Shooting Down the Price: Evidence from Mafia Homicides and Housing Prices

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Debates for a New Economy
Italy-Brazil Workshop

INTRODUCTION

- Organized crime has a significant impact on economic development and political institutions.
- Several dimensions of development already considered, such as GDP growth (Pinotti, 2015), foreign direct investment (Daniele and Marani, 2011), state capacity (Acemoglu et al, 2017) and allocation of public resources (Di Cataldo and Mastrorocco, 2020).
- This work estimates the effects of mafia violence on housing prices.

Related Literature

- The impact of mafia violence on public governance (mostly on electoral outcome) Dal Bo' et al. (2006); Acemoglu et al (2013); Alesina et al. (2019).
- Only few studies investigates the direct effect of organized crime activities on the real estate market Schheider (2004); Naheem (2017); Dugato et al. (2015).
- Impact of crime on property values Bowes and Ihlanfeldt (2001); Gibbons (2004); Linden et al. (2008); Ihlanfeldt and Mayock (2009); Pope and Pope (2012); Buonanno et al. (2013).
- Relatively small literature on the effect of violent attacks (homicides) on housing prices Tita et al. (2006); Pope (2008); Besley and Mueller (2012); Klimova and Lee (2014); Kim and Lee (2018).

THIS PAPER

- This work attempts to fill this gap studing how violence perpetrated by organized crime may impact on housing prices.
- Focus on Naples:
  - Newly collected data of mafia homicides that include latitude, longitude and exact date of the event;
  - Panel data analysis using Diff-in-Diff and GMM;
  - Spatial econometrics analysis.
- Results: We find that housing prices decrease in districts close to locations where an homicide has occurred and increase far from them, implying an increase in housing price dispersion.

Rate of intentional homicides per 100,000 inhabitants (2015)

Country	Ratio
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. Sources: UNODC (2018) and ISTAT (2018). Note that: MENA: Middle East and North Africa region; E_ASIA: East Asian Countries; EEC: East European Countries; SSA: Sub-Saharian Africa; LAC: Latin American countries; CAC: Central American countries.

TYPES OF ORGANIZED CRIME

- EUROPOL (2013) distinguish between hierarchical (e.g. Sicilian or Russian mafia) or horizontal (e.g. US or Brazilian gangs) organized crime, due to different coordination systems.

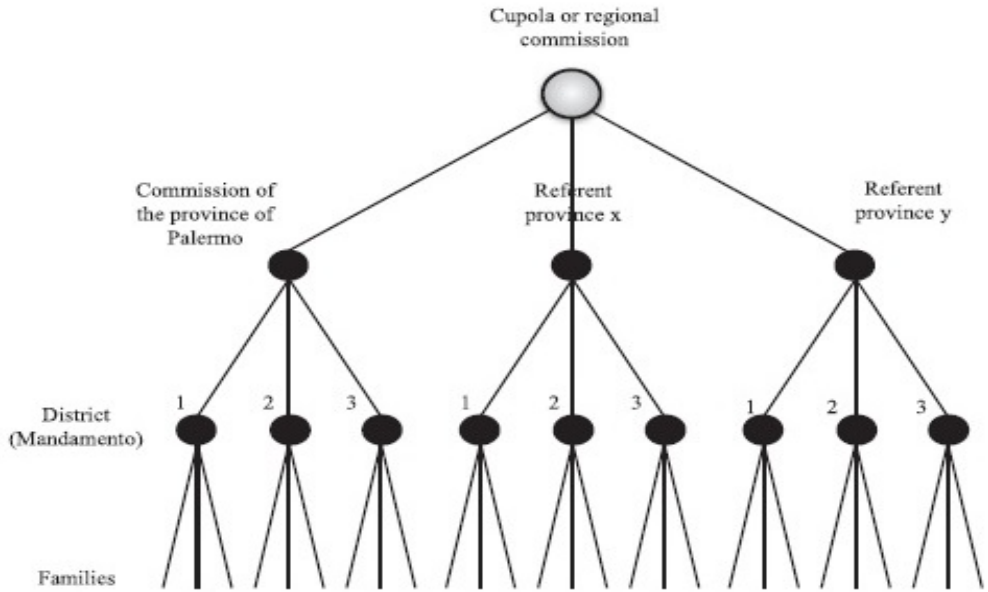
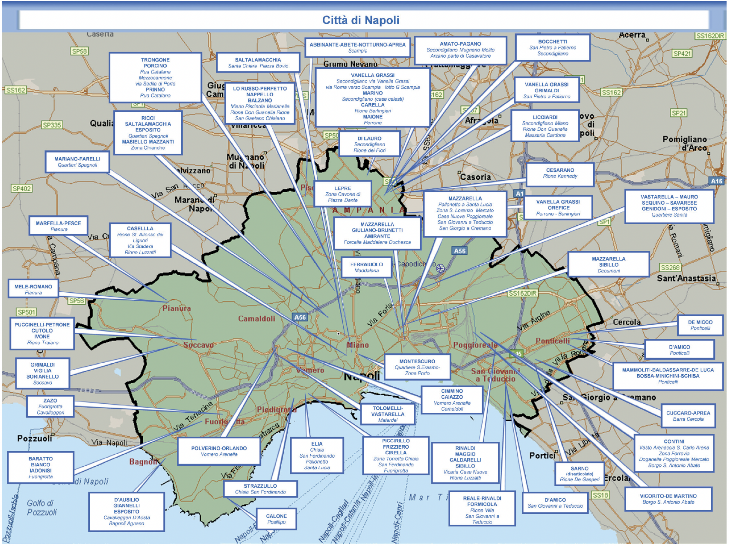


FIGURE: The organizational structure of the Cosa Nostra. (Catino, 2014)

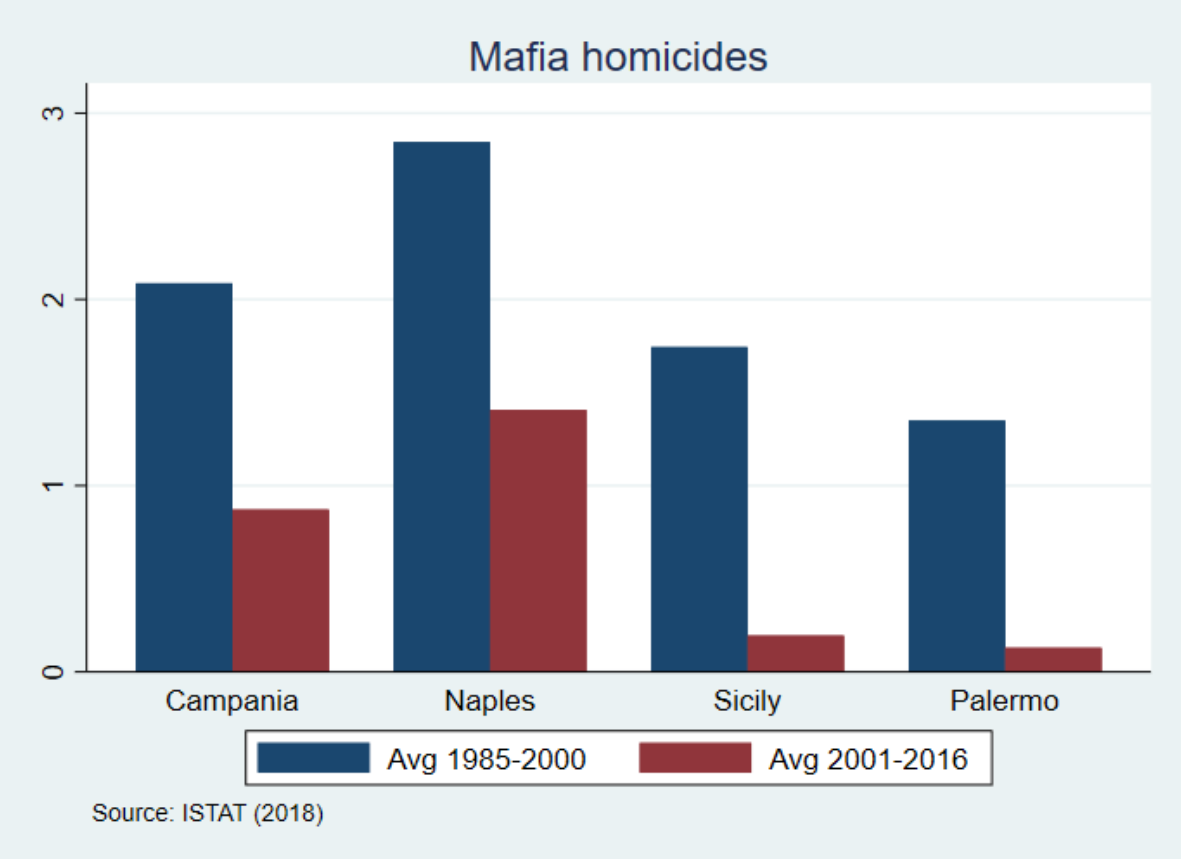
Types of organized crime

- The Neapolitan Mafia, named *Camorra* is not a unified organization and no single higher level of coordination exists able to coordinate the entire criminal system (Sciarrone and Storti, 2013).
- This horizontal organizational configuration is characterized by distributed power in which various clans are in competition and conflict with each other.


Città di Napoli
ABBINANTE-ABETE-NOTTURNO-APREA
Scampia
AMATO-PAGANO
Secondigliano Mugnano Melito
Arzano parte di Casavatore
BOCCHETTI
San Pietro a Patierno
Secondigliano
TRONGONE
PORCINO
Rua Catalana
Mezzocannone
via Sedile di Porto
PRINNO
Rua Catalana
SALTALAMACCHIA
Santa Chiara Piazza Bovio
LO RUSSO-PERFETTO
NAPPELLO
BALZANO
Miano Piscinola Marianella
Rione Don Guanella Rione
San Gaetano Chialano
VANELLA GRASSI
Secondigliano via Vanella Grassi
via Roma verso Scampia lotto G Scampia
MARINO
Secondigliano (case celesti)
CARELLA
Rione Berlingieri
MAIONE
Perrone
VANELLA GRASSI
GRIMALDI
San Pietro a Patierno
RICCI
SALTALAMACCHIA
ESPOSITO
Quartieri Spagnoli
MASIELLO MAZZANTI
Zona Chianche
LICCIARDI
Secondigliano Miano
Rione Don Guanella
Masseria Cardone
DI LAURO
Secondigliano
Rione dei Fiori
MARIANO-FARELLI
Quartieri Spagnoli
CESARANO
Rione Kennedy
LEPRE
Zona Cavone di
Piazza Dante
MAZZARELLA
Pallonetto a Santa Lucia
Zone S. Lorenzo Mercato
Case Nuove Poggioreale
San Giovanni a Teduccio
San Giorgio a Cremano
VANELLA GRASSI
OREFICE
Perrone - Berlingieri
VASTARELLA – MAURO
SEQUINO – SAVARESE
GENIDONI – ESPOSITO
Quartiere Sanità
MARFELLA-PESCE
Pianura
CASELLA
Rione St. Alfonso dei
Liguori
Via Stadera
Rione Luzzatti
MAZZARELLA
GIULIANO-BRUNETTI
AMIRANTE
Forcella Maddalena Duchesca
FERRAIUOLO
Maddalena
MAZZARELLA
SIBILLO
Decumani
MELE-ROMANO
Pianura
PUCCINELLI-PETRONE
CUTOLO
IVONE
Rione Traiano
DE MICCO
Ponticelli
D'AMICO
Ponticelli
MONTESCURO
Quartiere S.Erasmo-
Zona Porto
GRIMALDI
VIGILIA
SORIANELLO
Soccavo
MAMMOLITI-BALDASSARRE-DE LUCA
BOSSA-MINICHINI-SCHISA
Ponticelli
CIMMINO
CAIAZZO
Vomero Arenella
Camaldoli
ZAZO
Fuorigrotta
Cavalleggeri
TOLOMELLI-
VASTARELLA
Materdei
CUCCARO-APREA
Barra Cercola
POLVERINO-ORLANDO
Vomero Arenella
ELIA
Chiaia
San Ferdinando
Pallonetto
Santa Lucia
PICCIRILLO
FRIZZIERO
CIRELLA
Zona Torretta Chiaia
San Ferdinando
Fuorigrotta
RINALDI
MAGGIO
CALDARELLI
SIBILLO
Vicaria Case Nuove
Rione Luzzatti
CONTINI
Vasto Arenaccia S. Carlo Arena
Zona Ferrovia
Doganella Poggioreale Mercato
Borgo S. Antonio Abate
BARATTO
BIANCO
IADONISI
Fuorigrotta
SARNO
(disarticolato)
Rione De Gasperi
STRAZZULLO
Chiaia San Ferdinando
D'AUSILIO
GIANNELLI
ESPOSITO
Cavalleggeri D'Aosta
Bagnoli Agnano
CALONE
Posillipo
REALE-RINALDI
FORMICOLA
Rione Villa
San Giovanni a
Teduccio
D'AMICO
San Giovanni a Teduccio
VICORITO-DE MARTINO
Borgo S. Antonio Abate
Caserta
Acerra
Grumo Nevano
Casoria
Pomigliano d'Arco
Sant'Anastasia
Cercola
Pianura
Camaldoli
Soccavo
Miano
Poggioreale
Ponticelli
Vomero
Napoli
San Giovanni a Teduccio
San Giorgio a Cremano
Piedigrotta
Fuorigrotta
Bagnoli
Pozzuoli
Portici
Ercolano
Golfo di Pozzuoli
Marano di Napoli
Mugnano di Napoli
Qualiano
Afragola
Capodichino
Mar Tirreno

- The Neapolitan Mafia, named *Camorra* is not a unified organization and no single higher level of coordination exists able to coordinate the entire criminal system (Sciarrone and Storti, 2013).
- This horizontal organizational configuration is characterized by distributed power in which various clans are in competition and conflict with each other.
- Catino (2014) shows that Camorra has lower coordination implying a higher number of homicides and violent crimes much lower number of “excellent homicides" (e.g. journalists, judges, policemen, etc.).

OC and homicides per 100k inhabitants



Hypothesis

To sum up our hypotheses:

1. Horizontal organized crime $\rightarrow$ more homicides, and more innocent victims.
2. Innocent victims $\rightarrow$ negative effect on housing prices across districts.

Geo-localizing the Camorra Homicides and imputing their effects

- We make an explicit distinction between Camorra Homicides (CH) and Innocent Victims (IVH).
  - the latters affect individuals not affiliated to a Camorra clan who are killed accidentally (wrong person, stray bullet, etc);
- Data on IVH are from http://www.vittimemafia.it/, a portal collecting data on mafia homicides from 1861;
- Data on CH are from Naples' Prosecutor Office for the period 2009-2018 and secondary sources for the period 2007-2008[1];
- We geo-localized each homicide in Naples in the period 2002h2-2018h1.

Evidence for Naples: Average maximum price for sq mt 2002-2018 and Camorra Homicides

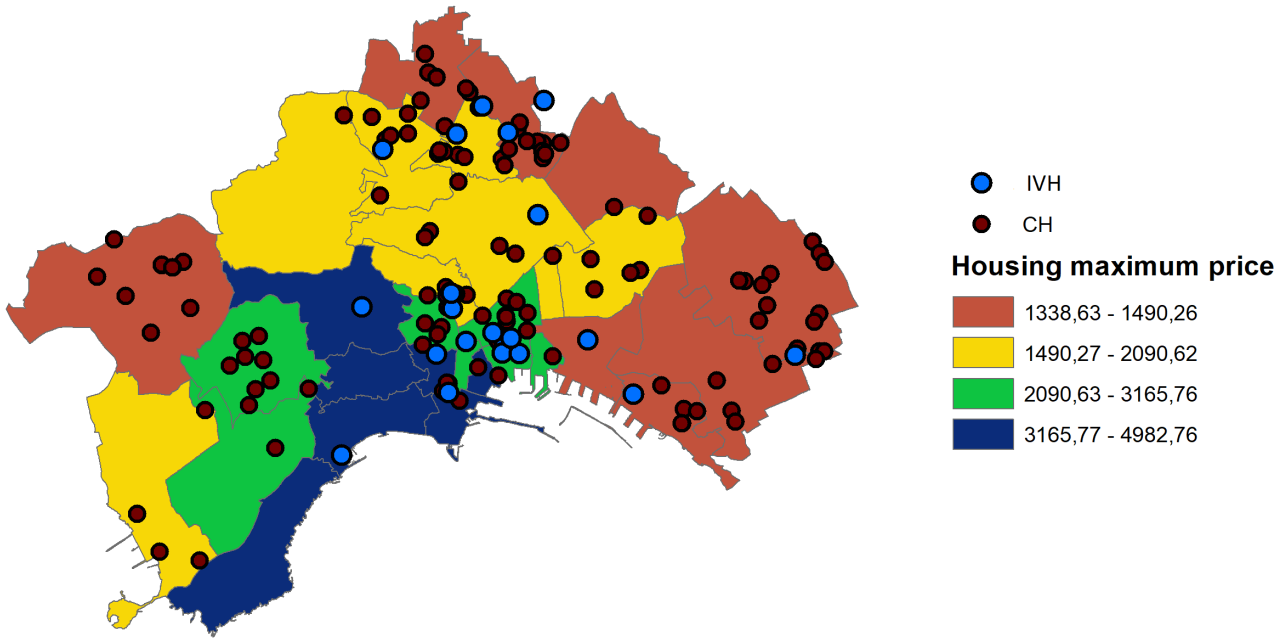


Figure: Average maximum price (in Euros) for sq. mt. (2002-2018) of residential houses, CH (2009-2018) and IVH (2002-2018). Social distress

Geo-localizing the Camorra Homicides and imputing their effects

- This framework considers IVH 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.
- IVH should matter more than other CH because they can affect population at large: i) anyone can be affected, ii) news about IVH are widely disseminated through traditional media (Dugato et al. 2017).

Geo-localizing the Camorra Homicides and imputing their effects

Table: News dissemination in the media: Innocent victims vs Camorra homicides

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

GEO-LOCALIZING THE IVH AND IMPUTING THEIR EFFECTS

For each IVH, we consider rays of different length (e.g. 200, 500, 700, 1000 mt) to “impute" its effect to the district

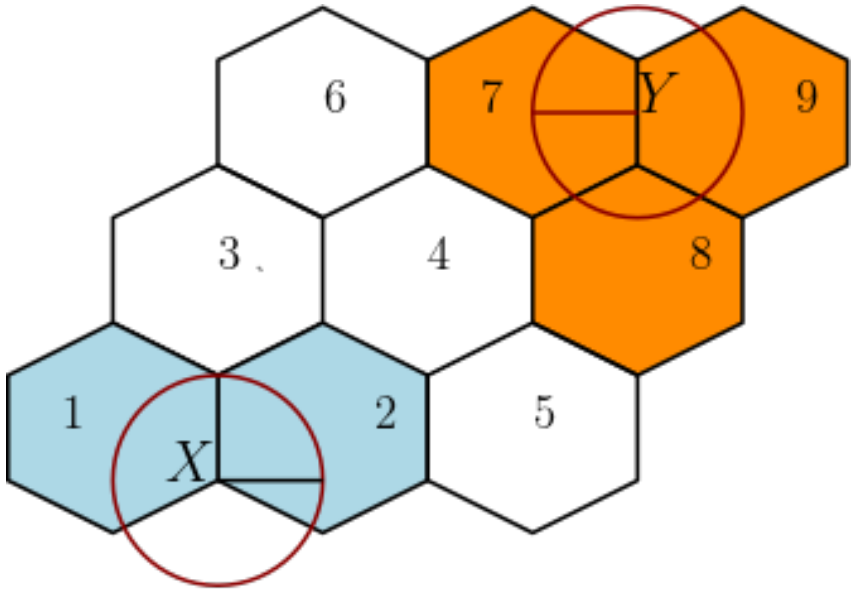


FIGURE: Geo-localization of homicides and their effects on housing prices

Geo-localizing the RH and imputing their effects

Table: Summary statistics on IVH in the district/semester panel (30x32) (2002h1-2018h2)

Innocent victims, (2002h2-2018h1)					
Variables	Observations	Mean	Std. Dev.	Min	Max
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

Geo-localizing the RH and imputing their effects

Table: Summary statistics on Camorra homicides in the district/semester panel (30x32) (2009h1-2018h1)

Camorra Homicides, CH (2009h1-2018h1)					
Variables	Observations	Mean	Std. Dev.	Min	Max
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

Data

- Data on real estate prices at micro-area level extracted from the *Osservatorio del Mercato Immobiliare* (OMI, 2019): half-yearly records on average sale and rent price for micro-areas of Italian cities. We aggregate data from micro-areas at district level (30 districts) ⏩ OMI. Period 2002h2-2018h1, four types of estates: civil housing, cheap civil housing, luxury civil housing, and villas
- Data on nightlight from NOAA (National Oceanic and Atmospheric Administration) as proxy of local amenities (Cecil et al. 2014; Xie and Liu 2018).

Panel Data Analysis - Diff-in-Diff

- To investigate whether the occurrence of *IVH* may affect housing prices we first implement a staggered diff-in-diff identification strategy.

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

- $lnPrice_{ijt-1}$ is the lagged of the average price of the estate *j* in district *i* which include the latent time-varyng information up to t-1;
- $IVH_{i,t}$ is a dummy variable denoting the occurrence of an *IVH* within a given distance from district *i* at time *t*. The indices *q* and *p* represent, respectively, the post-homicide and the anticipatory effect of an *IVH*.
- the matrix *X* contains the lag of the districts' nightlight.
- *DE* (District X Estate) are a fixed effects specific for the panel observation and T_t is a set of time dummies;
- $\mu_{i,t}$ is the error term clustered at district-estate level

PANEL DATA ANALYSIS - DIFF-IN-DIFF

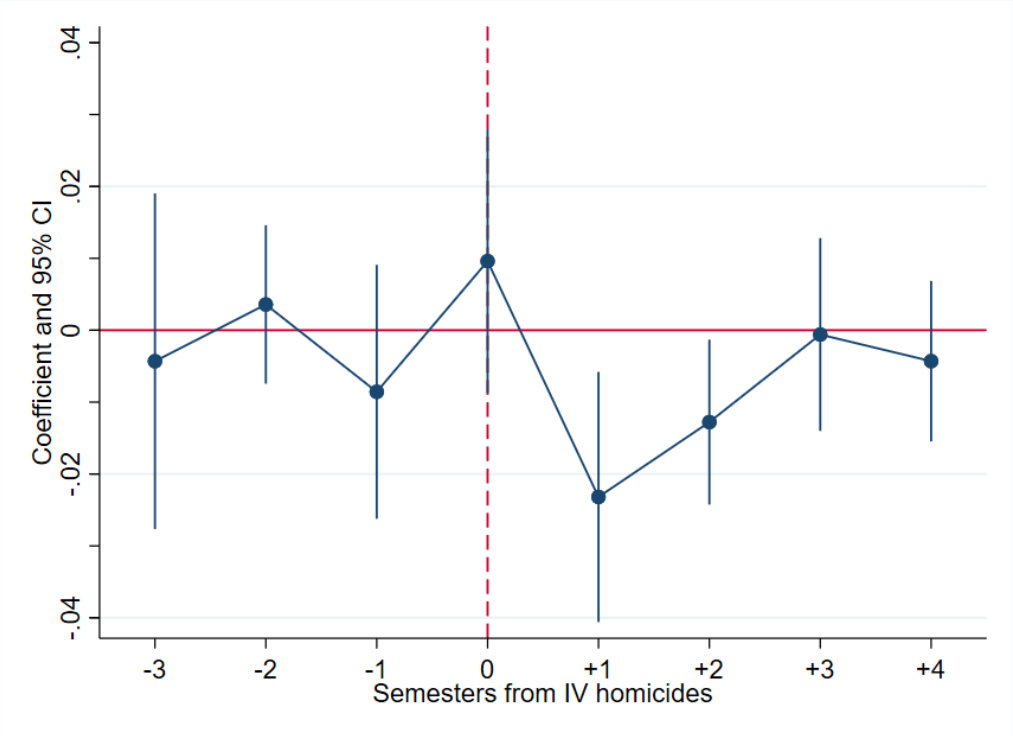


FIGURE: Maximun sale price before and after an *IVH*

Panel Data Analysis - Diff-in-Diff

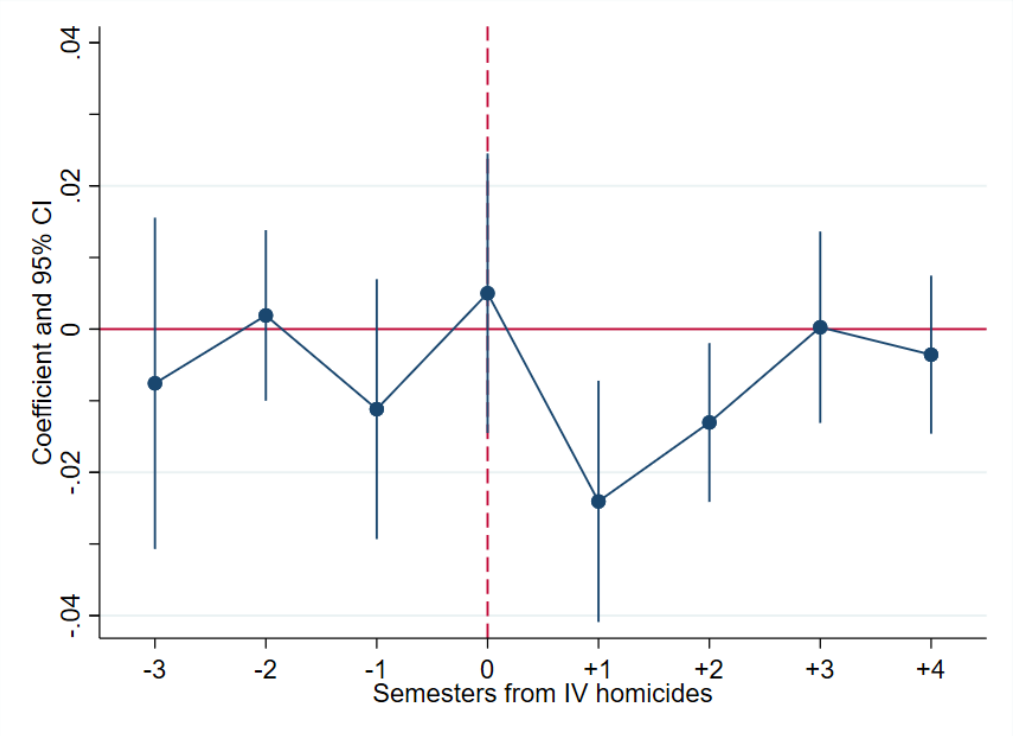


Figure: Minimum sale price before and after an *IVH* DID

Panel Data Analysis - GMM

- Estimation of a model with fixed effects and a lagged dependent variable $\rightarrow$ inconsistent estimates (Nickell,1981);
- Concerns in term of reliability of estimates and mis-specification issues when the time series is short $\rightarrow$ bias and inconsistent standard errors (Bertrand et al. 2004).

Panel Data Analysis - GMM

$$lnPrice_{ijt} = \beta_0 + \delta lnPrice_{ijt-1} + \lambda D_l VHi + \alpha X_{it-1} + \phi DE + \psi T_t + \mu_{it} \quad (2)$$

- $lnPrice_{ijt-1}$ is the lagged of the average price of the estate j in district i which include the latent time-varyng information up to t-1;
- $D_l VH$ is a variable capturing the number of murders to the first post-treatment period within a given distance from the district;
- the matrix X contains the lag of the districts' nightlight.
- DE (District X Estate) are a fixed effects specific for the panel observation and T_t is a set of time dummies which account for unobserved/persistant characteristics;
- $\mu_{i,t}$ is the error term clustered at district-estate level
- We estimate Eq. (2) by Arellano-Bond system-GMM estimation, Blundell-Bond level-GMM estimation (due to high persistence in price data), and the bias-corrected estimators suggested by Kiviet (1995)

PANEL DATA ANALYSIS - GMM

- We estimate Eq. 1 using Arellano-Bond GMM estimation that takes first difference of the tyme-varying variables;
- Eq. 1 has been also estimated using Blundell-Bond level specification and the bias-corrected LSVD dynamic model (Bruno, 2005).

GMM estimation

Table: Random homicide and housing prices in a dynamic panel framework (2002h1-2018h1) ⏩ panel

Variables	Max Sale (log) (1)	Min Sale (log) (2)	Max Sale (log) (3)	Min Sale (log) (4)	Max Sale (log) (5)	Min Sale (log) (6)
# IVH within 200m (lag)	-0.033***	-0.030***	-0.037***	-0.038***	-0.025***	-0.025***
	(0.011)	(0.011)	(0.008)	(0.008)	(0.006)	(0.006)
Max sale price (log, lag)	0.895***		0.979***		0.906***	
	(0.035)		(0.006)		(0.011)	
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
	(0.052)	(0.046)	(0.058)	(0.027)	(0.027)	(0.029)
Time Trend	-0.002***	-0.002***	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR(1) $Pr > z$	0.000	0.000	0.000	0.000	-	-
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	-	
Dynamic Model	Arellano-Bond	Arellano-Bond	Blundell-Bond	Blundell-Bond	Kiviet	Kiviet
Observations	2557	2557	2557	2557	2557	2557
Number of groups	103	103	103	103	103	103

GMM ESTIMATION (ROBUSTNESS)

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

Variables	Max Sale (log) 2009-2018 (1)	Min Sale (log) 2009-2018 (2)	Max Sale (log) 2007-2018 (3)	Min Sale (log) 2007-2018 (4)	Max Sale (log) 2009-2018 (5)
# IVH within 200m (lag)	-0.037**	-0.027*	-0.016**	-0.016**	-0.036**
	(0.018)	(0.016)	(0.007)	(0.008)	(0.017)
# CH within 200m (lag)	0.001	0.002	0.001	0.002	.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
# OH within 200m (lag)					-.002
					(0.001)
Max sale price (log, lag)	0.987***		0.983***		0.987***
	(0.004)		(0.003)		(0.003)
Min sale price (log, lag)		0.989***		0.984***	
		(0.004)		(0.003)	
Nightlights index (lag)	-0.027	-0.028	-0.007	-0.009	-.027
	(0.029)	(0.029)	(0.016)	(0.012)	(0.030)
Time Trend	Yes	Yes	Yes	Yes	Yes
AR(1) $Pr > z$	0.009	0.009	0.004	0.003	0.009
AR(2) $Pr > z$	0.019	0.025	0.013	0.016	0.018
AR(3) $Pr > z$	0.063	0.073	0.042	0.052	0.059
AR(4) $Pr > z$	0.114	0.129	0.079	0.094	0.112
Sargan Over-Id test $Pr > z$	0.509	0.205	0.524	0.157	0.722
Observations	1136	1136	1963	1963	1136
Number of groups	93	93	93	93	93

GMM estimation

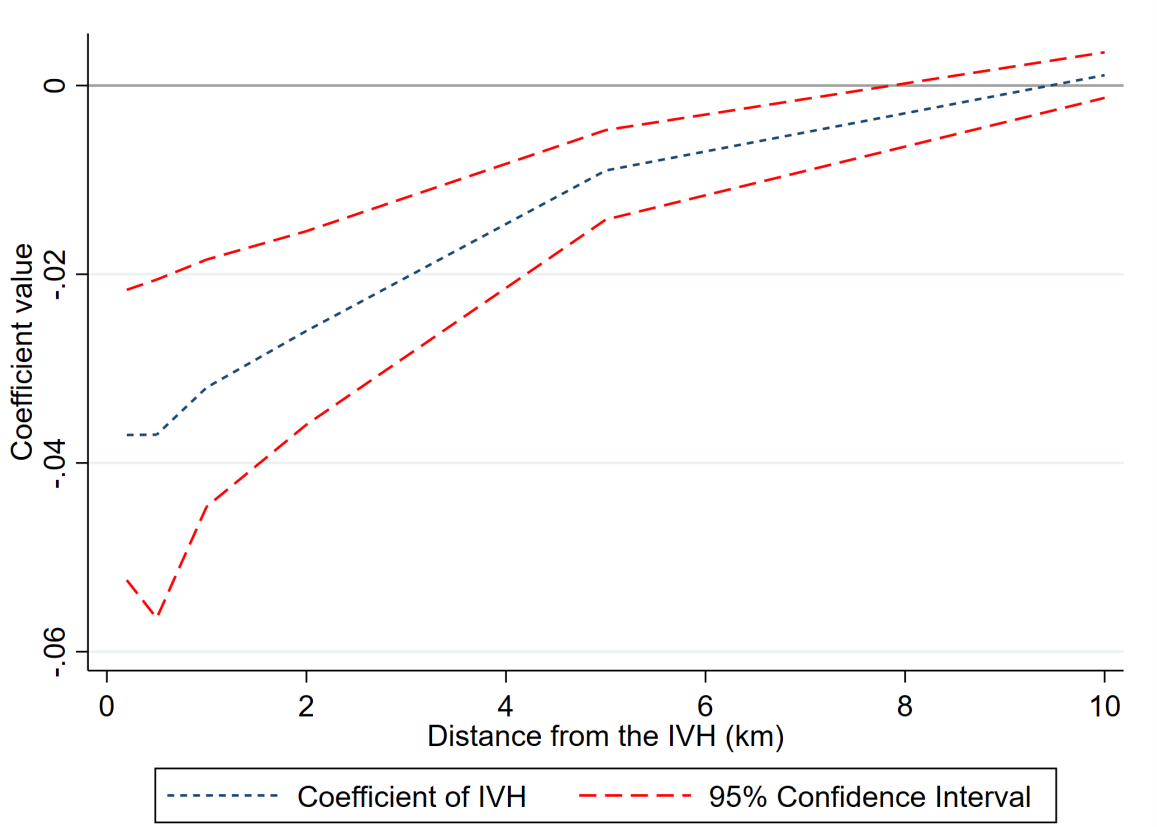


Figure: Effect of IVH at different distances from the district using Blundell-Bond and a panel of real estates (2002-2018)

Spatial Econometric Analysis

- Despite previous strategy reduce the bias caused by multiple unobserved time-invariant confounders, there can be still concerns about biases in the coefficients;
- In case of spatial correlation in the explanatory variables, the estimation will yield biased coefficients;
- Moreover, the panel approach cannot reveal spillover effects, that we expect to be important
- Given the limitation of the available data, we collapse the estates prices at district level and extend the approach to an Arellano-Bond Spatial Dynamic Linear Regression (Baltagi and Bresson, 2011).

Spatial Econometric Analysis

Starting from the general Cliff-Ord model:

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

where:

$$\upsilon_{it} = \lambda \mathbf{W} + \varepsilon \quad (4)$$

we test different hypothesis on the spatial dependence on a reduced form of Equation (3), i.e. without dynamic effects:

- $\rho \neq 0\ \gamma = 0\ \lambda = 0$ (SAR)
- $\rho = 0\ \gamma = 0\ \lambda \neq 0$ (SEM)
- $\rho \neq 0\ \gamma \neq 0\ \lambda = 0$ (SDM)

Spatial Econometric Analysis (reduced form, static model)

Variables	Max Sale (FD) (SEM) (1)	Max Sale (FD) (SAR) (2)	Max Sale (FD) (SDM) (3)
# IVH within 200m (lag)	-0.026***	-0.025**	-0.025**
	(.010)	(.010)	(.010)
Nightlights index (lag)	0.076	0.075	0.074
	(.056)	(.056)	(.056)
γX			
# IVH within 200m (lag)			-0.116*
			(.064)
Spatial			
$\hat{\rho}$		-0.624***	-0.657***
		(.142)	(.144)
$\hat{\lambda}$	-0.626***		
Spatial effects (short run)			
Direct			
# IVH within 200m (lag)		-0.025**	-0.022**
Indirect			
# IVH within 200m (lag)		0.010**	-0.059
Total			
# IVH within 200m (lag)		-0.015**	-0.081**
Observations	930	930	930
Number of groups	30	30	30

Spatial Econometric Analysis (reduced form, static model)

Variables	Min Sale (FD) (SEM) (4)	Min Sale (FD) (SAR) (5)	Min Sale (FD) (SDM) (6)
# IVH within 1000m (lag)	-.017***	-0.017***	-0.017***
	(.000)	(.006)	(.006)
Nightlights index (lag)	0.074	0.074	0.074
	(.056)	(.056)	(.056)
γX			
# IVH within 1000m (lag)			-.026
			(.044)
Spatial			
$\hat{\rho}$		-0.612***	-0.619***
		(.141)	(.142)
$\hat{\lambda}$	-0.602***		
Spatial effects (short run)			
Direct			
# IVH within 1000m (lag)		-0.017***	-0.017***
Indirect			
# IVH within 1000m (lag)		0.006**	-0.007
Total			
# IVH within 1000m (lag)		-0.010***	-0.024
Observations	930	930	930
Number of groups	30	30	30

Spatial Econometric Analysis

SAR: Short-run and Long-Run Effects (full dynamic model)

	Variables	Max Sale (log) (1)	Min Sale (log) (2)	Max Sale (log) (3)	Min Sale (log) (4)
	# IVH within 200m (lag)	-0.023**	-0.023**		
		(.010)	(.010)		
	# IVH within 1000m (lag)			-0.014**	-0.014**
				(.006)	(.006)
	$\hat{\rho}$	-0.563***	-0.557***	-0.573***	-0.566***
		(0.106)	(.109)	(.107)	(.000)
	Direct - # IVH 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
Spatial effect	**Indirect** - # IVH within 200m and 1000m (lag)	0.009**	0.009**	0.005**	0.005**
(Short run)	**Indirect** - Nightlights index (lag)	-0.016	-0.015	-0.016	-0.015
	Total - # IVH 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
	Direct - # IVH within 200m (lag)	-0.214**	-0.200**	-0.137**	-0.127**
	Direct - Nightlights index (lag)	0.399	0.335	0.415	0.367
Spatial effect	**Indirect** - # IVH within 200m (lag)	0.181**	0.167**	0.118**	0.107**
(Long run)	**Indirect** - Nightlights index (lag)	-0.335	-0.294	-0.353	-0.307
	Total - # IVH within 200m (lag)	-0.033**	-0.033**	-0.020**	-0.020**
	Total - Nightlightfkis index (lag)	0.064	0.061	0.062	0.059
	Observations	930	930	930	930
	Number of groups	30	30	30	30

Spatial Econometric Analysis

Robustness - Other Distance Matrices W

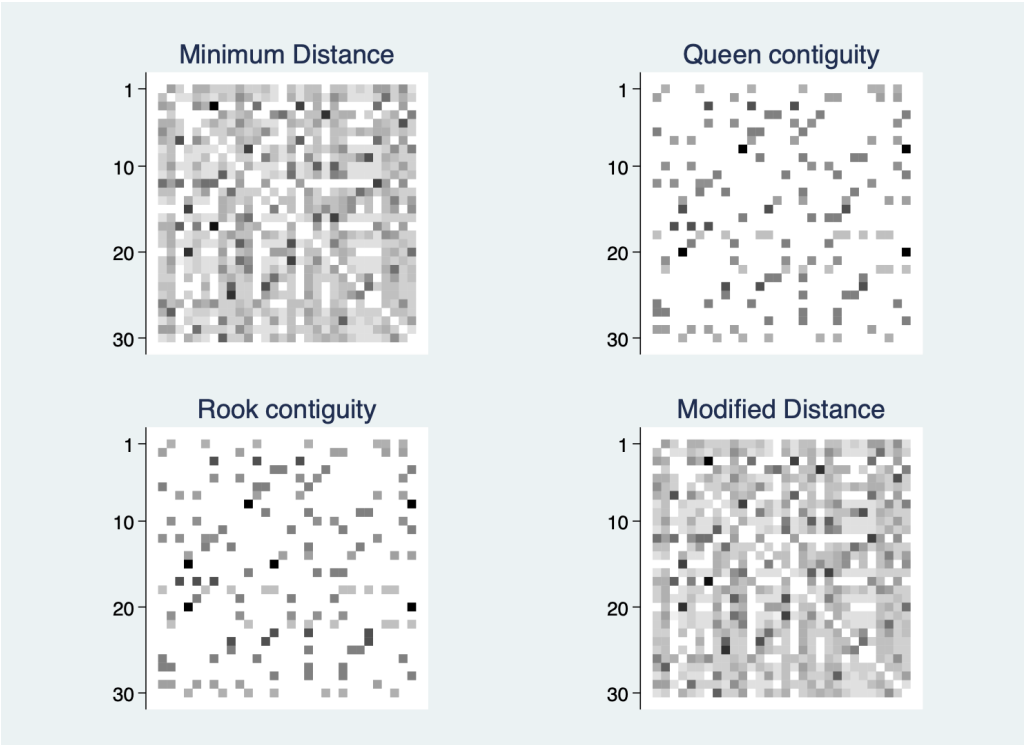


Figure: Distance matrix weights

Spatial Econometric Analysis

Robustness - Other Distance Matrices W

Table: Innocent victims and Real Estate Prices: SAR with Alternative Distance Matrices

Matrices	Minimum Distance Threshold	Queen Contiguity	Rook Contiguity	Minimum augmented Distance
Max Sale (log, lag)	0.844***	0.858***	0.858***	0.849***
	(0.017)	(0.030)	(0.024)	(0.025)
# IVH within 200m (lag)	-0.023**	-0.025**	-0.025**	-0.023*
	(0.010)	(0.012)	(0.012)	(0.012)
Nightlights index (lag)	0.038	0.050**	0.050**	0.037*
	(0.053)	(0.025)	(0.025)	(0.022)
$\hat{\rho}$	-0.563***	-0.118***	-0.116***	-0.362***
	(0.106)	(0.045)	(0.044)	(0.116)
Spatial effect (short run)				
Total - # IVH within 200m (lag)	-0.015**	-0.023**	-0.023**	-0.018**
Total - Nightlights index (lag)	0.028	0.046**	0.047***	0.028*
Spatial effect (long run)				
Total - # IVH within 200m (lag)	-0.033**	-0.101**	-0.102**	-0.048*
Total - Nightlights index (lag)	0.064	0.201**	0.205**	0.080
Observations	930	930	930	930
Number of groups	30	30	30	30
% of average links	23	4.7	4.6	19

CONCLUDING REMARKS

- Using geo-localized data for Naples we show evidence of impact of IVH by the Camorra on housing prices;
- More specifically, we show a negative direct effect on the place where murder occurs that reduces housing price in the district in a range of 2.5% and 3.8%;
- We identify spillover effects on other neighbors implying an increase of the housing prices far away from the location on their occurrence approximately of 1%;
- Long-run effects are higher in magnitude, pointing out some persistence in the dynamics identified by the short-run analysis.

Our conjecture

- Mafia violence in an urban context can increase the dispersion of housing prices within a city. As long as this is an important component of inequality (Glaeser and Gottlieb, 2009), organized crime activities can have have relevant negative effect also in this respect;
- In the long term and through segregation, this mechanism can influence long-run income inequality (Durlauf, 1996);
- So the long run policy implication is that cities in which organized crime are prevalent, unstable and violent are more reliable to lead higher across district inequality.

Maps Naples

Thanks

Giovanni Bernardo

Social Distress Index - Naples

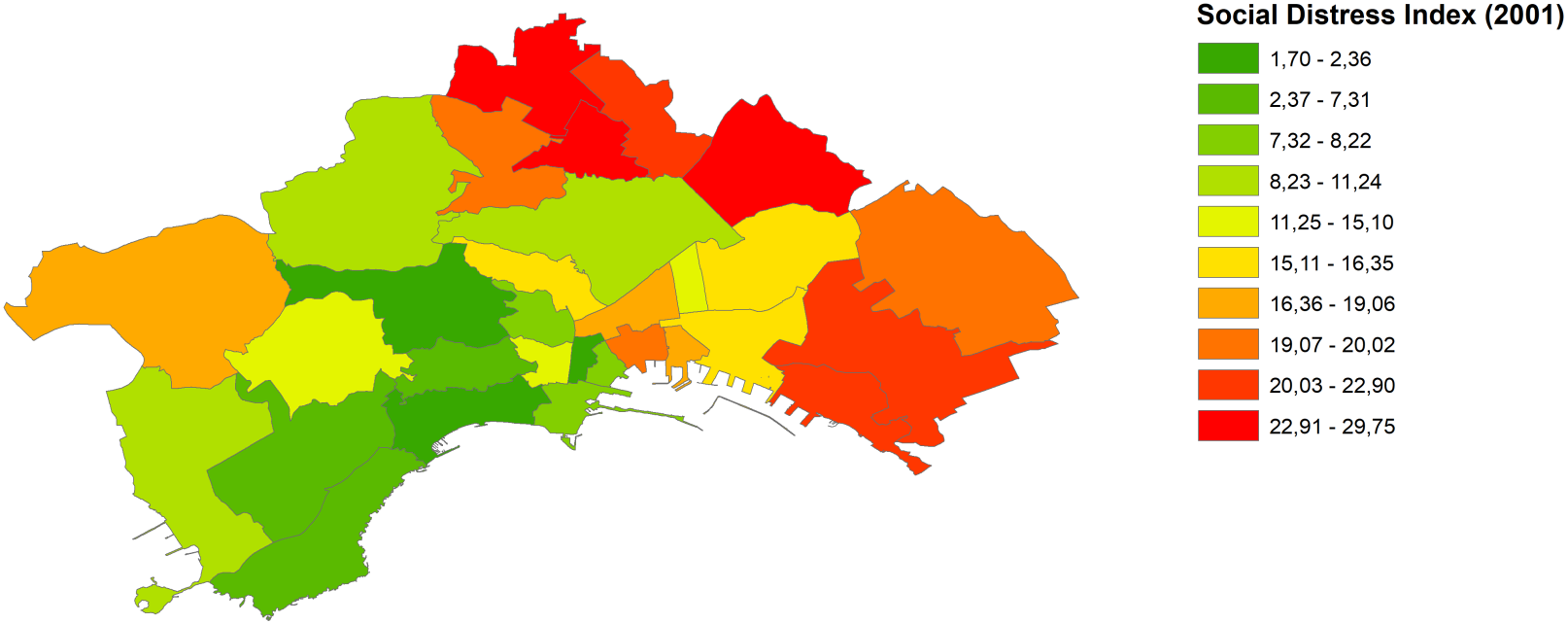


Figure: Social Distress Index in 2011 in the 30 administrative districts of Naples. Source: ISTAT 2017. back

DIFFERENCE-IN-DIFFERENCE FRAMEWORK

TABLE: *IVH* and housing prices (2003h1-2018h1) back

VARIABLES	Max Sale (log)	Max Sale (log)	Min Sale (log)	Min Sale (log)
# D_IVH within 200m (lag 3)	-0.004	-0.017	-0.008	-0.020*
	(0.012)	(0.012)	(0.012)	(0.012)
# D_IVH within 200m (lag 2)	0.004	-0.005	0.002	-0.007
	(0.006)	(0.007)	(0.006)	(0.008)
# D_IVH within 200m (lag 1)	-0.009	-0.020*	-0.011	-0.023*
	(0.009)	(0.011)	(0.009)	(0.012)
# D_IVH within 200m	0.010	0.002	0.005	-0.002
	(0.009)	(0.009)	(0.010)	(0.009)
# D_IVH within 200m (lead 1)	-0.023***	-0.034***	-0.024***	-0.035***
	(0.009)	(0.011)	(0.008)	(0.010)
# D_IVH within 200m (lead 2)	-0.013**	-0.019***	-0.013**	-0.019***
	(0.006)	(0.006)	(0.006)	(0.006)
# D_IVH within 200m (lead 3)	-0.001	-0.008	0.000	-0.007
	(0.007)	(0.006)	(0.007)	(0.006)
# D_IVH within 200m (lead 4)	-0.004	-0.012*	-0.004	-0.011*
	(0.006)	(0.007)	(0.006)	(0.006)
Time Trend	YES		YES	
Interaction FE*Time		YES		YES
Observations	1,934	1,934	1,934	1,934
R-squared	0.822	0.844	0.823	0.844
Number of id	102	102	102	102

Robustness - Panel estimation

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

VARIABLES	Max Sale Price (log)	Min Sale Price (log)	Max Sale Price (log)	Min Sale Price (log)
	(1)	(2)	(3)	(4)
Max sale price (log, lag)	0.817***		0.815***	
	(0.011)		(0.012)	
Min sale price (log, lag)		0.814*** *		0.816***
		(0.011)		(0.013)
#IVH within 200m	-0.028***	-0.030***	-0.030***	-0.032***
	(0.009)	(0.009)	(0.008)	(0.008)
Nightlights index (lag)	0.006	0.006	0.014	0.016
	(0.012)	(0.013)	(0.020)	(0.020)
Constant	1.532***	1.437***	1.738***	1.656***
	(0.086)	(0.083)	(0.097)	(0.100)
District-Estate FE	YES	YES		
District-Estate*time FE			YES	YES
Observations	2,557	2,557	2,557	2,557
R-squared	0.864	0.860	0.854	0.852
Number of id	103	103	103	103

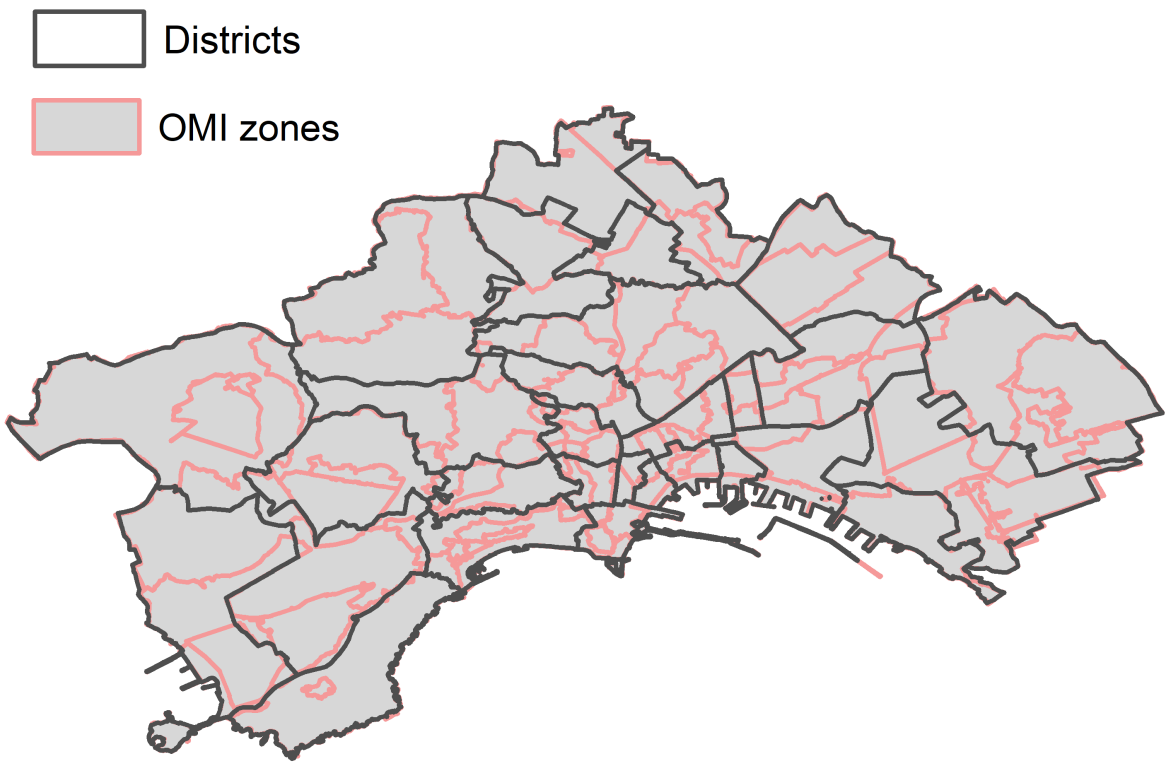
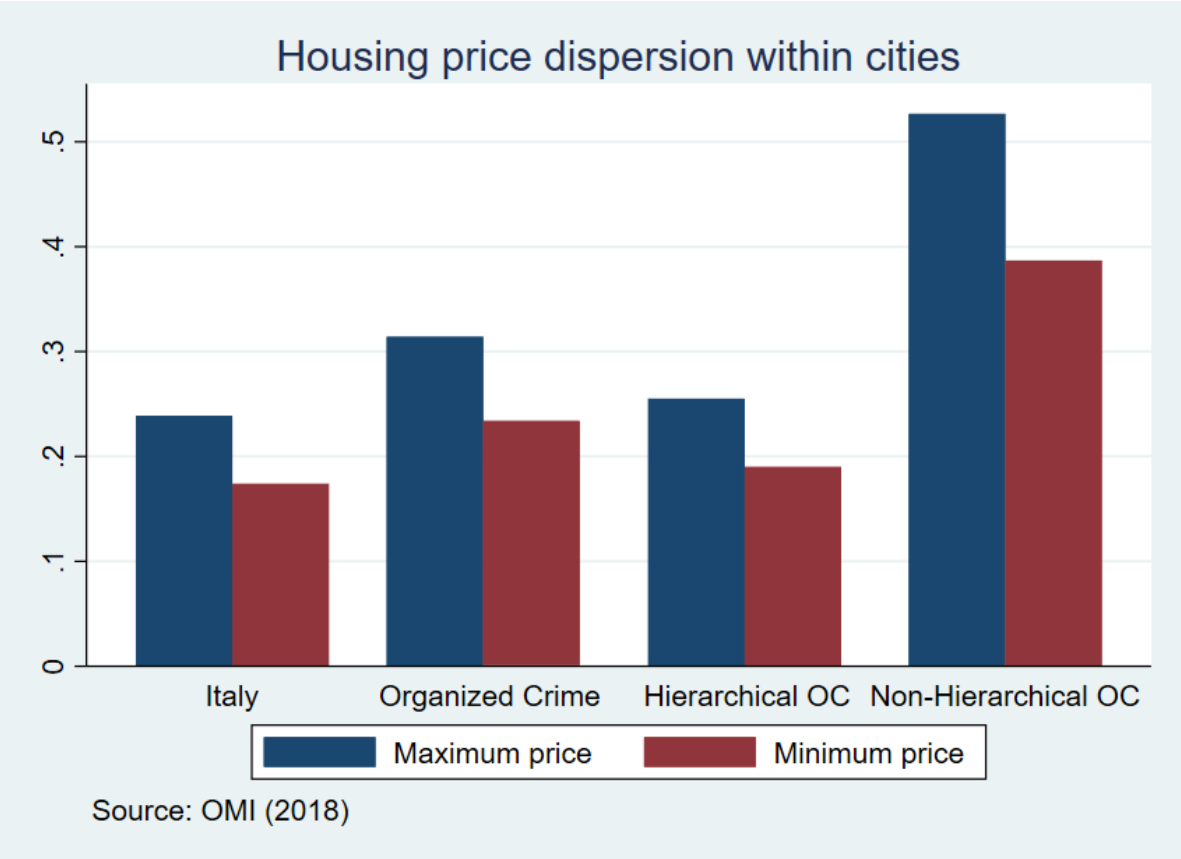


FIGURE: Districts' boundaries and OMI micro-zones back

Housing price dispersion and Mafia types

Housing price variance within-city and Mafia types



Cross-sectional investigation

Italy (provincial capitals)

- Results of cross-sectional investigation showing that alternative indicators of Mafia pervasiveness, given by the mafia index at provincial level provided by Calderoni (2011) and the number of mafia homicides, are positively and significantly correlated to the within-city variance of housing prices. cross-section 1
- The correlation between the dummy which account for the presence of non-hierarchical clustering and within-city variance of housing prices is very strong and shows positive sign. cross-section 2
- The positive correlation remains significant when control variables on district characteristics are considered.

cross-section 3

Cross-sectional investigation

Italy (provincial capitals)

$$VarPrice_c = \beta_0 + \lambda MI_c + \alpha X_c + u_c \quad \text{back} \tag{5}$$

- Data on real estate max and minimum prices at micro-area level extracted from the *Osservatorio del Mercato Immobiliare*[3] (OMI, 2017);
- Mafia index (Calderoni, 2013); Mafia Homicides (ISTAT, 2018); Organized crime structure (Europool 2013);
- Socio-demographic controls are extracted from the Italian 2011 Census;
- A variable counting the census areas (ACE) It takes into account the dimension of the city as a the potential determinants of housing prices

Cross-sectional investigation

Italy (provincial capitals - 2011)

Table: Housing price variances and OC variables back

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

CROSS-SECTIONAL INVESTIGATION

ITALY (PROVINCIAL CAPITALS - 2011)

TABLE: Housing price variances, OC and control variablesvariables back

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