	-0.027*	-0.016**	-0.016**
	(0.018)	(0.016)	(0.007)	(0.008)
# CH within 200m (lag)	0.001	0.002	0.001	0.002
	(0.002)	(0.002)	(0.001)	(0.001)
Max sale price (log, lag)	0.987***		0.983***	
	(0.004)		(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
	(0.029)	(0.029)	(0.016)	(0.012)
Time Trend	Yes	Yes	Yes	Yes
AR(1) $Pr > z$	0.009	0.009	0.004	0.003
AR(2) $Pr > z$	0.019	0.025	0.013	0.016
AR(3) $Pr > z$	0.063	0.073	0.042	0.052
AR(4) $Pr > z$	0.114	0.129	0.079	0.094
Sargan Over-Id test $Pr > z$	0.509	0.205	0.524	0.157
Observations	1136	1136	1963	1963
Number of groups	93	93	93	93

Notes: the table reports estimates obtained from system GMM Blundell-Bond on the house prices panel sub-sample. The estates in the sample are civil housing, cheap civil housing, luxury civil housing. The dependent variables are the natural log of the maximum sale price (column 1 and 3), the natural log of the minimum sale price (column 2 and 4). The instrument vary from 2 to 4 lags to keep the number of instrument lower than the number of groups and avoiding autocorrelation issues. All specifications control for the total number of mafia murders within 200m from the district (lag), nightlight index (lag), and the lag of the dependent variable. Robust standard errors in parentheses. Level of significance are *p<10%; ** p<5%; *** p<1%.

Table 11: Mafia killings and real estate prices: SAR with alternative spatial distances

Matrices	Minimum Distance Threshold (1)	Contiguity Distance (2)	Minimum Distance Price Threshold (3)
Max Sale (log, lag)	0.844***	0.858***	0.853***
	(0.017)	(0.030)	(0.025)
# RH within 200m (lag)	-0.023**	-0.025**	-0.024*
	(0.010)	(0.012)	(0.012)
Nightlights index (lag)	0.038	0.050	0.060**
	(0.053)	(0.025)	(0.024)
$\hat{\rho}$	-0.563***	-0.118***	0.093***
	(0.106)	(0.045)	(0.032)
Spatial effect (short run)			
Total - # mafia murders within 200m (lag)	-0.015**	-0.023**	-0.027**
Total - Nightlights index (lag)	0.028	0.046**	0.069***
Spatial effect (long run)			
Total - # mafia murders within 200m (lag)	-0.033**	-0.101**	-0.131
Total - Nightlights index (lag)	0.064	0.201**	0.702
Observations	930	930	930
Number of groups	30	30	30

To have a feel of the differences with respect to the minimum threshold matrix, that is the one used for our main results, consider that the latter implies an average number of neighbors for each district equal to 12, and a connectivity percentage (i.e. the percentage of the non-zero elements of the matrix) of 79% of the whole 30x30 district matrix. The simple contiguity matrix and the socio-economic distance matrix, respectively, have an average number of links for each district of 4.7 and 5.7, and connectivity percentages of 16% and 20%. In Figure AB1 in Appendix A we present a graphical representation of the different connectivities implied by the different matrices.

In Table 11 we present a comparison of the spatial estimation for the static and dynamic SAR models (other results are available upon request). Table 11 shows that results hold are robust to the consideration of totally different weight matrix schemes.

While the estimated coefficients of interest have same signs (negative for homicides and positive for nightlights) and similar magnitudes, as expected, the different spatial frameworks

least one neighbor for each district.

implies a different spatial multipliers effects, so that the matrices with lower connectivity imply a decline in the magnitude of ρ, that rests negatively and highly significant. The short-run effects are consistent, while long-run effects are not significant just in the Model (3).

6 Concluding remarks

This paper analyzed the effect of "random" mafia homicides on housing prices in the city of Naples for the period 2002-2018. Naples represents an interesting case study for the pervasive presence of the Italian criminal organization called *Camorra*, characterized by a horizontal organization, that the literature has identified as a crucial determinant for the high number of murders committed where such organizations are present.

Motivated by the finding of a positive relationship the characteristic of having an horizontal organization and the dispersion of housing prices, we performed an econometric analysis which showed that a random homicide reduces house prices in the district in a range of 2% and 4%. In addition, we identified spillover effects according to which random homicides imply an increase of the housing prices far away from the location of their occurrence.

These results are robust to the problem of taking into account all Camorra homicides, as a proxy for the organized crime violence within a district that may act as confounding factor, and to the consideration of different spatial matrices.

While the fact that crime episodes as homicides reduce housing price is not new in the literature, although no other work so far analyzed homicides by crminal organization of Mafia-type, we identify a more general effect on housing price inequality within a city.

Therefore, this paper brings evidence of the impact of organized crime on inequality at city level, operating through housing prices. As Borri and Reichlin (2017) suggest, this imply other economic outcomes, as the city average income (Glaeser et al., 2009). Moreover, in the long run housing price inequality, by affecting income inequality (Weil, 2015) can influence long-run income inequality, through segregation (Durlauf, 1996).

As remarked by Glaeser and Gottlieb (2009, pag. 43) within-city dispersion of housing prices may be a dimension of inequality that takes into account space much better than the within-country one as: "failure to think fully about space will tend to make within-country inequality estimates overstate the level of real income inequality".

Acknowledgement: We are grateful to Davide Fiaschi, Angela Parenti, Fabiano Schivardi and Francesco Sobbrio for valuable comments. We also thank to Prosecutor Dr. Fragliasso for the kind assistance and partecipants to seminars and conference in Universities of Luiss, Messina, Naples and Pisa for discussions. Usual caveats apply.

References

Acemoglu, Daron, James A. Robinson, & Rafael J. Santos (2013). The monopoly of violence: Evidence from Colombia, *Journal of the European Economic Association* 11, 5-44.

Acemoglu, D., De Feo, G. & De Luca, G. (2017). Weak States: Causes and Consequences of Sicilian Mafia, NBER Working papers no. 24115 .

Alesina, A., Piccolo, S. & Pinotti, P. (2018). Organized Crime, Violence, and Politics. *Review of Economic Studies*, forthcoming.

Anselin, L., Cohen, J., Cook, D., Wilpen, G. & Tita, G. (2000). Spatial Analyses of Crime, in *Criminal Justice: Measurement and Analysis of Crime and Justice*, 213-262.

Arbia, G., Battisti, M. & Di Vaio, G. (2017). Institutions and geography: Empirical test of spatial growth models for European regions, *Economic Modelling*, 27, 12-21.

Bandiera, O. (2003). Land reform, the market for protection, and the origins of the Sicilian mafia: theory and evidence, *Journal of Law, Economics, and Organization*, 19(1), 21844.

Baltagi, B.H. & Bresson, G. (2011). Maximum likelihood estimation and Lagrange multiplier tests for panel seemingly unrelated regressions with spatial lag and spatial errors: An application to hedonic housing prices in Paris. *Journal of Urban Economics*, 69(1), 24-42.

Battisti, M., Bernardo, G., Kostantinidi, A., Kourtellos, A. & A.M. Lavezzi (2019). Socio-economic inequalities and Organized Crime: an Empirical Analysis, in *Understanding Recruitment to Organized Crime and Terrorism: Social, Psychological and Economic Drivers*, ed. by D. Weisburd, E. Savona, B. Hasisi, and F. Calderoni, Springer-Verlag publisher, forthcoming.

Bayer, P., McMillan, R. & Murphy, A. & Timmins, C. (2016). A Dynamic Model of Demand for House and Neighborohoods, *Econometrica*, 84(3), 893-942.

Behrens, K. & Robert-Nicoud, F. (2014). Survival of the Fittest in Cities: Urbanisation and Inequality. *Economic Journal*, 124(581), 1371-1400.

Berry, C. & Glaeser, E.L. (2005). The Divergence of Human Capital Levels Across Cities, *Papers in Regional Science*, 84(3), 407-444.

Blundell, R. & Bond, S. (2000). GMM Estimation with persistent panel data: an application to production functions, *Econometric Reviews*, 19(3), 321-340.

Borri, N. & Reichlin, P. (2017). The housing cost disease, *Journal of Economics and Dynamics Control*, 87, 106-123.

Bruno, G. (2005). XTLSDVC: Stata module to estimate bias corrected LSDV dynamic panel data models.

Buonanno, P., Durante, R., Prarolo, G. & Vanin, P. (2015). Poor Institutions, Rich Mines: Resource Curse in the Origin of the Sicilian Mafia, *Economic Journal*, 125, F175-F202.

Calderoni, F. (2011). Where is the mafia in Italy? Measuring the presence of the mafia across Italian provinces,*Global Crime*, 12(1), 41-69.

CAMBRIDGE ECONOMETRICS (2016). European Regional Database. Cambridge Econometrics. URL:http://www.camecon.com/SubNational/SubNationalEurope/RegionalDatabase.aspx

Case, A.C. (1991). Spatial patterns in household demand, *Econometrica* 59, 953-965.

Case, A.C., Rosen, H.S., Hines Jr., J.R. (1993). Budget spillovers and fiscal policy interdependence: evidence from the states, Journal of Public Economics 52, 285-307.

Catino, M. (2014). How Do Mafias Organize?: Conflict and Violence in Three Mafia Organizations. *European Journal of Sociology*, 55(2), 177-220. doi:10.1017/S0003975614000095

Cecil, D. J. & Buechler, D. E. & Blakeslee, R. J. (2014). Gridded lightning climatology from TRMM-LIS and OTD: Dataset description.,*Atmospheric Research*, 135, 404-414.

Cliff, A. D., & Ord, J. K. (1981). Spatial processes: models & applications. Taylor & Francis.

Dal Bo', E., Dal Bo', P., & Di Tella, R. (2006). "Plata o Plomo?": Bribe and Punishment in a Theory of Political Influence. *American Political Science Review*, 100(1), 41-53.

Daniele, G., & Dipoppa, G. (2017). Mafia, elections and violence against politicians. *Journal of Public Economics*, 154, 10-33.

Daniele, V. & U. Marani (2008), "Organized crime, the Quality of Local Institutions and FDI in Italy: a Panel Data Analysis", *European Journal of Political Economy* 27, 132-142.

Dimico, A., Isopi, A. & Olsson, O. (2017). Origins of the Sicilian Mafia: The Market for Lemons, *Journal of Economic History*, 77(4), 1083-1115.

Dugato, M & Calderoni, F. & Berlusconi, G. (2017). Forecasting Organized Crime Homicides: Risk Terrain Modeling of Camorra Violence in Naples, Italy. *Journal of Interpersonal Violence*,first published online, June 13.

Durlauf, S.N. (1996). A theory of persistent income inequality, *Journal of Economic Growth*, 1(1), 75-93.

EUROPOL (2013). Threat Assessment Italian Organized Crime, The Hague Report, FILE NO: EDOC#667574 v8

Frazzica, G., Lisciandra, M., Punzo, V. & Scaglione, A. (2016). The Camorra and protection rackets: the cost to business, *Global Crime*, 17(1), 48-59.

Glaeser, E.L. & Gottlieb, J.D. (2009) The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States. *Journal of Economic Literature*, 47(4), 983-1028.

Fullin, G. & Reyneri, E. (2011). Low unemployment and bad jobs for new immigrants in Italy., *International Migration*, 49(1), 118-147.

Glaeser, E.L., Gottlieb, J.D. & Ziv, O. (2016). Unhappy Cities. *Journal of Labor Economics*, 34(S2), S129-S182.

Glaeser, E.L., Resseger, M. & Tobio, K. (2009). Inequality in Cities. *Journal of Regional Science*, 49(4), 617-646.

Gibbons, S. (2004). The Costs of Urban Property Crime. *The Economic Journal*, 114, F441-463.

ISTAT (2011). Linked Open Data (LOD). *downloadable http://datiopen.istat.it/datasetCOM.php*.

ISTAT (2018). Statistiche giudiziali e penali. *downloadable http://dati.istat.it/Index.aspx* .

Klimova, A. & Lee, A.D. (2014). Does a Nearby Murder Affect Housing Prices and Rents? The Case of Sydney. *Economic Record*, 90, 16-40.

Lam, C. & Souza, P.C.L. Detection and Estimation of Block Structure in Spatial Weight Matrix, *Econometric Reviews*, 35(8-10), 1347-1376.

Lavezzi, A. M. (2014). Organised crime and the economy: a framework for policy prescriptions, *Global Crime*, 15(1-2), 164-190.

Linden, Leigh, & Jonah E. Rockoff (2008). Estimates of the impact of crime risk on property values from Megan's laws, *American Economic Review* 98(3), 1103-27.

Maclennan, D., and Miao, J. (2017). Housing and Capital in the 21st Century. *Housing, Theory and Society*, 34(2), 127-145.

Nickell, S.J. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica*, 49(6), 1417-1426.

OMI (2018). Osservatorio del Mercato Immobiliare, Agenzia delle Entrate, Rome.

UNODC (2018). United Nations on Drugs and Crime - Data and Statistics - *downloadable https://dataunodc.un.org/crime/intentional-homicide-victims*

Pinotti, P. (2015). The Economic Costs of Organised Crime: Evidence from Southern Italy. *Economic Journal*, 125, 203-232.

Pope, J.C. (2008). Fear of crime and housing prices: Household reactions to sex offender registries. *Journal of Urban Economics*, 64, 601-614.

Reyneri, E. (1998). The role of the underground economy in irregular migration to Italy: cause or effect?. *Journal of ethnic and migration studies*, 24(2), 313-331.

Sciarrone, R. & Storti,(2014). The territorial expansion of mafia-type organized crime. The case of the Italian mafia in Germany *Crime, Law and Social Change*, 61(1), 37-60.

Tita, G. E., Petras, T. L., & Greenbaum, R. T. (2006). Crime and residential choice: a neighborhood level analysis of the impact of crime on housing prices. *Journal of quantitative criminology*, 22(4), 299.

Weaver, D. A. and Bimber, B. (2008). Finding News Stories: A Comparison of Searches Using Lexisnexis and Google News. *Journalism & Mass Communication Quarterly*,85,3,515-532, 10.1177/107769900808500303.

Weil, D.N. (2015).Capital and Wealth in the 21st Century. *NBER Working Paper* 20919.

Zenou, Y. (2003).The Spatial Aspects of Crime. *Journal of the European Economic Association* 1, 2-3, 459-467, https://doi.org/10.1162/154247603322391099.

A Appendix

Table A1 contains the values of an indicator of Mafia presence (Calderoni, 2011) for the provincial capitals of Campania, Calabria and Sicily, the type of criminal organization operating in their territories and the classification (horizontal/vertical) of the dominant criminal organization from (EUROPOL, 2013).

Table A1: 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	Sicilia	Sicilian Mafia	VC
Catania	82.5	Sicilia	Sicilian Mafia	VC
Crotone	81.22	Calabria	'Ndrangheta	VC
Trapani	77.86	Sicilia	Sicilian Mafia	VC
Catanzaro	76.97	Calabria	'Ndrangheta	VC
Vibo Valentia	74.13	Calabria	'Ndrangheta	VC
Agrigento	71.75	Sicilia	Sicilian Mafia	VC
Ragusa	61.82	Sicilia	Sicilian Mafia	VC
Messina	60.82	Sicilia	Sicilian Mafia	VC
Enna	57.74	Sicilia	Sicilian Mafia	VC
Salerno	57.65	Campania	Camorra	HC
Bari	55.72	Apulia	Camorra Barese	HC
Siracusa	50.71	Sicilia	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	Societ Foggiana	VC

Notes: Mafia Index from (Calderoni, 2011), OC and Type of OC from (EUROPOL, 2013).

Table A2: Variables definition and sources

Variables	Source
Homicide Mafia	Murder committed by Mafia reported by the police forces to the judicial authority (2011) - ISTAT (Statistiche giudiziali e penali - omicidi per motivi di mafia, camorra o 'ndrangheta)
Mafia index (rank)	Calderoni F. (2011), "Where is the mafia in Italy? Measuring the presence of the mafia across Italian provinces" Calderoni F. (2011), Global Crime Vol. 12, Iss. 1, 2011
Real GDP	Cambridge econometrics (2015)
Share of population with tertiary education	Percentage of people aged 25-64 with tertiary education level Population and housing census 2011 (ISTAT) - LOD downloadable http://datiopen.istat.it/datasetCOM.php#
Unemployment rate	Population and housing census 2011 (ISTAT) - LOD downloadable http://datiopen.istat.it/datasetCOM.php#
Share historical buildings	Historical and residential buildings - Population and housing census 2011 (ISTAT) - The Linked Open Data (LOD) - downloadable http://datiopen.istat.it/datasetCOM.php#
Housing area and population density	Housing density - Population and housing and housing census 2011 (ISTAT) - The Linked Open Data (LOD) - downloadable http://datiopen.istat.it/datasetCOM.php#
Max Sale (ln)	The natural log of the maximum sale price OMI (2017) - Osservatorio del Mercato Immobiliare.
Min Sale (ln)	The natural log of the minimum sale price OMI (2017) - Osservatorio del Mercato Immobiliare.

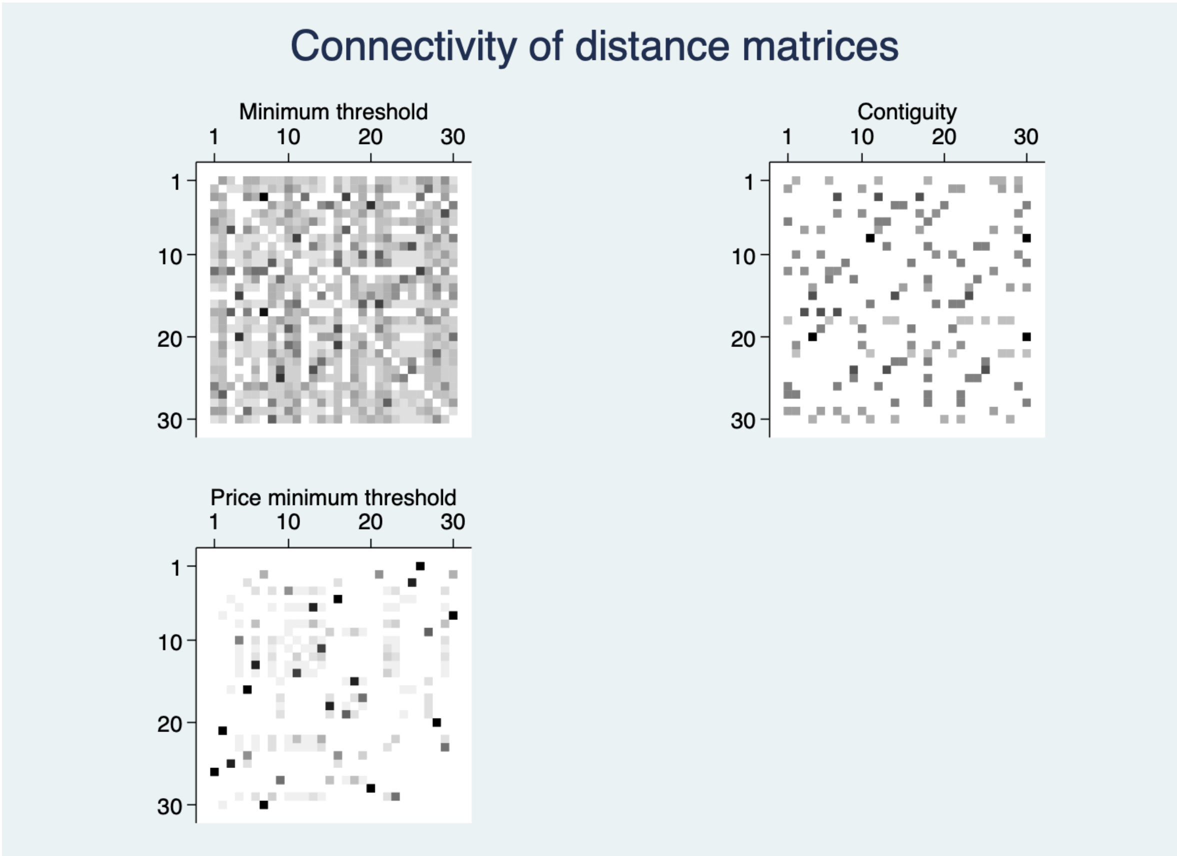

Figure AB1: Distance matrix weights

Figure AB2: Variance of housing prices Naples