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

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Abstract

In this work, we assess the role of a specific type of organized crime in influencing choices on where living within the city territory, and consequently, volatility in house prices. More specifically, we test how organized crime killing may influence house pricing behaviors. Firstly, we show evidences about how horizontally organized crime is associated with higher inequality of housing prices for Italian cities in the census year 2011. Then, by collecting and geo referencing data on the city of Naples for the period 2002-2018, we test for the direct influence of homicides on the relevant territory, as on the neighboring districts. Results show a negative and significant impact of killing innocent victims on the house prices either for sales or for rents and a positive effect in neighboring district, driving increases in within-city inequality. Evidences are robust even by taking into account geo-localization of all homicides for the period 2011-2018 and different thresholds for distances or spillover neighboring schemes.

Keywords: organized crime, spatial interactions, panel data estimations.

JEL Classification Codes: C40, D01, O33

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1 Introduction

In this paper we estimate the effect on housing prices in the city of Naples of murders committed by the *Camorra*, the Neapolitan Mafia. In particular, we build a dataset of geo-localized Mafia homicides of persons not involved in Camorra activities or fighting against them (i.e. cops, judges,..) that we term as innocent victims - henceforth i.v. or random homicides - in Naples for the period 2002-2018 and assess their effect on district-level housing prices' dispersion.

Criminal organizations such as the Italian Mafias pose a serious threat to economic development. For example, recent literature highlighted the detrimental effects that Mafias can have on foreign direct investments (Daniele and Marani, 2011), GDP growth (Pinotti, 2015) and state capacity (Acemoglu et al., 2017). In this work we focus on the effect that Mafia violence can exert on housing prices' dispersion, an important component of inequality (see e.g. Maclennan and Miao, 2017). The nexus between organized crime and inequality is a topic so far overlooked in the literature, with the exception of Battisti et al. (2018).

We focus on the case study of the city of Naples. This is motivated by 2 facts: i) this city had a huge number of homicides, most of which involving *Camorra* affiliates. While Italy seems to be one of the safest countries worldwide with a rate of 0.7 per 100,000 for 2015, 36 intentional homicide have been reported in Naples with a ratio of 3.7. Moreover, the average homicide rate from 2010 to 2015 is also quite stable over time with a value of 3 per 100,000 population that is significantly higher than OECD countries' average for 2015 (see tab 1). ii): there is the presence of non hierarchically coordinated organized crime.

As pointed out by Catino (2014), the high number of homicides by the Camorra can be explained by its horizontal structure, which differentiates it from vertically organized groups such as the Sicilian Mafia. The lack of a hierarchical structure implies that clashes among rival gangs or families to control turf and illicit trades (most notably drugs) occur frequently.

Table 1: Intentional homicides 2015 (per 100 000 people)

Country	Mean	Median
OCSE	1.14	0.96
MENA	1.58	1.33
E_ASIA	2.74	2.20
EEC	2.96	2.26
Napoli (2010-2015)	**2.97**	**3.02**
SSA	9.71	7.87
LAC	12.26	8.92
CAC	29.46	20.33

Notes: the table shows data for intentional homicide victims obtained from the United Nations on Drugs and Crime (UNODC, 2018).

In particular, Catino (2014) compares the Camorra model of organization in Campania, the region whose capital is Naples, with two other organizations such as the *'Ndrangheta* and *Cosa Nostra*, whose main territories are the regions of, respectively, 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[1]. Notwithstanding 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 of politicians, policemen and judges, due to its historically lower

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

coordination at a provincial (or even higher) level.

In this paper we consider a specific type of homicides: those implying individuals not affiliated with a Camorra gang, that we denote as " i.v." or "random" homicides. Our insight is the following: i.v. 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 and, even in places plagued by organized crime, denote a dangerous lack of capacity in monitoring the territory. This type of homicides, therefore, are those expected to have a sizable effect on the demand for houses. In particular, we expect that the effect of a i.v. or random homicide 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 the within-city housing price dispersion.

To strengthen our assumption, there are empirical evidences suggesting that random homicides receive a great deal of attention by the media and the spread of this kind of news should influence public opinion and consumer choice. In particular, table 2 shows evidences about the dissemination of news of a mafia murder 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. As expected, homicides that involve individuals not affiliated with a Camorra gang are widely disseminated through traditional media, while camorra homicides do not catch the attention. Moving the attention on Google trend, we can see that random homicides capture the interest of public opinion generating a peak of searches about victim's name during the day of the tragic event and this remains higher even in the following days, with a much slower decay

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

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

Notes: the table compare two cases of involuntary homicide with other two cases of camorra homicides occurred on the same day. These are the only two cases with these proximity dates, that we identified in our sample (details available upon request). The value assumed by the variable *Google Trends* indicates a relative frequency of a given search term into Google's search engine divided by the total searches conducted of the geographical area under consideration. The value of *LexisNexis* provide information about the number of articles which include a given search term 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 the Italian language news.

process.

This work speaks to two different strands of literature. First, it contributes to the literature, by investigating the connection between crime and residential choice. Among others, Tita et al. (2006) find that crime affects the individual decisions about changing residential location and find that violent attacks convey the greatest cost in term 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 implications on across district pricing dynamics 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.

Our main finding is that this kind of mafia 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 i.o.homicides associated to it is associated to higher house price dispersion both for the Italian cities and for the city of Naples. Secondly, we show that, in a panel data framework, i.o. 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 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 decrease 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 Organized Crime and Housing Prices Dispersion: Some Evidence

Following the definition of EUROPOL (2013), we define Camorra as a *horizontal* crime organization, different from, e.g., the Sicilian Mafia and the Calabria's 'Ndrangheta which have a vertical, hierarchical organization. In particular, Camorra clans are more fragmented in structure with many of the typical features of gangsterism (a phenomenon present in many different countries such as USA and Brazil) especially in the Naples' metropolitan area (Sciarrone and Storti, 2014). This is in line with the analysis of Catino (2014) of coordination within criminal organizations that, as we noted before, suggests that having an horizontal organization such as the *Camorra*, implies a high number of homicides and a low number of "excellent" ones.

Fig. 1 reports the values of per-capita Mafia homicides[3] of the two Southern regions where criminal organizations are rampant (i.e. Campania and Sicily), and of their main provinces (i.e. where the Regional capitals are located).

We see that Naples in the recent period experienced more homicides than Palermo. This suggests that even within the subgroup of regions or cities controlled by organized crime, the uncertain control of the territory makes it much unsafer.

In Figg. 2 and 3 we compare the variance of housing prices (minimum and maximum) across administrative districts for each Italian provincial capital to the average variance

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

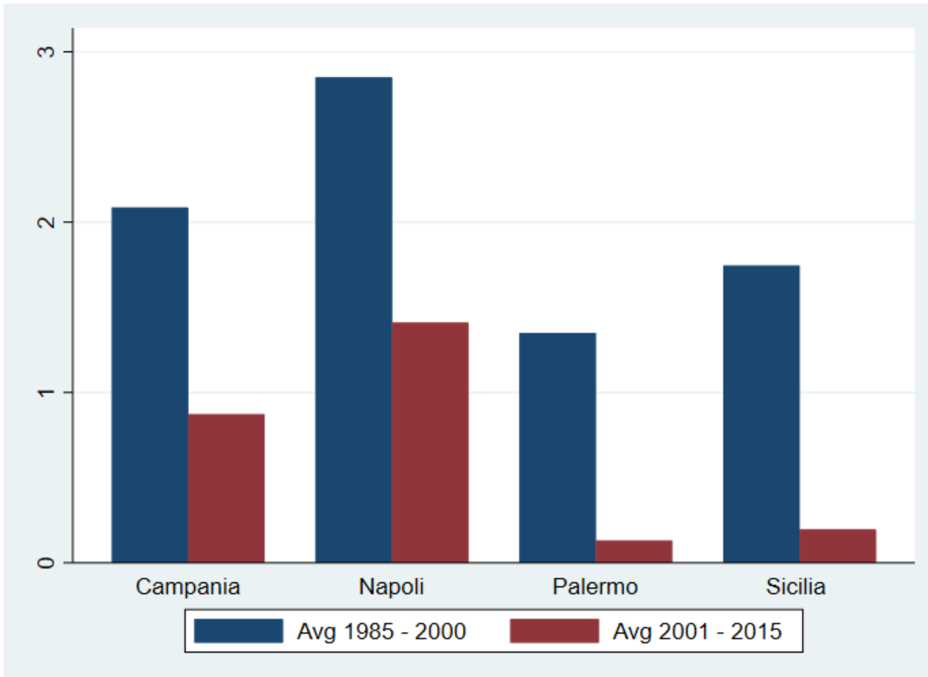

Figure 1: Mafia homicides for 100k persons

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 the year of last census that is 2011.[4]

[4]Table A1 in Appendix A reports the type of organization characterizing provincial capitals based on the EUROPOL (2013) classification. Data on house prices derive from OMI (2018), described in the data section.

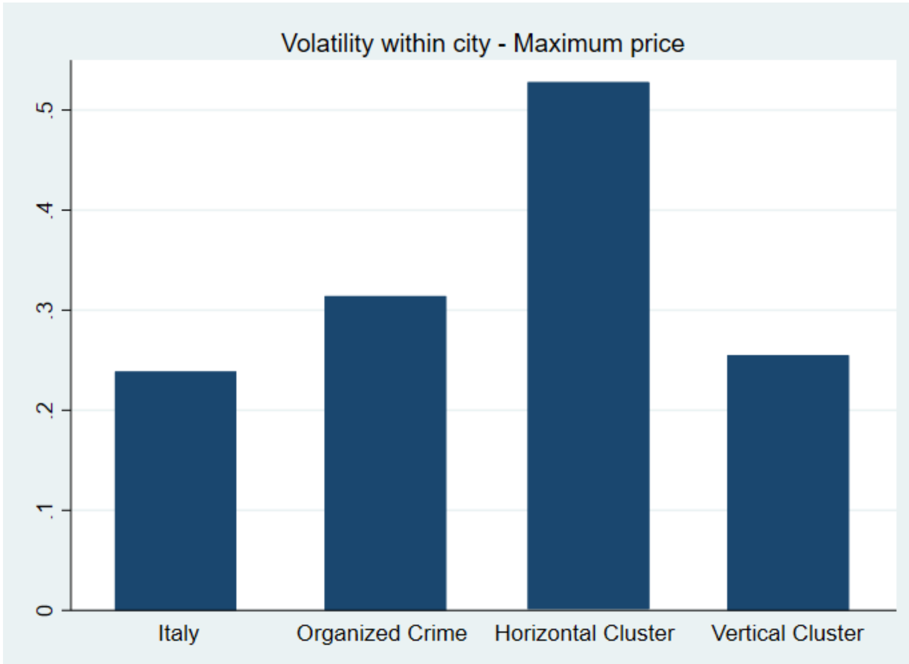

Figure 2: Variance of Minimum House prices for types of OC

Figure 3: Variance of Maximum House prices for types of OC

Figg. 2 and 3 clearly shows that the dispersion of housing prices is much higher in cities where organized crime is strong and, in particular, where it has an horizontal structure.

In a more general perspective, if we perform a variance decomposition of housing prices across and within Italian cities we see that the within-component of the dispersion accounts for 45% of total housing price variance, pointing out that the within component is an important factor of inequality among households.

In the next section we provide a more detailed econometric analysis aiming at identifying the effects of mafia homicides on housing price dispersion, including the spillover effects that we expect to characterize this relationship.

3 Data for Econometric Analysis

Data on real estate prices are obtained 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. Due to the low number of observations, for the cross-sectional analysis we matched micro-areas with city districts and computed the average prices for 12 different types of real estate within every district for the period 2002h2-2018h1.[5] For the panel analysis, we consider the prices of what are defined "residential houses".[6]

To investigate the relationship with Mafia violence, we do not utilize the crude number of mafia homicides as in Section 2 but consider those that, following the insights presented

[5]The types of real estate considered are: civil housing, cheap civil housing, luxury civil housing, garage, industrial building, shed, laboratories, warehouses, shops, parking, offices, mansion, and villas. See Table A3 in Appendix A for descriptive statistics. Data on housing prices are available for the period 2003h1-2018h1.

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

in Section 1, implied people non-affiliated with the *Camorra*. Data on mafia homicides are extracted from `http://www.vittimemafia.it/`[7], a portal collecting information and news articles on all the civilians killed by the Italian mafias from 1861 onwards. Focusing on the homicides of civilians not affiliated to Mafias also guarantees to exclude any causality from mafia affiliation to the mafia murder occurrence. This selection also implies the exclusion from the sample of all the homicides of individuals that with their activities or behavior are determining a direct or indirect damage to the mafia organization, such as policemen and judges. Also, individuals which are murdered after having refused to pay an extortion are assumed to create a direct and indirect damage to the organization, so we exclude them from the final dataset. In contrast, if a civilian is randomly shot for the initiation of a new member to the mafia organization, this is considered as i.o. homicide. The final sample includes all the i.o homicides occurred in the period 2002h2-2018h2 in Naples (henceforth, whenever we mention a murder utilized for the empirical analysis we refer to this type of homicide).

In this period, the city witnessed several blood feuds between 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 event involving an innocent victim by the latitude and the longitude, and merged those belonging to the district of occurrence, obtaining district-level number of homicides. Table 3 contains the descriptive statistics of the i.o.homicides. In particular, we computed the number of homicides with respect to the distance from the district border to the point of homicide occurrence. This approach is justified by the spatial linkage between a murder and the the location where it occurred. Estate buyers, indeed, are likely to respond to

[7] We integrated this with the sample of identified homicides of Procura di Napoli. Thanks to Prosecutor Dr. Fragliasso for the kind assistance.

murders taking place near the estate, independently whether this happens within or outside the administrative boundaries of the district. In this sense, the killing 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 mafia killings at different thresholds of distance form the district.

Table 3: Summary statistics on mafia murders in the district/semester panel (2002h1-2018h2)

Homicides of innocents (2002h2-2018h1)					
Variables	Observations	Mean	Std. Dev.	Min	Max
Total murders within district	960	0.03	0.17	0	1
Total murders within 200m	960	0.05	0.25	0	3
Total murders within 500m	960	0.9	0.33	0	3
Total murders within 700m	960	0.11	0.36	0	3
Total murders within 1000m	960	0.17	0.44	0	3
Homicides of affiliated to camorra (2011h1-2018h1)					
Variables	Observations	Mean	Std. Dev.	Min	Max
Total murders within district	450	0.32	0.73	0	5
Total murders within 200m	450	0.47	0.86	0	5
Total murders within 500m	450	0.76	1.12	0	6
Total murders within 700m	450	0.99	1.35	0	8
Total murders within 1000m	450	1.33	1.60	0	10

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

We will perform both cross-sectional and panel econometric analyses. The set of controls is more limited for the panel compared to the cross-sectional analysis, due both to lack of time-varying data at district level, and to the fact that fixed effects would correlate with time-invariant controls. The cross-sectional analysis uses the same set of controls for the sample of Italian cities and for the case study on Naples, but in different forms. For the national level analysis, the control variables are computed as within-city variances, while for the case study these variables are kept at their level. This set of controls involves an indicator of the variability of districts' characteristics, proxied by the share of buildings in the district built before 1950 [8], as well as other indicators about the share of population with tertiary education level, unemployment rates and housing density across city districts.[9] These districts' socio-economic characteristics are more related to the perceived quality of life in a district in terms of services, income and labor market.

Table 4 reports descriptive statistics of the explanatory variables employed for the case study, including the total number of Camorra homicides occurred in a given district, and a set of socio-demographic controls extracted from the Italian 2011 Census. The panel analysis includes as the only control the nighttime light data from the National Oceanic and Atmospheric Administration (NOAA), for the period 2002-2013 (Cecil et al., 2014) to proxy for local income levels. We locally interpolate these data to generate half-yearly observations.

[8] This choice is dictated by the fact that, 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 the usage on large scale of cement for the new housing.

[9] Table A2 in Appendix A reports data sources, explanation and coverage of the data we use in this section.

Table 4: Summary statistics on the cross-sectional controls

Variables	Obs	Mean	Std. Dev.	Min	Max
# Mafia Murders in the District	346	0.74	1.02	0	4
Unemployment rate	346	0.10	0.02	0.05	0.14
Share of pop. with tertiary education	346	0.15	0.11	0.04	0.38
Share of historical buildings	346	0.64	0.26	0.21	0.99
Housing density (area of inhabited houses/population)	346	31.19	6.20	24.08	45.78

Notes: Cross-sectional summary statistics for the control variables. The sample is type of building/area

To test whether the key variables, housing prices and homicides, display any geographical pattern, we use quantile spatial maps at district level to show respectively maximum house prices of transactions, the time-averaged percentage difference between maximum and minimum price and homicides within districts. Fig. 4 shows that there exists a clear pattern in housing prices, with higher prices in the South-West of Naples.[10] Differently, in Fig. **??** shows that the within-district average difference between minimum and maximum price do not show a clear spatial pattern across districts.

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

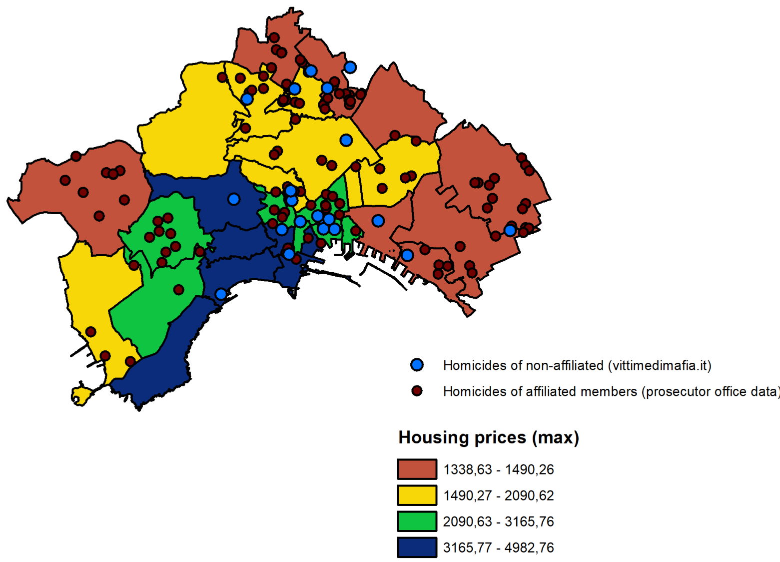

Figure 4: Homicides and Average maximum price for sq mt 2002-2018, civic houses

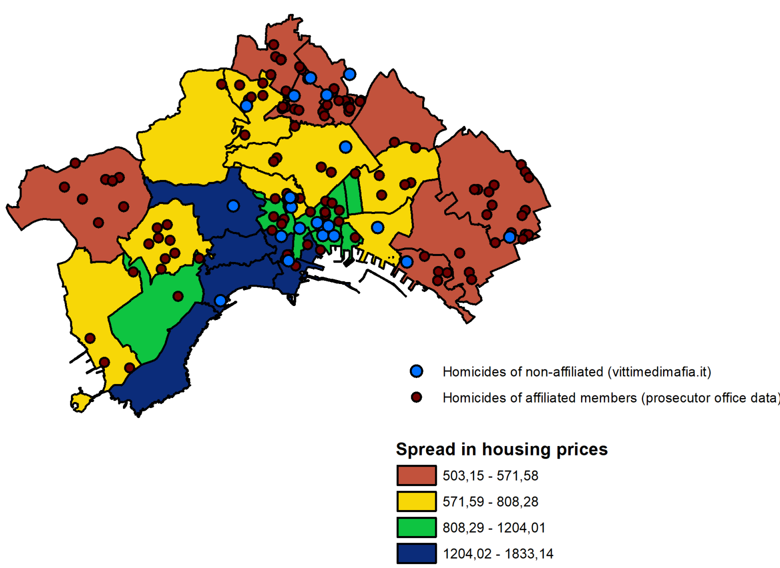

Figure 5: Homicides and spread max-min price for sq mt 2002-2018, civic houses

Then, the geo-localization of i.v. homicides does not show a clear district pattern related to price levels, while the total number of homicides has a concentration on the highest levels in the districts of Scampia in the Northern part of the city, and of Stella, Montecalvario, San Lorenzo, Zona Industriale, in the Southern part. Hence, a spatial pattern of homicides appear in which the "riskiest" neighborhoods are clustered in two areas. The spatial distribution of random homicides is in line with the risk map built by Dugato et al. (2017)[11], in which the probability of a Camorra homicide in 2012 has been predicted using variables such as past homicides, intensity of drug dealing, confiscated assets, and rivalries among groups. From these three figures we draw the following conclusions: the spatial pattern of prices and of homicides do not seem related. In addition, the spatial pattern of within-district price dispersion does not seem related to homicides either. Overall, this makes very unlikely the possibility that causality runs from housing prices to (random) homicides. Therefore, except for structural characteristics captured by the fixed effects, we may consider the random homicides as exogenous and not expected.

4 Empirical Model

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, and repeat the same exercise for the level of prices and rents across Naples' districts. Then, we take into account the dynamics, by a panel analysis on the case study. Finally, we consider the asymmetric spatial dynamics of homicides the districts whehe homicides occurred and neighboring districts, and estimate short-run and long-run effects.

[11] While they use homicides between 2004 and 2010, our sample of i.v. homicides cover a longer period 2002-2018 and our sample for total homicides is more recent (2011-2018).

4.1 Benchmark cross-sectional strategy

So, how does the presence and the actions of organized crime influence housing price dispersion within cities? In order to answer this question we correlate a measure of housing price dispersion, the variance of log prices across census areas, (both minimum and maximum sale prices), to indicators of mafia presence and other controls.[12]

A cross-sectional approach to study the dynamics of the variance of housing prices across Italian capital of provinces can take the following form:

$$VarPrice_c = \beta_0 + \lambda MI_c + \alpha X_c + \mu_c \tag{1}$$

where $VarPrice$ denotes the within-city variance of natural log of maximum and minimum prices for city c, β_0 is the intercept, MI_c may represent, respectively, the mafia index at provincial level provided by Calderoni (2011), the number of mafia killings, or dummies indicating the presence of an horizontal or vertical organized crime, with λ the associated vector of coefficients. In addition, X_c is a vector of controls, discussed in Section 3 and μ_i is the i.i.d. error term.

For the case study, the above specification varies to include the mafia homicides occurred within or close to a district, taking the following form:

$$lnPrice_{ij} = \beta_0 + \alpha X_i + \lambda MK_i + \gamma EstateType_{ij} + \mu_i \tag{2}$$

where $lnPrice_{ij}$ is the natural log of time-averaged maximum and minimum nominal sale

[12] 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.

price[13] of real estate of type j in district i, $EstateType_{ij}$ denotes a set of dummies on the types of estate in the sample, MK refers to our measure of mafia killings occurred within the district and within a pre-determined threshold of distance (200m, 500m, 700m, 1000m) from the district's border to the homicide location; X_i is a set of district-level controls. Finally, μ_i denotes the error term, β_0 the intercept, and again, α, λ, and γ are vectors of parameters to be estimated.

Tables 5 and 6 contain the results of OLS estimations of Eq. (1). In particular, Table 5 contains the results of OLS regressions considering Mafia indicators only, while 6 contains the results with additional controls. Table 5 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.[14]

[13] All specifications involve the nominal sale/rent prices in combination with fixed effects and year dummies, allowing to control for common increases due to inflation. As a robustness, the same specification has been run using real prices and the results from all the specifications are consistent (available under request).

[14] 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 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%.

In Table 6 we add to Models 5 and 6 of Table 5 the control variables on district characteristics to check if the coefficients of interest remain significant.

Table 6: 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	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 house prices, computed across city districts. Bootstrapped standard errors, with 100 replications, in parentheses. Level of significance are *p<10%; ** p<5%; *** p<1%.

These regressions 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 has an important relationship with inequality as showed for example by Berry and Glaeser (2005) and Glaeser et al. (2009).

Turning to the district-level results for the city of Naples, Table 7 presents the estimates of the cross-sectional specification, where the total number of mafia killings denotes the sum of all the mafia killings occurred within 200m from the district during the period 2002h2-2018h1.

Table 7: Cross-sectional investigation on the effect of the number of mafia killings within the district on real estate prices

Variables	Max Sale (log)	Min Sale (log)	Max Rent (log)	Min Rent (log)
	(1)	(2)	(3)	(4)
# mafia murders within 200m	-0.016***	-0.015***	-0.020***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
Share of pop. with tertiary education	3.314***	3.313***	3.242***	3.208***
	(0.51)	(0.50)	(0.56)	(0.56)
Unemployment rate	-8.745***	-8.678***	-9.385***	-9.218***
	(1.47)	(1.37)	(1.45)	(1.61)
Housing density (area of inhabited houses/population)	-0.047***	-0.047***	-0.047***	-0.047***
	(0.01)	(0.01)	(0.01)	(0.01)
Share of historical building	0.315***	0.308***	0.401***	0.389***
	(0.05)	(0.05)	(0.05)	(0.06)
Estate Type Dummies	Yes	Yes	Yes	Yes
Number of Districts	30	30	30	30
Number of Estates' types	12	12	12	12
Observations	346	346	346	346
R-squared	0.910	0.919	0.892	0.897

Notes: the table reports estimates obtained from an OLS regression on a cross-sectional samples of estate types district observations. The estates in the sample are civil housing, cheap civil housing, luxury civil housing, garage, industrial building, shed, laboratories, warehouses, shops, parking, offices, mansion, and villas. 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). All specifications control for the total number of mafia killings committed within 200m from the district, the share of population with tertiary education, the unemployment rate, housing density and the share of buildings edified before 1950s. Bootstrapped standard errors, with 100 replications, in parentheses. Level of significance are *p<10%; ** p<5%; *** p<1%.

An increase in one mafia killings is associated to a decrease by more than 1.7 percent in the maximum sale prices of the estate.[15] This impact is consistent when the dependent variable is the minimum sale price. The estimates are robust to the inclusion of Estate types dummies, which are likely to capture cross-sectional differences in prices between the estate types. The coefficients of the control variables take on the expected signs and magnitudes: the unemployment rate negatively correlates with house prices, the coefficient of the population with tertiary education is positive and significant, an increase in housing density is negatively associated to the price.

Two mechanisms can explain this finding. First, higher competition from higher population densities in given districts may be pushing up the prices compared to zones less densely populated. Secondly, this coefficient may derive from the well-known non-linearity in prices per square meters for large holdings. According to this interpretation, districts with larger estates may observe lower maximum and minimum prices compared to districts with smaller estates, keeping everything else equal. Finally, the number of historical buildings, a proxy to capture closeness to city-centers, correlates positively with prices.

4.2 Extension to a panel approach

The cross-sectional approach works if the murders are randomly distributed across the districts, or if the presence of omitted-variable bias can be excluded. In case of omitted-variable bias, or selection bias in homicide occurrence, e.g. the homicides are more likely in districts under the control of the criminal organization, the estimated parameters will overstate the impact of mafia homicides on estate prices. This may occur because mafia homicides can be correlated with other estate and district characteristics, such as low access

[15] Given the low number of observations, these results are presented at real-estate level, assuming that the prices for different estates within the same districts are highly correlated. However, when restricting to the sample of housing the results remain consistent for homicides occurring within 200-500-700-1000 meters from the districts' border. We report later, a set of results for this kind of housing in dynamic and spatial panel estimations.

to infrastructure, poor supply of public goods, low quality in the governance, etc. Since these dimensions are strong determinants of prices, failure of controlling for these will bias upwards the coefficients.

As second complication, using a cross-sectional approach it is not possible to determine whether the decrease in price has preceded or followed the mafia homicide. An alternative explanation to the cross-sectional findings could be that a district has observed a strong decrease in house prices caused, for example, by the economic crisis, and this has determined a growth in the illegal mafia-related activities, including murders.[16]

Data on murders we collected, however, 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 an increase in the state budget allocated for the law enforcement agencies controlling the territory, or the impact of 2008 economic crisis. 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 estimate this equation using by OLS with fixed effects, as follows:

[16]Figure AB2 in Appendix A reports the pattern of district level housing price variance in Naples. We see how the such variance, normalized at 1 in the initial year, is decreasing at the onset of the crisis, showing a tendency to return to its initial level at the end of the period.

$$lnPrice_{ijt} = \beta_0 + \delta lnPrice_{ijt-1} + \lambda MK_{it-1} + \phi DistrictEstate_{ij} + \psi T_t + \alpha X_{it-1} + \mu_{it} \quad (3)$$

where $lnPrice_{ijt-1}$ is the lagged natural log of the average price of the estate j in district i; MK is a variable capturing the number of murders at time $t-1$ within a given distance from the district; $DistrictEstate$ are a fixed effects specific for the panel observation; T is a set of time dummies (half-year), μ is an error term clustered at district-estate level. The matrix X contains the lag of the districts' nighttime lights,[17] a proxy for local economic development, interpolated half-yearly. We take the lag of this variable to reduce any reverse causality in the estimation. Finally, μ 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. To strengthen our results, we restrict the analysis on few types of housing (classified as civilian, cheap, and luxury houses), and 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 Arellano-Blundell level specification, and the bias-corrected LSDV dynamic panel data model (Bruno, 2005).

Table 8 displays the results of the OLS-fixed effect regression.

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

Table 8: Effect of the number of killings on a panel of housing prices by districts estimated by OLS with Fixed Effects (2002h2-2018h1)

Variables	Max Sale (log)	Min Sale (log)	Max Rent (log)	Min Rent (log)
	(1)	(2)	(3)	(4)
# mafia murders within 200m (lag)	-0.024***	-0.024***	-0.026***	-0.027***
	(0.01)	(0.01)	(0.01)	(0.01)
Max sale price (log, lag)	0.817***			
	(0.01)			
Min sale price (log, lag)		0.814***		
		(0.01)		
Max rent price (log, lag)			0.803***	
			(0.01)	
Min rent price (log, lag)				0.798***
				(0.01)
Nightlights index (lag)	0.006	0.006	0.006	0.006
	(0.010)	(0.010)	(0.010)	(0.010)
District-Estate FE	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Districts	30	30	30	30
Observations	2557	2557	2557	2557
R-squared	0.864	0.860	0.899	0.899

Notes: the table reports estimates obtained from an OLS with District/Estate Fixed effects and Time period dummies on a panel composed by estate type, district, semester. 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). All the specifications control for the total number of mafia murders, nightlight index, district-estate fixed effects, and time dummies. Robust standard errors in parentheses. Level of significance are *p<10%; ** p<5%; *** p<1%.

According to our estimates, an additional mafia homicide at time $t-1$ leads to a variation of the maximum/minimum price of estate sale of about -2.5%.[18] The estimated coefficient is significant across al specifications, and supports the hypothesis that the fear of crime reduces the individual willingness to pay (Pope, 2008; Bayer et al., 2016). This coefficient is lower in magnitude than the one in Table 14, with an average difference of about 5.2%, indicating that the unobserved characteristics, such as average housing or district's level institutional quality, are likely to bias upwards the cross-sectional estimates, as predicted.

We now turn to the the estimation of Eq. (3) as a dynamic panel. Results are reported in Table 13. As it is possible to notice, the coefficient on the number of murders is negative and significant for all specifications. The estimated coefficient suggest an impact of an additional homicide equal to about -2.6% and -3.8% of the housing price. 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. [19] Column (7) uses only one type of housing, by using district averages of the four residential types of housing. This is important, because in the next subsection we cannot use the dimension district-type of house. In a spatial framework we would have that block of elements of the weight matrices would have zero distance (i.e. cheap and luxury housing in the same district have zero distances), implying a non meaningful sparse block-stacked distance matrix (Lam and Souza (2016)). As we see i.v. effects rest consistent.

[18] Table A4 in Appendix A shows that the results are robust when focusing we extend the analysis to a larger number of estate types.

[19] 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)

Table 9: Mafia homicides 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)
# mafia murders 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 total number of mafia murders 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%.

To sum up, in this section we showed that the Camorra homicides negatively impact on house prices levels in presence of fixed effects and 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.

4.3 Spatial dynamics in the effect of murders on housing prices

While previous section highlighted the negative effects of Mafia murders in the district or nearby on district's housing prices, evidence presented in Section 2 suggested a more general effects of organized crime violence on within-city housing price dispersion. In addition, in the following robustness section 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 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 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 variance of homicides across the Naples' districts, and examine their correlation across the period of observation. Table 10 shows that the coefficient of the variance of murders is positive with respect to the cross-district variance of house prices, and decreases with the distance of murders from the district.[20]

[20] To have a proxy of district amenities we keep the index of nightlight in the regressions.

Table 10: Housing price variances and Mafia murders

	(1)	(2)	(3)	(4)	(5)	(6)
Variance Mafia murders	0.016**			0.017**		
	(0.008)					
Variance Mafia murders 200 mt		0.006***			0.006**	
		(0.002)			(0.003)	
Variance Mafia murders 1000 mt			0.002**			0.003**
			(0.001)			(0.001)
Variance Nightlight				0.003*	0.003*	0.003***
				(0.002)	(0.002)	(0.001)
Constant	0.137***	0.141***	0.138***	0.109***	0.113***	0.109***
	(0.010)	(0.009)	(0.010)	(0.013)	(0.015)	(0.01)
Obs.	26	26	26	26	26	26
R-squared	0.18	0.16	0.15	0.33	0.30	0.30

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

From an econometric point of view, despite the strategy in Eq. (3) 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.[21] Another possibility is that murders may have an heterogeneous spatial effect when interacting with individual preferences. The 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 play the role of geographical constraints for the individual choice about where to

[21] A general presentation of the spatial diffusion impacts of crime is in Anselin et al. (2000).

reside. We hypothesize, therefore, that when a mafia killing 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, as follows:

$$lnPrice_{i,t} = \tau lnPrice_{i,t-1} + \rho W_t lnPrice_{i,t} + \psi W_{t-1} lnPrice_{i,t-1} + \beta \mathbf{X}_{i,t} + \gamma W_t \mathbf{X}_{i,t} + \upsilon_{it} \quad (4)$$

where:

$$\upsilon_{it} = \lambda W_{t-1} + \epsilon, \quad (5)$$

and $\mathbf{X}$ containing nightlight and mafia murders.

The generality of this approach allows to test different hypotheses on spatial dependence, obtained by setting at zeros part of the coefficients in the model. The first specification consists in a Spatial Autoregressive model (SAR). This model derives from a Cliff-Ord model when $\rho \neq 0$, $\psi \neq 0$, $\gamma = 0$ $\lambda = 0$. The second specification implies a Spatial Error Model (SEM), obtained by setting $\rho = 0$, $\psi = 0$, $\gamma = 0$, $\lambda \neq 0$. Finally, the third specification considers a Spatial Durbin Model (SDM), where $\rho \neq 0$, $\psi \neq 0$, $\gamma \neq 0$ and $\lambda = 0$.

Given we have a large degree on freedom in interpretating which kind of spatial dependence matters, first of all we estimate all these alternative models on a static reduced form of Eq. (4) where we use first differences of prices to eliminate dynamic issues. Then, after we detected the main channel of spatial influence on prices, we estimate the full model with this proper space-time dynamics. Therefore, in the case of SDM we estimate for instance:

$$\triangle lnPrice_{ijt} = \rho W_t lnPrice_{i,t} + \beta \mathbf{X}_{i,t} + \gamma W_t \mathbf{X}_{i,t} + \upsilon_{it} \tag{6}$$

Results are obtained using 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.[22] Table 11 reports these SEM estimates in columns 1 and 4, showing a negative significant effect of murders on prices across all the specifications considered. The impact of a murder decreases in magnitude but remains consistent and significant across all the specifications. The magnitude varies from -2.9% when considering the murders occurring within 200 meters, to -1.8% for the murders occurred within 1000 meters.[23]

Using the SAR and SDM model it is possible to compute the long-run direct, indirect, and total effect of a murder, as reported in the bottom part of Table 11. The direct effect denotes the impact of the murder in the district of occurrence, while the indirect effect measures the impact on the neighboring districts. While the direct effect of a murder is again negative and significant, the same murder appears to have a positive impact (+1%) on the prices of the neighboring districts. Taken together, these effect may be pointing toward a process of higher price wedge among the areas where murders occur and do not occur. This effect, however, is captured only by the SAR model, meaning that the effect of murders of other neighbors are transmitted indirectly to house prices, through price dynamics (see effects in 7 and 8 below).

[22] We estimated the model using Stata *xsmle* routine. This kind of matrix, for these data, implies an average number of links for each district equal to 12 and a connectivity percentage of 76% of the whole 30x30 district matrix. See figure AB1 in the appendix. We tried the alternative case of a simple contiguity matrix, implying a very different picture with an average number of links for each district of 4.7 and a connectivity of 16% and results for our coefficients of interest are the same, up to the third digits. Results are available upon request.

[23] 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 11: Mafia homicides and real estate prices in a spatial framework

Variables	Max Sale (FD) (SEM)	Max Sale (FD) (SAR)	Max Sale (FD) (SDM)	Max Sale (FD) (SEM)	Max Sale (FD) (SAR)	Max Sale (FD) (SDM)
# mafia murders within 200m (lag)	-0.026***	-0.025**	-0.025**			
	(.010)	(.010)	(.010)			
# mafia murders 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						
# mafia murders within 200m (lag)			-0.116*			
			(.064)			
# mafia murders within 1000m (lag)			.093			-.026
			(.341)			(.044)
Nightlights index (lag)						.066
						(.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 effect (long run)						
Direct						
# mafia murders within 200m (lag)		-0.025**	-0.022**			
# mafia murders within 1000m (lag)					-0.017***	-0.017***
Nightlights index (lag)		0.074	0.074		0.073	0.071*
Indirect						
# mafia murders within 200m (lag)		0.010**	-0.059			
# mafia murders within 1000m (lag)					0.006**	-0.007
Nightlights index (lag)		0.03	0.027		-0.028	0.011
Total						
# mafia murders within 200m (lag)		-0.015**	-0.081**			
# mafia murders 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 Arellano-bond panel model on the house prices panel sample. The dependent variables are the natural log of the maximum sale price (column 1), the natural log of the minimum sale price (column 2). All specifications control for the total number of mafia murders within the district (lag) and its 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%.

The total effect, however, remains negative and significant, suggesting an overall decline of prices due to this criminal activity. The coefficient associated to the control variables reports the expected signs and magnitude. Nightlight positively correlates with increases in price (+0.005%) of the same district and negatively correlates with the prices of the neighborhood, denoting competition between neighboring districts in the housing market prices.

Finally, since prices are likely to depend substantially on their lagged realization, we extend the model in Table 11 to a spatial dynamic framework by adding the lag of the house prices into the specification. Table 12 reports the output of this empirical exercise for the SAR model. Adding the lagged price does not impact substantially on the magnitude and the statistical significance of the coefficients of the mafia murders. The occurrence of a murder is still associated to a reduction in price of about -2.4% for the murders occurring in a radius of 200 meters, while its effect decreases to -1.4% for murders within 1000 meters.

The dynamic nature of the 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 X variable of interest on the Y (for instance MK), 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):

$$\frac{\partial y_{i,t}}{\partial X_{i,t}^{MK}} = (I_n - \rho W_t)^{-1}[\beta_{i,t}^{MK} I_n] \tag{7}$$

The long-run coefficients are obtained by setting y=y* in the steady state. In the case of SAR (i.e. with $\gamma = 0, \lambda = 0$) they take on a form such as:

Table 12: Mafia killings and real estate prices in a spatial framework

Variables	Max Sale (log) (SAR)	Min Sale (log) (SAR)	Max Sale (log) (SAR)	Min Sale (log) (SAR)
Max Sale (log, lag)	0.844***	0.839***		
	(.017)	(.018)		
Min Sale (log, lag)			0.848***	0.842***
			(0.017)	(0.018)
# mafia murders within 200m (lag)	-0.023**	-0.023**		
	(.010)	(.010)		
# mafia murders 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 - # mafia murders 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 - # mafia murders 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 - # mafia murders 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 - # mafia murders within 200m (lag)	-0.214**	-0.200**	-0.137**	-0.127**
Direct - Nightlights index (lag)	0.399	0.335	0.415	0.367
Indirect - # mafia murders within 200m (lag)	0.181**	0.167**	0.118**	0.107**
Indirect - Nightlights index (lag)	-0.335	-0.294	-0.353	-0.307
Total - # mafia murders 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

$$\frac{\partial y_{i,t}}{\partial X_{i,t}^{MK}} = ((1-\tau)I_n - (\rho+\psi)W_t)^{-1}\left[\beta_{i,t}^{MK} I_n\right] \tag{8}$$

The bottom panel of Table 12 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 a mechanism of opposite price dynamics of districts, when more homicides occur in a short or medium period.

5 Other homicides and different spatial effects

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

1. We didn't put homicides other than i.v. in our regressions. The lack of these data for the whole period prevented us to insert in the regression. The problem can be that in a place with many homicides the probability of a random i.h. is higher. If this is the case we could have an explaining omitted factor that is: house pricing goes down, not due to i.v. homicides but by the presence of (chaotically) organized crime, that make more reliable the probability of random shots.

2. The weight matrix we considered is based on pure distance so the relevant neighbors are the closest districts. A literature as Case (1992) and Arbia et al. (2010) highlights the role of socio-economic weighted distance, so that the relevant distance is a multidimensional concept, not restricted to geography. In addition to this, fixing the relevant interval to 200 meters is something we should relax to show that spatial effects remain robust even with different thresholds.

5.1 Differential effect of "innocent victims" homicides

In order to deal with the first problem we were able to localize total homicides (almost all due to Camorra fighting) for the period 2011-2018. In the table below we report panel and spatial estimation for period 2011-2018 that take into account this issue. As we see results are still robust to this problem and total homicides are not significant (so fixed effects already proxied for these characteristics). An additional element arising is the higher robustness for maximum prices, either sales or renting, that is justified by the higher possibilities to move of people that may pay more.

Table 13: Different types of homicides and housing prices in a SYS-GMM (2011h1-2018h1)

Variables	Max Sale (log)	Min Sale (log)	Max Rent (log)	Min Rent (log)
# mafia i.v. murders within 200m (lag)	-0.039**	-0.027*	-0.045**	-0.033
	(0.017)	(0.015)	(0.022)	(0.023)
# mafia other murders within 200m (lag)	0.002	0.002	0.003	0.003
	(0.003)	(0.002)	(0.003)	(0.003)
Max sale price (log, lag)	0.987***			
	(0.004)			
Min sale price (log, lag)		0.989***		
		(0.004)		
Max rent price (log, lag)			0.992***	
			(0.006)	
Min rent price (log, lag)				0.992***
				(0.005)
Nightlights index (lag)	-0.030	-0.027	-0.006	-0.010
	(0.028)	(0.029)	(0.058)	(0.027)
Time Trend	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.001)	(0.001)	(0.001)
AR(1) $Pr > z$	0.009	0.010	0.007	0.006
AR(2) $Pr > z$	0.017	0.023	0.022	0.023
AR(3) $Pr > z$	0.058	0.069	0.099	0.109
AR(4) $Pr > z$	0.112	0.123	0.233	0.270
Hansen/Sargan Over-Id test $Pr > z$	0.950	0.939	0.941	0.955
Observations	1136	1136	1136	1136
Number of groups	93	93	93	93

Notes: the table reports estimates obtained from system GMM Blundell-Bond on the house prices panel subsample. 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 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%.

5.2 Alternative distances and spatial weighting

Then, in this section we present robustness evidences about alternative types of spatial influences. Firstly, let us consider the impact of homicides on prices at different distance thresholds.

Tables 14, 15 present regressions with homicides computed at 500, 700, 1000 meters, with specifications that are equivalent to cross section and panel did in the previous section. We see that the main result is that coefficients of i.v homicides are still negative and strongly significant with magnitude that has a decreasing decay on longer distances by the geo-localization of homicides.

Table 14 shows the results obtained when the threshold distance of the mafia homicides variable increases.

Table 14: Cross-sectional investigation on the effect of the number of mafia killings at different distances on real estate prices

Variables	Max Sale (log)	Max Sale (log)	Maxi Sale (log)
	(1)	(2)	(3)
# mafia murders within 500m	-0.018***		
	(0.000)		
# mafia murders within 700m		-0.018***	
		(0.000)	
# mafia murders within 1000m			-0.016***
			(0.000)
Share of pop. with tertiary education	3.244***	3.351***	3.160***
	(0.58)	(0.47)	(0.54)
Unemployment rate	-8.350***	-8.149***	-9.466***
	(1.50)	(1.38)	(1.54)
Housing density (area of inhabited houses/population)	-0.044***	-0.047***	-0.047***
	(0.01)	(0.01)	(0.01)
Share of historical building	0.361***	0.372***	0.454***
	(0.06)	(0.06)	(0.06)
Estates Dummies	Yes	Yes	Yes
Number of Districts	30	30	30
Number of Estates	12	12	12
Observations	346	346	346
R-squared	0.912	0.921	0.895

Notes: the table reports estimates obtained from an OLS regression on a cross-sectional samples of estate types district observations. The estates in the sample are civil housing, cheap civil housing, luxury civil housing, garage, industrial building, shed, laboratories, warehouses, shops, parking, offices, mansion and terraced house. The dependent variables is the natural log of the maximum sale price (column 1-4). All specifications control for the unemployment rate, share of population with tertiary education, share of historical buildings and housing density. The explanatory variable of interest is the total number of mafia killings committed within 500m (column 1); 700m (column 2); 1000m (column 3) from the district border. Bootstrapped standard errors, with 100 replications, in parentheses. Level of significance are *p< 10%; ** p< 5%; *** p< 1%.

Table 14 presents only the estimates on the maximum sale price, but the result is consistent also for the minimum sale price. An additional mafia killing in a district is associated to a decrease in maximum sale prices by -1.7 percent. 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 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. Table 15 report the results.

Table 15: Mafia killings at different thresholds and real estate prices an OLS with Fixed Effect (2002h2-2018h1)

Variables	Max Sale (log)	Min Sale (log)	Max Rent (log)	Min Rent (log)	Max Sale (log)	Min Sale (log)	Max Rent (log)	Min Rent (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
# mafia murders within 700m (lag)	-0.013***	-0.012***	-0.015***	-0.015***				
	(0.002)	(0.002)	(0.003)	(0.003)				
# mafia murders within 1000m (lag)					-0.012***	-0.011***	-0.011***	-0.013***
					(0.002)	(0.002)	(0.003)	(0.003)
Max sale price (log, lag)	0.802***				0.803***			
	(0.010)				(0.010)			
Min sale price (log, lag)		0.798***				0.798***		
		(0.006)				(0.006)		
Max Rent price (log, lag)			0.787***				0.788***	
			(0.006)				(0.006)	
Min Rent price (log, lag)				0.781***				0.782***
				(0.010)				(0.010)
Nightlights index (lag)	0.002**	0.002***	0.003***	0.004***	0.002**	0.002**	0.003**	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
District-Estate Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Time dummies	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2257	2257	2257	2257	2257	2257	2257	2257
R-squared	0.84	0.83	0.88	0.88	0.84	0.83	0.88	0.88
Number of Groups (District x Estates)	103	103	103	103	103	103	103	103

Notes: the table reports estimates obtained from an OLS with District/Estate Fixed effects and Time period dummies on a panel composed by estate type, district, semester. 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 1-4). All the specifications control for the total number of mafia murders, nightlight index, district-estate fixed effects, and time dummies. Robust standard errors in parentheses. Level of significance are *p<10%; ** p<5%; *** p<1%.

The estimated coefficient decreases in absolute value when moving from 200 mt. to 700 mt. and 1000 mt., but remains negative and significant, suggesting that the captured effect is decaying with the distance from the homicides. All the specifications reports that the coefficient of the level of nightlight is still positive and significant.[24].

For the second issue we consider a new matrix where nearest neighbor is district with the closer price level. The ratio is that if I perceive a district as unsafe I could look for another

[24]The results, available upon request, remain consistent when focusing on a larger number of estate types.

district that is similar in terms of price I want to pay, following reasoning for instance in Bayer et al. (2016). We present the spatial estimation in table below and see how still results hold even in presence of a totally different weight matrix scheme.

We use a standardized inverse matrix based on minimum threshold, but here the distance is the absolute difference with respect to the -i district price and obtain similar results.

6 Concluding remarks

This paper analyzed the effect of “random” mafia homicides on housing prices in the city of Naples for the period 2003-2016. Naples represents an interesting case study for the pervasive presence of the Italian criminal organization called *Camorra*, characterized by an horizontal organization, that literature has identified as a crucial determinant for the high number of murders registered 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%.

These results are robust to the problem of taking into account all homicides, as a proxy for the organized crime violence inside district that may act as confounding factor, and to consider that people may choose a district to live with other criteria, than the geographical distance, as that with closest price.

While the fact that crime episodes as homicides reduce housing price is not new in the empirical we identify a more general effect on price inequality within the city.

In a spatial GMM estimation we find evidence of second order positive effects on the neighboring districts, so that the global effect consists in an increase in the spread in prices among districts more and less affected by mafia homicides. 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 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: "failure to think fully about space will tend to make within-country inequality estimates overstate the level of real income inequality".

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A Other Tables and Figures

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.

Table A3: Summary statistics for the dependent variables

Variables		Max Sale (euro/m2)		Min Sale (euro/m2)		Max Rent (euro/m2)		Min Rent (euro/m2)	
	N	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Civil Housings	780	3160.23	1388.77	2095.95	922.12	9.09	4.57	6.09	3.06
Cheap Housings	780	2239.29	961.32	1486.38	638.16	6.59	3.36	4.42	2.24
Luxury Housings	222	6129.57	1661.15	4065.14	1111.28	15.74	5.56	10.49	3.72
Garage	840	1744.71	897.79	1170.92	591.05	6.07	3.14	4.11	2.08
Sheds	705	852.44	232.02	477.54	127.97	3.43	1.02	2.01	0.76
Pre-Fabricated	60	1983.02	948.63	1342.67	630.33	8.56	4.49	5.83	2.99
Laboratories	831	2463.30	1225.83	1367.48	734.51	8.88	5.66	5.13	3.74
Warehouses	840	1553.97	942.31	879.76	603.67	5.82	4.73	3.44	3.13
Shops	840	4140.19	2001.23	2228.34	1090.07	16.28	9.80	8.97	5.85
Parking	765	1038.37	563.99	697.55	368.74	3.62	1.9	2.46	1.26
Offices	784	3378.87	1464.73	2246.18	970.52	11.43	5.87	7.66	3.92
Villas	586	3522.46	1979.79	2358.65	1310.02	11	6.84	7.42	4.56

Table A4: Effect of the number of killings on a panel of real estate prices and districts using an OLS with Fixed Effect (2002h2-2018h1)

Variables	Max Sale (log) (1)	Min Sale (log) (2)	Max Rent (log) (3)	Min Rent (log) (4)
# mafia murders within 200m (lag)	-0.022***	-0.021***	-0.025***	-0.024***
	(0.004)	(0.000)	(0.000)	(0.000)
Max sale price (log, lag)	0.903***			
	(0.010)			
Min sale price (log, lag)		0.911***		
		(0.010)		
Max rent price (log, lag)			0.905***	
			(0.010)	
Min rent price (log, lag)				0.914***
				(0.005)
Nightlights index (lag)	0.023*	0.028**	0.055***	0.061***
	(0.01)	(0.01)	(0.02)	(0.02)
District-Estate FE	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Districts	30	30	30	30
Observations	8673	8673	8673	8673
R-squared	0.887	0.899	0.896	0.923

Notes: t: the table reports estimates obtained from an OLS with District/Estate Fixed effects and Time period dummies on a panel composed by estate type, district, semester. The estates in the sample are civil housing, cheap civil housing, luxury civil housing, garage industrial building, shed, laboratories, warehouses, shops, parkings, offices, mansion and terraced house. 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). All the specifications control for the total number of mafia murders, nightlight index, district-estate fixed effects, and time dummies. Robust standard errors in parentheses. Level of significance are *p<10%; ** p<5%; *** p<1%.

Table A5: Effect of the number of killings on real estate prices' *growth rate* using an OLS with Fixed Effect (2002h2-2018h1)

Variables	Max Sale (growth rate)	Min Sale (growth rate)	Max Rent (growth rate)	Min Rent (growth rate)
	(1)	(2)	(3)	(4)
# mafia murders (lag)	-0.022***	-0.022***	-0.024***	-0.024***
	(0.000)	(0.000)	(0.000)	(0.000)
Max sale price (growth rate, lag)	-0.078***			
	(0.020)			
Min sale price (growth rate, lag)		-0.068***		
	(0.020)			
Max rent price (growth rate, lag)			-0.082***	
			(0.010)	
Min rent price (growth rate, lag)				-0.066***
				(0.010)
Min rent price (growth rate, lag)	0.041***	0.049***	0.075***	0.084***
	(0.020)	(0.020)	(0.020)	(0.020)
District-Estate Fixed Effects	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Observations	8319	8319	8319	8319
R-squared	0.138	0.079	0.307	0.249

Notes: the table reports estimates obtained from an OLS with District/Estate Fixed effects and Time period dummies on a panel composed by estate type, district, semester. The estates in the sample are civil housing, cheap civil housing, luxury civil housing, garage industrial building, shed, laboratories, warehouses, shops, parkings, offices, mansion and terraced house. The dependent variables are the growth rate of the maximum sale price (column 1), the growth rate of the minimum sale price (column 2); the growth rate of the maximum rent price (column 3); the growth rate of the minimum rent price (column 4). All the specifications control for the total number of mafia murders, nightlight index, district-estate fixed effects, and time dummies. Robust standard errors in parentheses. Level of significance are *p<10%; ** p<5%; *** p<1%.

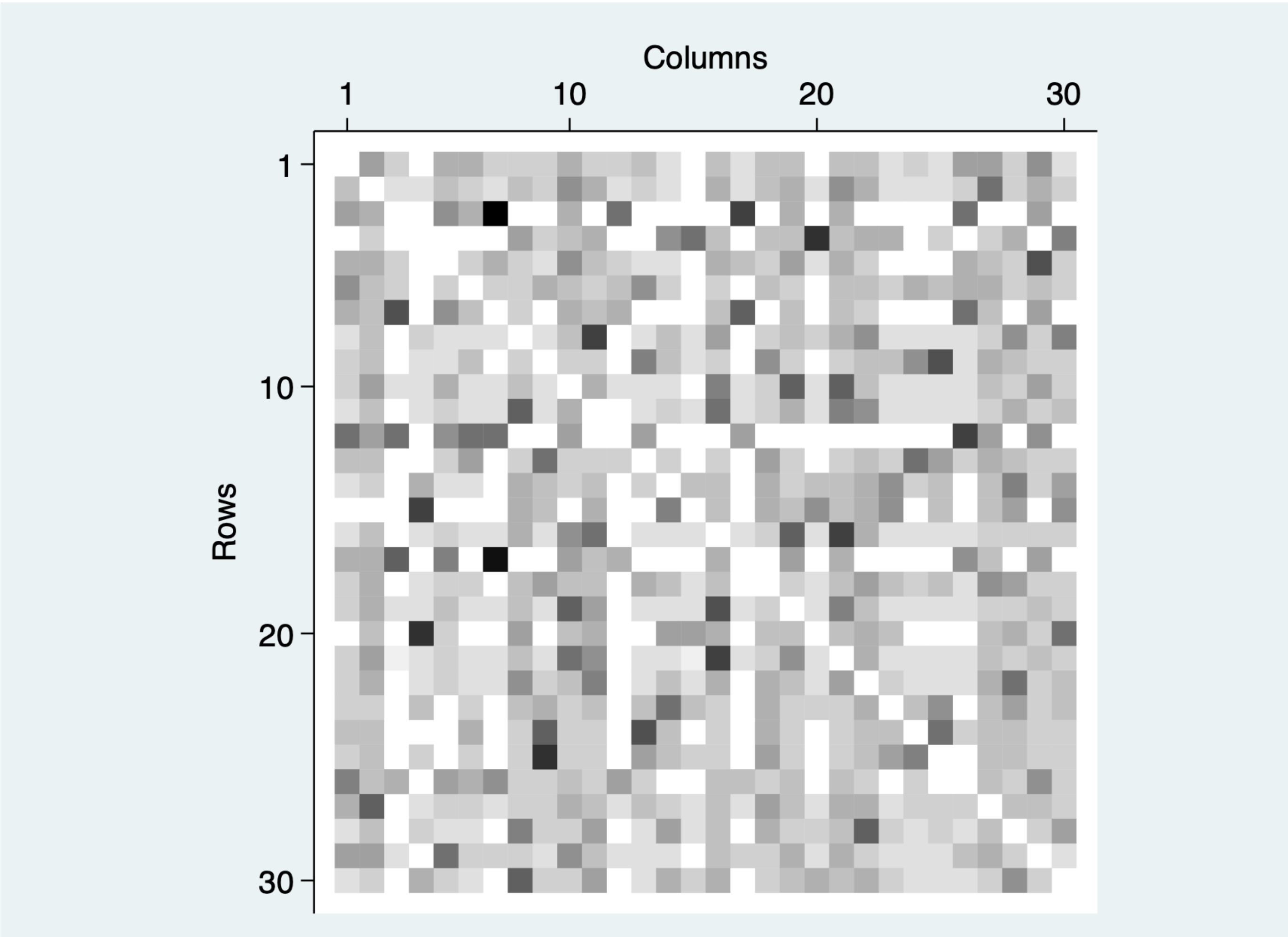

Figure AB1: Distance matrix weights

Figure AB2: Variance of houses prices Naples