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The Impact of Crimes on House Prices in LA County

Abstract
This paper focuses on analysing the impact of crime on the housing market in Los Angeles County. By looking at different types of crime instead of general crime measures and controlling by spatial dimension of prices and crime as well as endogeneity, a model is developed that allows for the understanding of how a specific crime impacts the housing market transaction price. To perform the analysis, the paper merges different datasets (crime, housing transaction and census data) and then computes the distances to crucial transports modes to control the accessibility features affecting housing prices. The latter allows to estimate the association of housing prices and crime in the distance and estimate the impact on housing depending on it.
This paper focuses on the following crimes: aggravated assault, burglary (property crime), narcotics, non-aggravated assault and vandalism. The paper shows firstly how incidents of reported crime are distributed across space and how they are related to each other - thus highlighting crime models with spatial influences. Secondly, the research utilises instrumental variables within the methodology to estimate house prices using spatial analysis techniques and while controlling for endogeneity. Thirdly, it estimates the direct impact of crime on house prices and explores the impact of housing and neighbourhood features. Results suggest that house transaction prices and crime are closely correlated in two senses. Housing prices are endogenously negatively associated with the levels of narcotics and aggravated assaults. For narcotics, the impact of distance is shorter (1000 metres). However, for burglary, vandalism and non-aggravated assaults, the price reaction suggests a positive association: the further away the crime occurs, the higher the prices. The paper also shows the large spatial association of different crimes suggesting that they occur together and that their accumulation would make negative externalities to appear affecting the whole neighbourhood.

Keywords: Housing Market, Crime, House Sale, Spatial Analysis, Temporal Analysis, LISA, K-Nearest-Neighbours, Kernel, Aggravated Assault, Burglary, Narcotics, Non-Aggravated Assault, Vandalism

1. Introduction
Crime is a continuously occurring phenomenon that has received growing attention in the academic knowledge base, particularly in the context of property markets. Much of this research has sought to understand if crime negatively affects the pricing of residential property, although results have established that impact is influenced by much greater complexity and wider socioeconomic conditions. The latter has often been focused on in the crime-related house price literature, with separation from other property market considerations resulting in a less established understanding of the effects on performance and house price (McIlhatton et al., 2016).

The research presented in this paper seeks to advance the knowledge base in this area by analysing the spatial relationships that may exist between different crime variables and the sale price of residential properties. The hypothesis underpinning this paper is that the impact of location in the housing market is considered vital; however, the relationship between these spatial effects and crime, and more specifically, types of crime, are non-linear. Specifically, the research investigates whether a distance effect would exist for crime types affecting housing prices, the causal direction and the differences among crime types

The research conducted is new and original in a number of ways. After a deep literature revision, first, the paper shows how incidents of reported crime are distributed across space and how they are related to each other - thus highlighting crime models with spatial influences. Secondly, the research utilises instrumental variables within the methodology to estimate house prices using spatial analysis techniques and while controlling for endogeneity; in particular, a spatially weighted two step least squares method is used with instruments of the crime types, which is a relatively novel contribution to the hedonic house price literature . Thirdly, it estimates the direct impact of crime on house prices and explores the impact of housing and neighbourhood features. Results show statistically significant but quantitatively small effects from crime on house prices, which largely seems to hold regardless of spatial scale[1].

The paper is structured as follows. Section two considers issues from the literature stressing the international context of the subject matter and how spatial analysis has been used in studies to explore these relationships. Section three examines the datasets and variables that underpin the analysis, and section four develops the particular models utilised in this paper. Section five then discusses the results from applying the models described and is based on analysing different crime types. Section six draws conclusions.

2. Literature Review

Since the 1960s and following the influential studies carried out by Lancaster (1966) and Rosen (1974), there has been a strong focus within the extant knowledge base on hedonic analysis. This body of research is well established with significant research evidence emerging in areas that analyse the relationship between house prices and property attributes (Linneman, 1980; Haurin et al., 1991), the development of house price indices (Geltner, 1993, Adair et al., 1996; Clapp, 2003), the isolation and investigation of speculative components and their impact on house price (Taltavull and McGreal, 2009), as well as the impact of different characteristics or externalities on house prices (Goodman and Thibodeau, 1995; Clapp and Giacotto, 2002; Bourassa et al., 2004; McCord et al., 2014; McIlhatton et al., 2016). Further research on hedonic analysis focuses on how hedonic models capture demand interaction through housing features. Indeed, research conducted by Taltavull and McGreal (2009) highlights that such components reflect the degree to which demand satisfies residential needs and do not interact with short-run demand components like expectations, suggesting that attributes may establish the price differences among heterogeneous units in every location.

[1] We thank to an anonymous referee for highlight this issue.

Externalities

Hedonic models have also been used to price the impact of neighbourhood features on housing prices. The price effect is attributed to the existence of externalities derived from those (out-of-housing) attributes over the demand perception, which affects the willingness to pay and then prices. These studies have explored whether these impacts have had negative effects (such as proximity to industrial sites) or a positive influence (associated with access to open space and pleasant views) However, the literature is also clear that some externalities can prove to be a double-edged sword insofar as they have the potential to influence both negatively and positively with research on the effect of emissions providing a strong example of this (Taltavull et al, 2019).

There are several examples of how hedonics can capture externalities affecting housing prices, For instance, in the railway station and its proximity to housing. In the literature, this externality has been found to have both favourable and unfavourable impacts on house prices. Potential homeowners may pay a premium to live near a railway station because of access advantages (Hess and Almeida, 2007). However, these positive effects may be offset by the physical infrastructure of the station (mainly when parking facilities are available) alongside noise pollution and the tendency of railway stations to attract criminal activity (Bowes and Ihlanfeldt, 2001). Other examples can be on the impact of cell phone towers (Bond, 2007); or visual externalities, as the presence of poorly maintained or abandoned buildings (Yau et al. 2008) who estimated that refurbishing the building would increase a 6.6 per cent the value of homes located in the immediate vicinity of such buildings. Numerous studies have shown that pleasant views and open space positively affect house prices (Benson et al. 1998, who demonstrated that Ocean views increase property values by as much as 60 per cent; Bourassa et al., 2004 or McCord et al., 2014, among others). However, the results of some of these studies have proven inconclusive findings and the effects on prices can differ by type of view and open space. Some parks, for example, may be viewed as a liability as they can potentially attract criminality (Troy and Grove, 2008), or that parks, water and vegetation did not significantly impact property values (in Glasgow, Scotland, Lake et al., 2000).

Crime and House Prices

One externality that has been extensively studied in the extant literature base is the impact of crime, or the perception of crime, on property values, with a vast body of research documenting an inverse relationship between housing values and local crime rates. In an important early study conducted by Thaler (1978) in Rochester, New York, it was estimated that a one standard deviation increase in the incidence of property crime reduces property prices by about 3 per cent. This holds true for later studies such as that undertaken by Gibbons (2004), who likewise demonstrated that a one standard deviation increase in property crime decreased property values by as much as 10 per cent.

However, Ihlanfeldt and Mayock (2010) argue that a large majority of the studies exploring the influence of crime on property values treat crime measures as exogenous independent variables while both events occur simultaneously and should be endogenous related.

Similarly, Olajide and Lizam (2016) suggest that many of the studies exploring the impact of crime on house prices are hampered by the fact that it is difficult to separate the precise variables. This makes it hard to conclusively argue that crime acts as the causal variable depressing property values. This point is illustrated in Schwartz et al. (2003), who found that falling crime rates positively impacted real estate values by 6 percentage points of the overall 17.5 per cent increase in property values that New York witnessed from 1994 to 1998. However, the researchers also made clear that this increase in values was only partly attributable to falling crime rates, pointing out that New York's poorer neighbourhoods had also undergone a period of revitalisation over the same period. In a study that examined the impact of seven different types of crime and the influence these crimes had on property values, Ihlanfeldt and Mayock (2010) concluded that only robbery and aggravated assault crimes (per acre) exerted any significant influence upon property values. While some studies have shown a link between violent crime and lower house prices, the evidence that property crime impacts negatively on property values has proven more ambiguous.

A study conducted by Boggess et al. (2013) measured the impact of violent, property and overall crime on the rate of housing transaction across Los Angeles neighbourhoods between 1993 and 1997. In their study, Boggess et al. (2013) disaggregated the analysis by broad crime categories in order to examine the differential impacts of violent and property crimes on the neighbourhood demand for housing. They found evidence to suggest that if the crime rate increases, the rate of home sales also increases, and again showed that an increase in violent crime in particular had a substantially larger impact than total crime or property crime. Indeed, much of the literature suggests that violent crime exerts a negative impact resulting in depressed property values (Hellman and Naroff, 1979; Tita et al., 2006).

In a study by McIlhatton et al (2016) in Belfast, Northern Ireland, the analysis found a negative relationship among several measures of crime and housing prices, with the extent of the relationship depending on the type of crime. Specifically, The research identified significant complexity and that burglary and theft were identified in higher-income neighbourhoods, whereas violence against persons, criminal damage and drugs offences were evident to a much greater extent in lower-priced neighbourhoods. Those results support Ihlanfeldt and Mayock (2010) findings that suggest both crimes committed and house transaction price happen simultaneously, thus addressing the endogeneity issue in this field. Research by the Centre for American Progress demonstrated that a 10 per cent decrease in murders would translate to a 0.83 per cent appreciation in housing values the subsequent year (Shapiro and Hassett, 2012).

Other scholars have also sought to examine the impact of unique types of crime and non-property crime on the impact of property values. For example, Linden and Rockoff (2008) focused their attention on what impact the presence of sex offenders had within a neighbourhood. Combining data from the housing market with data from sex offender registrations, they found a considerable decline in house prices following the arrival of a sex offender within a neighbourhood. Again, as in much of the literature, the impact of these effects is highly localised. While homes in close proximity declined by 12 per cent, no impact was found on homes located more than a tenth of a mile away from the offender's location.

Looking at the impact of non-property crime on property values, Braakmann (2012), drawing on street-level data in the UK, found that each additional case of anti-social behaviour reduced house prices in the same street by approximately 1 per cent. Further, each additional case of violent crime resulted in a decrease of 2 per cent. Interestingly, Braakmann (2012) found no evidence that drug crime significantly impacted property values. Research relating to the impact of the drug economy and its influence on property values is scant; nevertheless, where drug crime is reduced, violent crime might also decrease, which can positively impact property values.

In a recent study by Law et al. (2020), they followed the approach put forward by Anselin et al. (2000) and utilised Bayesian multivariate spatial models to identify general and crime specific hotspots in Ontario, Canada. Their research showed evidence demonstrating that crimes are concentrated; therefore, the majority of crime-general clusters had very strong evidence of being a hotspot. Indeed, the multivariate method used allowed them to identify spatial processes associated with both crime-general and/or crime specific patterns.

In summary, the literature indicates much complexity in the relationships between crime, the spatial location of crime, and the resulting sale price of residential properties. Complexity on relationships of crime and housing prices (McIlhatton et al., 2016) and endogenous – simultaneous (Ihlanfeldt and Mayock, 2010) occurrences suggest that crime would become a 'neighbourhood feature' affecting housing prices, and then crime existence would be stabilised in the area as a component of prices. Such an idea is linked to permanent crime hotspots (Law et al., 2020), which permanently affect house price formation. If this is the case, then the policy intervention to reduce or eliminate such crime hotspots is of high relevance to guarantee the normal equilibrium on housing markets.

3. Data and Measurement

For this study, we focus exclusively on houses sold in 2016 in LA County, USA and have excluded sales information for the Channel Islands. The property sales data is sourced from the Los Angeles County Assessor, and includes a comprehensive detailing of property characteristics, sale price and location data. Such data is combined with information from other datasets as explained below. The data matching/joining was made using spatial tools, as all data was geocoded, and by using a unique identification code for each property, which aligned with data from the US Census. All data is observed for 2016, monthly.

3.1. LA Sales Data

The LA sales database provides information on the final sale price and the spatial location of the property, as well as detailing attribute data for different house characteristics, such as the number of bedrooms and bathrooms, the size in square feet, and the year in which the property was constructed – allowing us to calculate the age of the property[2]. The data also provided an understanding of the type of house (e.g. condominium or single family home) and whether the property had a swimming pool. In addition, the geocode in the dataset allows us to control for the spatial dimensions and autocorrelation.

[2] We calculate the house age as, house age = 2016 - year built + 1

The dataset was cleaned of potential outliers and extreme values. Then, observations where the natural logarithm was below 8, and over 18 were excluded. The full database (Figure 2) included more than 150,000 observations and after the data was cleaned, the data comprised 128,442 housing transactions and therefore represented a significantly large dataset (Table 1).

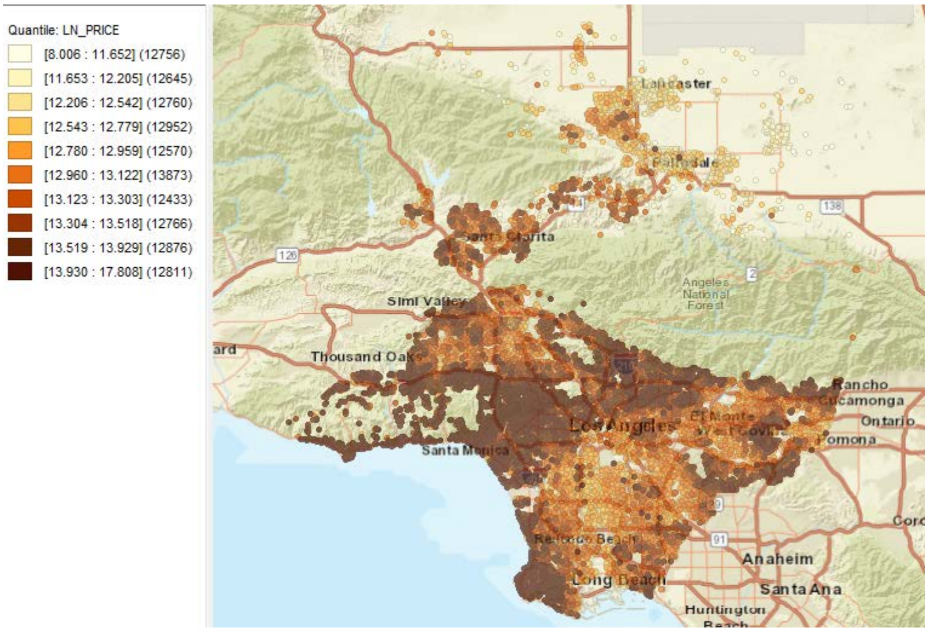
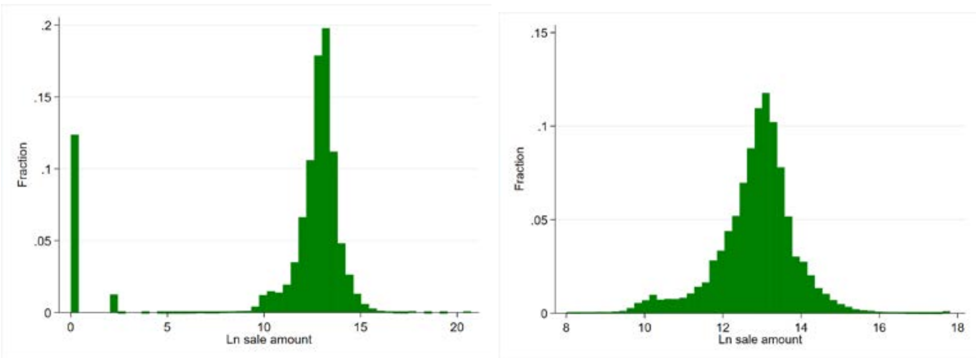


Figure 1: Database Spatial Distribution



(a) Full Dataset (b) No Extreme Values
Figure 2: Histogram Ln Sale Amount

Table 1. Descriptive Statistics

	N	Mean	Std. Dev.	Min	Max
poly_id	128442	64228,99	37080,03	1	128451
bedrooms	128442	3,06	1,02	0	18
bathrooms	128442	2,31	1,05	0	17
sqftmain	128442	1775,73	968,31	40	27470
saleamount	128442	657565,33	1946223,39	3000	54200000
longitude	128442	-118,26	0,22	-118,9	-117,7

latitude	128442	34,10	0,21	33,7	34,8
newyearbui	128442	1964,19	24,41	1900,0	2016,0
n_dis_bike	128442	2989,00	2967,87	2,0	27359,5
n_dis_chu	128442	1581,23	2677,30	2,5	41470,5
n_dis_bike	128442	2989,00	2967,87	2,0	27359,5
n_dis_uni	128442	3164,83	3330,46	31,6	44153,8
n_dis_fuel	128442	4685,06	3292,10	68,9	28079,8
n_dis_bus	128442	5308,26	11113,71	9,1	69049,6
n_dis_met	128442	11638,43	13576,71	56,6	73888,7
n_dis_sch	128442	580,74	543,02	0,1	21187,6
n_dis_shop	128442	2027,66	2252,39	40,2	40754,5
n_dis_air	128442	8998,25	5499,92	172,0	43969,5
n_dis_bc	128442	18301,68	15170,41	142,3	84167,3
n_dis_hall	128442	3809,54	2958,63	46,9	43808,9
n_dis_golf	128442	3118,36	2056,70	19,6	38753,6
n_dis_heli	128442	3118,54	1879,58	24,1	19701,3
n_dis_shlt	128442	3925,31	3337,35	14,9	45829,9
n_dis_hosp	128442	3424,08	3123,45	30,5	44611,5
n_dis_lake	128442	934,75	954,27	0,1	7025,5
n_dis_lcbd	128442	8431,94	11257,27	12,2	70847,8
n_dis_nat	128442	4830,39	3051,85	32,3	19210,6
n_dis_park	128442	988,59	905,89	1,4	17178,8
n_dis_cops	128442	3280,18	2761,14	46,0	43534,4
n_dis_sprt	128442	8688,46	9676,21	134,8	70508,6
n_dis_fire	128442	3509,38	2838,73	26,8	25932,6
tot_pop	128442	4925,21	1594,80	43	12622
male_pop	128442	2411,90	799,46	12	6651
female_pop	128442	2513,31	823,09	31	6088
age_under5	128442	5,32	2,26	0	18
age5to9	128442	5,76	2,16	0	15,8
age10to14	128442	6,06	2,33	0	15,7
age15to19	128442	6,20	2,71	0	48,5
age20to24	128442	6,52	3,12	0	74,7
age25to29	128442	7,18	3,38	0	31,5
age30to34	128442	6,84	3,09	0	24,4
age35to39	128442	6,63	2,21	0	18,1
age40to44	128442	7,10	1,97	0	20,9
age45to49	128442	7,27	1,95	0,1	22,3
age50to54	128442	7,43	2,06	0	15,0
age55to59	128442	6,89	2,11	0	16,5
age60to64	128442	5,86	1,95	0	16,2
age65to69	128442	4,66	1,90	0	13,8
age70to74	128442	3,36	1,59	0	11,9
age75to79	128442	2,01	1,42	0	23,0
age80to84	128442	1,91	1,22	0	18,6
age_over85	128442	2,09	1,65	0	22,9

unemployed	128442	7,90	3,36	0	34,9
meanincome	128442	104860,83	51710,78	20456	398286,0
poverty	128442	12,10	8,56	0,60	76,8
highschool	128442	0,19	0,08	0	0,5
bachelorde	128442	0,24	0,11	0	0,6
single	128442	1,00	0,00	1	1,0
condominiu	128442	0,00	0,00	0	0,0
highvalue	128442	0,00	0,02	0	1,0
pool	128442	0,15	0,36	0	1,0
recordingm	128442	6,89	3,32	1	12,0
age5to14	128442	11,82	3,85	0	26,7
age20to34	128442	20,54	6,99	4	85,0
age35to49	128442	21,00	3,71	2,10	39,7
age50to64	128442	20,19	4,35	0,00	39,6
age_over65	128442	14,49	5,84	0,40	52,5
near_van	128442	0,01	0,01	0,00	0,1
near_agg	128442	0,01	0,01	0	0,2
near_bur	128442	0,01	0,01	0	0,1
near_nas	128442	0,01	0,01	0	0,1
near_nar	128442	0,01	0,01	0	0,1
totcrimes	128442	1336,59	1337,31	0	7158
agg0to500	128442	4,47	10,86	0	348
agg0to1000	128442	17,97	38,10	0	653
agg0to2000	128442	70,29	135,13	0	1561
van0to500	128442	8,00	12,73	0	218
van0to1000	128442	31,40	45,18	0	587
van0to2000	128442	120,36	157,01	0	1294
nas0to500	128442	10,29	28,89	0	1172
nas0to1000	128442	41,16	87,08	0	1551
nas0to2000	128442	158,78	287,24	0	4216
nar0to500	128442	3,33	8,72	0	180
nar0to1000	128442	13,43	27,84	0	346
nar0to2000	128442	51,95	85,99	0	647
bur0to500	128442	12,93	19,11	0	283
bur0to1000	128442	49,73	67,82	0	675
bur0to2000	128442	186,29	231,77	0	1776
house_age	128442	52,81	24,41	1	117
ln_price	128442	12,85	1,02	8,01	17,81

3.2. Crime Data

The data for Los Angeles County crime is a separate geocoded dataset containing information about five different types of crimes: aggravated assault, non-aggravated assault, narcotics, burglary, and vandalism[3] and was sourced from the Los Angeles Police Department for 2016. Note that aggravated assault is considered as a violent crime and burglary as a property crime. Vandalism is considered as a visible crime. The research approach examined three different measures for the crime variables. First, the distance at which the closest aggravated assault, non-aggravated assault, narcotics, burglary, and vandalism crimes occurred was calculated using an industry-leading commercial GIS measuring Euclidean distance. For the second measure, a spatial buffer and spatial join within the commercial GIS software was used to calculate the number of different crimes happening within 500, 1000 and 2000 meters, respectively.

Lastly, we calculate the total number of accidents, aggravated assaults, arson, burglary, homicides, misconducts, alcohol offences, felonies, rapes, gambling, vehicle thefts, larceny, narcotics, non-aggravated assaults, robberies, sex offences, vagrancy, vandalism, and breaches of weapon laws that happened in 2016 at the zip code level.

3.3. Infrastructure and Resources Data to calculate distances

For each property, we calculate, through GIS, the Euclidean distance to the closest bike pathway, church, university, fuel station, bus stop, metro station, school, shopping centre, airport, business centre, city hall, golf course, heliport, shelter, hospital, lake, local business centre, natural reserve, park, police station, sports venue and fire station. These are consistent attributes identified in other crime-related studies.

3.4. Demographic Data from Census

We use the following demographics variables as controls in line with previous research: age category, total population, total male population, the percentage of the population below poverty level, the unemployment rate, mean income in dollars, educational level (the percentage of the population with a high school degree or higher, and the percent of the

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[3] Crime Descriptions:
Aggravated Assault: “An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. This type of assault usually is accompanied by the use of a wor by means likely to produce death or great bodily harm. Simple assaults are excluded." Non-Crime
Aggravated Assault, i.e. Other Assaults (Simple): \Assaults and attempted assaults where no weapon was used or no serious or aggravated injury resulted to the victim. Stalking, intimidation, coercion, and hazing are included." Drug Abuse Violations, including Narcotics: “The violation of laws prohibiting the production, distribution, and/or use of certain controlled substances. The unlawful cultivation, manufacture, distribution, sale, purchase, use, possession, transportation, or importation of any controlled drug or narcotic substance. Arrests for violations of state and local laws, specifically those relating to the unlawful possession, sale, use, growing, manufacturing, and making of narcotic drugs. The following drug categories are specified: opium or cocaine and their derivatives (morphine, heroin, codeine); marijuana; synthetic narcotics-manufactured narcotics that can cause true addiction (demerol, methadone); and dangerous nonnarcotic drugs (barbiturates, benzedrine)." Burglary: “(breaking or entering) The unlawful entry of a structure to commit a felony or a theft. Attempted forcible entry is included.", Vandalism: ”To wilfully or maliciously destroy, injure, disfigure, or deface any public or private property, real or personal, without the consent of the owner or person having custody or control by cutting, tearing, breaking, marking, painting, drawing, covering with filth, or any other such means as may be specified by local law. Attempts are included." https://ucr.fbi.gov/crime-in-the-u.s/2010/crime-in-the-u.s.-2010/o_ense-de_nitions, consulted the 4 December 2018.

population with a bachelor degree or higher). This data was sourced from the latest census tract record in USA for 2010.

The datasets were then merged by assigning the variables to each property transaction using a unique location-based identifier. In the case of crime, the number of crime types is assigned to a transaction when it occurs in the area of the property transacted at the different distances calculated, that is, assigned to each property transacted which is located close (at those distances) to the place where the crime was committed.

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4. Methodology

The research presented in this paper tests the effects that crime has on house prices and controls for the location where the crime occurs. The study area, as identified previously, is Los Angeles County in the United States. The methodology is developed in two stages.

Stage 1

First, the research looks for evidence of the spatial association between prices and crime types to show how crime acts are distributed across space, related to each other, and spatially related to house sales. The analysis is based on both univariate and multivariate approaches. The univariate analysis presents the existing spatial autocorrelation in each crime and price variable, while the bivariate analysis identifies the spatial spillover between each pair of variables, with a specific focus on crime types and house prices. Our approach follows Anselin (2019) in this step and calculates the bivariate and multivariate version of the local –LISA- cluster test[4]. The bivariate spatial association concept captures the spillover effect of a variable x and the spatially lagged values of a neighbour variable y, and the test is expressed as (1)[5]. Moran's I and LISA tests are used in this step

$$(1) \qquad I_{biva} = \frac{\sum_i \sum_j (W_{ij} y_j \times x_i)}{\sum_i x_i^2}$$

The evidence of spatial cross-correlation patterns and local clusters suggest crime hotspots that could explain the differences in the impact of different crime types on house prices. The calculation of how the crime types could define spatial concentration in Los Angeles County is made by estimating spatial hotspots for all five types and the specific property crime (burglary)[6]. The definition of a spatial hotspot follows the methodology described in Anselin and Li (2019), and defines the co-location cluster or Local Joint count. For two variables x and z, the bivariate local joint count statistic is defined as a non-symmetric statistic BJC (op.id, pp 197) in (2).

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[4] Geary local tests were also applied but the bivariate LISA gives more appealing results.

[5] Anselin (2019) warns that the bivariate statistic does not take into account the correlation existing between the two variables analysed which could overestimate the spatial correlation measure.

[6] The literature supports that crime hotspots determining spatial patterns for each type of crime would have different impact on property prices (Law et al, 2020)

(2) $BJC_I = x_i \sum_j w_{ij} z_j$

With BJC being bivariate, the joint count or local joint count for two variables. The co-location cluster extends this definition to capture the events happening close to each other, also bilaterally co-located, forming (co-location) clusters that concentrate events in closer points. Then, the co-location cluster is formed by estimating the probability that the event is spatially located together as close neighbours. It is represented by (3).

(3) $CLC_I = x_i . z_i \sum_j w_{ij} x_j z_j$

Stage 2

The second step in the research analysis utilises instrumental variables to estimate house prices through spatial analysis while controlling for endogeneity. It estimates the direct impact of crime on house prices and includes the analysis of housing and neighbourhood features, developing the spatial estimation in a 'step-by-step' mode to identify which variables capture the impact of unobservable features in the spatial association between crime and housing prices.

The hypothesis tests whether the crimes committed around the house sold have driven a discount in the transaction price. To find the evidence, this paper embraces the hedonic definition of housing prices following the conventional semilogarithmic functional form of housing prices as (4)

(4) $LnPh_i = \alpha + \sum_{k=1}^{k} \beta_k X_{k,i} + \sum_{j=1}^{j} \gamma_j Z_{j,i} + \epsilon_i$

Where Ph_i is the transaction of house 'i' in logs, $X_{k,i}$ is a matrix of $x_1 \ldots x_k$ housing attributes for the 'i' individual observations, including distances to main infrastructures; Z_j is a set of 'j' crime variables as explained above associated to each transaction observation 'i'. The parameters α, β_κ and γ_φ are the matrix of parameters to be estimated.

In the literature base, a significant body of research supports the existence of spatial autocorrelation in housing prices. In line with this evidence, the methodology of this research adopts the Durbin model and includes the spatial components for the hedonic model in equation (4) and controls for the existence of the two spatial association components: the spatial lags (to control for housing price spillover effect across geographic space) and controlling for spatial errors as equation (5-6) defines[7].

(5) $LnPh_i = \alpha + \rho W LnPh_{i-1} + \sum_{k=1}^{k} \beta_k X_{k,i} + \sum_{l=1}^{l} \sum_{j=1}^{j} \gamma_j D_l Z_{j,i} + \epsilon_i$ w with

(6) $\epsilon_i = \lambda W \epsilon_{i-1} + \mu_i$

[7] As data corresponds to observations in just one year, it is impossible to observe changes on time, so spatio-time models cannot be estimated

Where r is the spatial autoregressive parameter that captures the housing price spillover effect across space, λ is the spatial autoregressive error that measures the unobservable spatial influences existing in the neighbourhood. D_l refers to the distance from the property and $D_l Z_{ji}$ defines areas within a ratio of 'l' meters around the property transacted (l=500, 1000 and 2000 metres) containing different crime types committed in the property radio; W is the spatial matrix, and μ_i is a white noise error.

There are two sources of endogeneity in the model proposed here. Durbin model considers that spatial associations are endogenous to the dependent and independent variable. Thus, the method uses an IV approach (a Two Step Spatial Least Square method) in which all variables included in the model need to be instrumented by using the spatial lagged variables to avoid the effect of spatial endogeneity. Thus, the model uses instruments to capture spatial dependence, the (all) spatial lagged independent variable (W^*x_{ki}). With this procedure, the method controls for an endogenous spatial relationship.

In addition, the methodology also supports the idea that crime events affect housing prices, simultaneously showing that crimes are endogenously determined with the property value (Ihlandfeldt and Mayock, 2010). Regarding that evidence, endogeneity between prices and crime should also be addressed. Such endogeneity between prices and crime is different in nature to the one explained above and emerges from the empirical evidence that the existence of crime implies an effect on housing prices when the property is transacted. This causal relationship may be controlled by applying the IV tool in the same spatial model. Then, the endogenous models control for two types of endogeneity: the spatial and the causal one. The latter requires a different instrument for the crime variable, which then fulfils the instrument rules.

The econometric methodology then discovers the spatial patterns in crimes (both aggregated and crime types), and analyses the existence of spatial association (and consequently endogenous relationship) and the different patterns that exist, depending on the type of crime. The spatial analysis follows a univariant analysis (identifying the spatial patterns), and multivariant to determine the hotspots of crime types affecting housing price transactions. Results allow identifying the location, influence areas and the specific points from which affect housing prices.

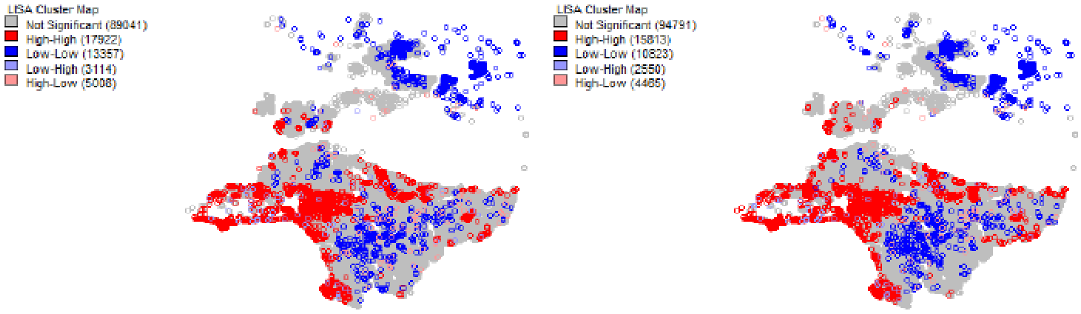
Secondly, the causality is explored by estimating equations (5) and (6) to find evidence of the impact of each crime type on house prices and the role and type of spatial association.

5. Empirical evidence

1. Univariate Spatial Analysis

The first step of our analysis is to look at the spatial distribution of the sale price and crime variables. To do so, we perform univariate spatial analysis with LISA and Moran's I. We used three different approaches to calculate the weight matrices. The Queen contiguity-based spatial weights approach is the first we used. As our data is points-based, we then created Thiessen polygons and calculated Queen weight matrices of contiguity order 1, 4 and 8. We then used the neighbours' histogram of the Queen weight matrix of contiguity order 1 to choose the optimal criteria, and the number of neighbours for the distance-band spatial weights approach. The second approach used was the K-Nearest-Neighbours, and the third approach used was the adaptive Kernel approach with uniform function, diagonal weights equal to 1, and the number of neighbours as adaptive bandwidth. We performed this analysis by treating the data as cross-sectional, decomposing the dataset by month, and examining if the house price and the crime data followed different patterns throughout the year.

2. Ln Sale Amount as cross-sectional data



(a) Queen Contiguity Order 1, Global Moran's I of 0.30597

(b) K-Nearest-Neighbours, Global Moran's I of 0.323742

Figure 3: Univariate Moran's I, Ln Sale Amount

Figure 3 represents the correlation between the Ln Sale Price of house i's neighbours and the Ln Sale Price of house i. The high-high category represents a positive correlation between the two, meaning the highest is the ln sale price of house i's neighbours, the highest is the ln sale price of house i. The low-low category a positive between the two, meaning the lowest is the ln sale price of house i's neighbours, the lowest is the ln sale price of house i. The low-high category represents a negative correlation between the two, meaning the highest is the ln sale price of house i's neighbours, the lowest is the ln sale price of house i. The high-low category represents a negative correlation between the two, meaning the lowest is the ln sale price of house i's neighbours, the highest is the ln sale price of house i.

There are clear patterns showing how the sale amount is spatially autocorrelated, distinguishing (1) areas with increasing effect on prices (red areas) which can be seen along the coast, in the Los Angeles city area or at the border of the Angeles National Forest, and (2) withç a reducing effect, in localities such as the south-east area of the map, as well as the north (Lancaster and Palmdale area), clear low-low spatial clusters appears (predominantly blue areas). Those patterns appear using a Queen matrix with contiguity order 1, and the results are robust if higher contiguity orders are used[8].

[8] The same patterns also appear with the KNN and Kernel approaches with very few differences. There are clearer patterns with KNN and Kernel than with the contiguity approach between Agoura Hills and Simi Valley; the zone between Chino Hills and Brea is a high-high area and there is no more a low-low area around Santa Clarita. However, both KNN and Kernel tend to identify highest global Moran's I but lowest local significance.

3. Total Crime as cross-sectional data

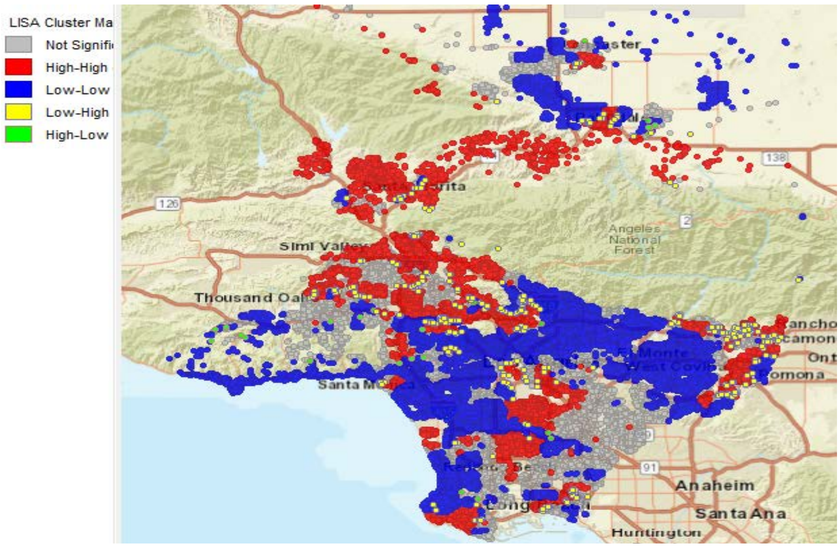


Figure 4. Crime cluster distribution across space. Total crime. Morans'I=0.923

Regarding the total crime, the spatial analysis illustrates that it is very concentrated in some areas, with the High-High (red in Figure 4) mostly evident in the northern, central and eastern areas of Los Angeles County, with a clear low-low pattern in between, There are, however, large areas where crime is not spatially significant, and these are captured as grey in Figure 4. Three large areas are high-high: around Lancaster and Palmdale, North of San Fernando, and the area between Inglewood, Downey and Norwalk: and three smaller high-high areas: around Hawthrone, South-East Long Beach, and the area around Montebello and Whittier. Similar results can be observed for KNN and Kernel. It is surprising how the transition areas (Low to High and High to Low) are minimal and mainly suggest an expansion of high-high areas (green points).

The Global Moran's I has large value, closer to the unity, suggesting clear spatial patterns which delimitate the crime areas.

Crime category as cross-sectional data

The spatial pattern for the four types of crimes are shown in the Figure 5

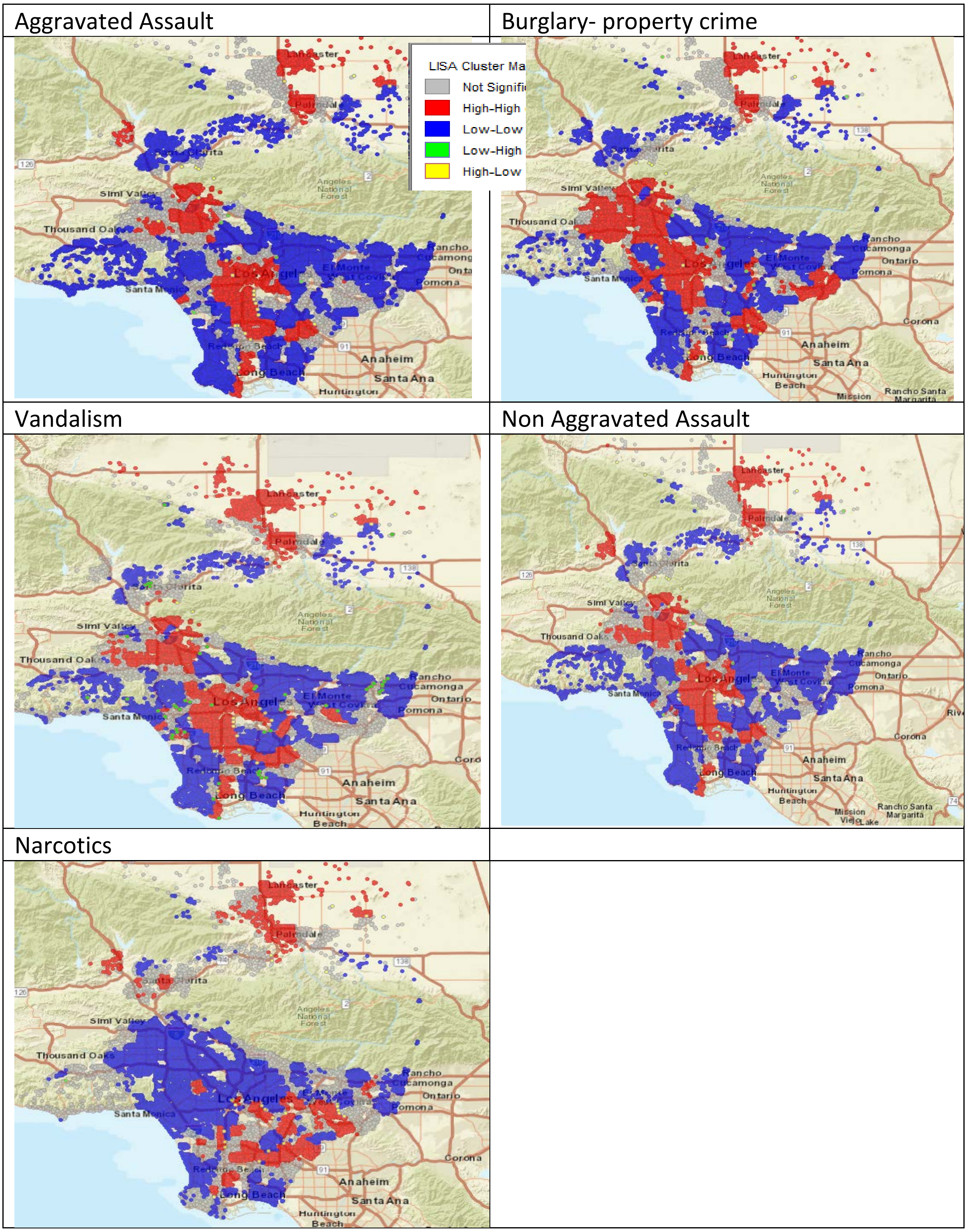


Figure 5. Spatial patterns of crime typology

Interesting patterns can be found for the different types of crimes. The north of the map, the area delimited by Hawthorne, Torrance, Long Beach, Norwalk and Arcadia, is low-low except for Rancho Palos Verde and Chino Hills that exhibits a high-high pattern. Up to the Simi Valley, Porter Ranch and San Fernando, Los Angeles city is high-high while the North, Santa Clarita, Lancaster and Palmdale, are predominantly low-low areas. Low-high and high-low regions are very small and literally imperceptible. The maps show how the high-high differs in a few areas, and all types of crime, but vandalism is present in the same areas and as 'islands' with few spilling over to the low-low areas.

Interesting patterns can also be observed with narcotics. In Los Angeles County, Torrance, Rancho Palos Verde, Long Beach, Norwalk, Chino Hills and Arcadia follow a mixed pattern of high-high and low-high. The middle area, Hawthorne, Los Angeles city, Glendale is low-low. The area delimited by Agoura Hill, Simi Valley, La Crescenta is low-low. The North (Santa Clarita, Lancaster and Palmdale) has predominantly low-low areas but high-high in between with large parts being insignificant. It is evident that areas which are low-low in most crime types (Simi Valley and Thousand Oaks), are predominantly impacted by narcotics.

The key issue is how both distributions of transaction price and crime types are related and the extent that they are related. The spatial distribution suggests a significant correlation among four out of five types of crime. Correlation is shown in table 2 and should be controlled for in order not to bias the estimation

Table 2. Correlation among crime types

	AGG	Bur	NAR	NAS	VAN
AGG	1.000	**0.790**	0.418	**0.836**	**0.836**
BUR		1.000	0.345	**0.876**	**0.897**
NAR			1.000	0.357	0.411
NAS				1.000	0.896
VAN					1.000

2. Bivariate spatial analysis

The high correlation suggests the existence of common clusters of crime. It is a relevant issue in analysing their impact on housing prices due to the effect of crime on house prices resulting from a combination of multiple crime occurrences and not only one (Law et al., 2020). Two tools are used here to approach this issue. The first is the bivariate local Moran's I which captures the relationship between the one variable in a given area and the second variable (average) in adjacent areas (Anselin and Xun, 2019). This test estimates the spatial cross-correlation between two variables defining the spatial pattern that both variables follow.

The second tool is the co-location joint count test. It is a multivariate spatial test that identifies the existence of common spatial clusters. These clusters are a sign of co-location and can be interpreted as two (or multi) events occurring in the same space. Applying this to spatial data points identifies the hotspot of crime, which are those common points statistically significant at spatial dimension.

This section focuses on the spatial relationships of the crime against properties (Burglary) type and how it would affect house prices. Table 3 present the Moran's I tests, both univariate and bivariate, associated with the crime and transaction price variables previously identified in this paper.

Table 3. Univariate and bivariate Moran's I test. Detail among variables

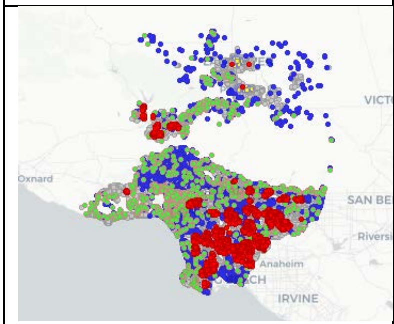
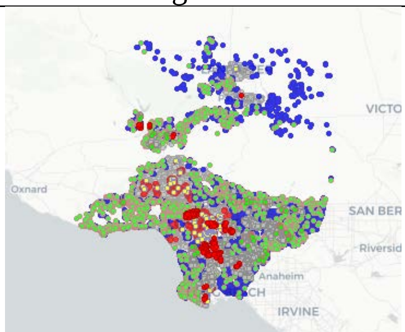
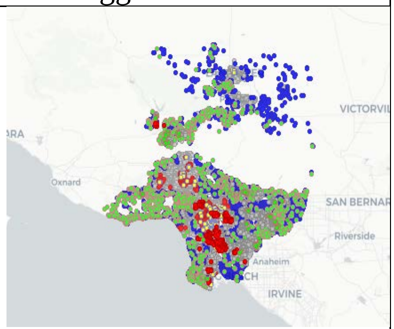
MORAN'S I test

Crimes committed at 1000 m from the property	LPR	AGG	BUR	VAN	NAS	NAR
LPR-log transaction prices	0.306	**-0,098**	**0,02**	**-0,079**	**-0,052**	**-0,171**
AGG - Aggravated Assault		0,972	0,671	0,861	0,871	0,333
BUR- Burglary- property crime			0,974	0,815	0,692	0,219
VAN- Vandalism				0,971	0,841	0,486
NAS- Non-Aggravated Assaults					0,959	0,311
NAR- Narcotics						0,969

Note: All the estimations use Queen weight matrix of order 1.
Source: author's elaboration

The sequence of Moran's I tests in Table 5 indicates that spatial correlation strongly affects crime variables, including burglary, vandalism, non-aggravated assault and aggravated assault, while narcotics is the crime with the lowest spatial correlation. It is interesting to see that the statistics reject the null of existence spatial cross-correlation between any type of crime and housing transaction prices, as Moran's I present values close to zero suggesting a random spatial co-distribution (first row, Table 5).

However, LISA test identifies the sub-areas where different crimes exhibit spatial association with transaction prices in local clusters. Figure 6 shows the spatial bilateral clusters maps, in which the high-high zone is red-coloured to remark the specific location where the high housing transaction prices are associated with the high crime events.

LnPr * Narcotics	LnPr*Non Ag Assaults	lnPr*Agg Assaults
		
LnPr*Burglary	LnPr * Vandalism	B-LISA cluster maps spatial significance

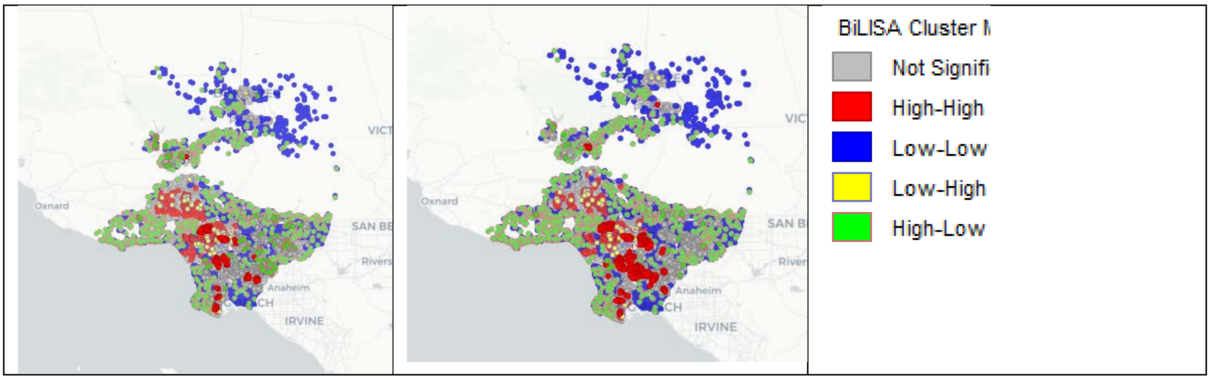
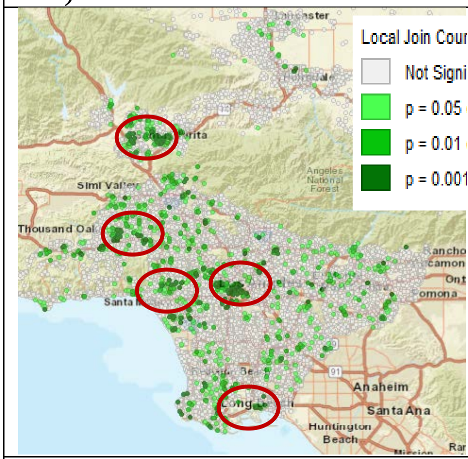
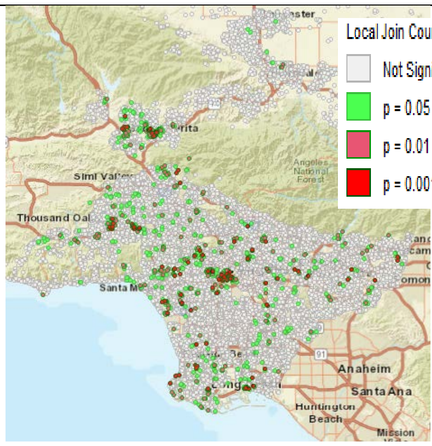
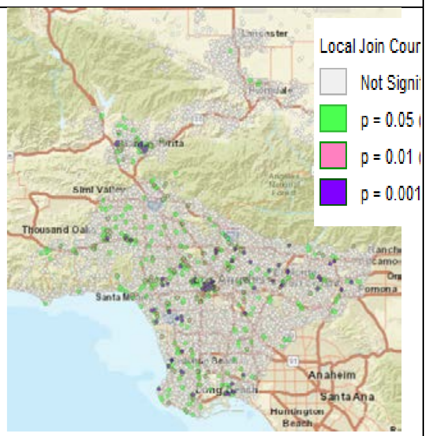


Figure 6.- Bivariate Local Moran's I. Log transaction prices and crime by distance (1000 metres). High-high clusters

The test identifies different prominent areas where the highest prices are, a larger number of crimes crime are committed, showing a clear different spatial spillover pattern between narcotics and the rest of the crime types' hot areas. All those suggest different patterns of crime affecting housing prices.

Multivariate tests allow for the identification of the typical crime hotspots and their spatial distribution across LA. Figure 7 shows the estimated co-location regarding the whole crimes and the bivariate location between burglary and the rest of crimes by type. The distribution across space gives empirical evidence of their impact on transaction prices associated with the property proximity[9].

<table>
<tr><td>All crimes (Agg, bur, nar,nas, van)</td><td>Burglary*aggravate assaults</td><td>Burglary*non aggravate assaults</td></tr>
<tr><td>
</td><td>
</td><td>
</td></tr>
<tr><td>Burglary* Narcotics</td><td>Burglary * Vandalism</td><td>Local joint count significance</td></tr>
</table>

[9] Each point represents the probability to the different types of crime to be committed together. The test estimated them at 0,1%, 1% and 5% of probability. Points in grey means they are non-significant

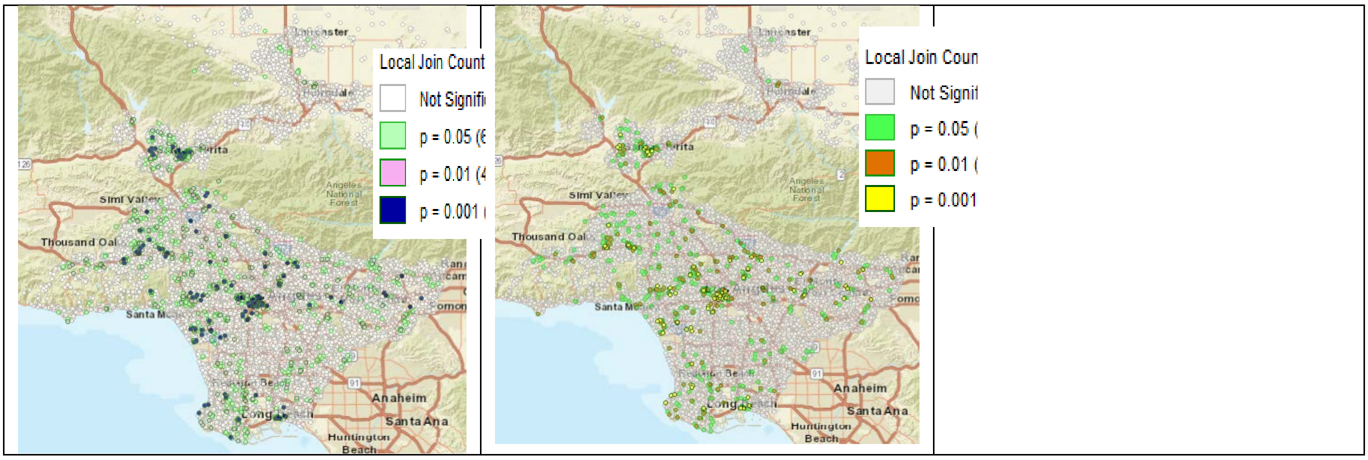


Figure 7.- Hotspots of crime. Cases of co-location with property crime (Burglary)

The spatial maps demonstrate two features of this crime perspective from the points where crime happens. The first sight is that the hotspots are spread across the LA territory. In all cases, five main hotspots can be identified in LA: in the area between Sta. Monica and Sta Ana boulevards; woodland Hills, Santa Clarita area, Long Beach, and the axes between Beverly Hills and West Hollywood (see the ellipses in Figure 7, map 1). The bivariate Local Joint count identifies the same hotspots, although with a lighter distribution in narcotics or vandalism.

The spread of crime location will be captured by the causal model developed in the next section.

5. Causal Analysis

This section presents the causal evidence of the effect of crime on housing transaction prices in LA: The estimation of models 4 to 6 above are calculated sequentially to identify, firstly, the type and strength of spatial impact.

The causality is explored by estimating equations (4) and (5-6) to find evidence of the impact of each crime type on house prices and the role and type of spatial association. The estimation follows a step-by-step procedure starting with the hedonic model expressed in (4), estimated using Ordinary Least Square including a set of variables reflecting the housing characteristics (like housing age, size, number of rooms and bathrooms, if the house has a higher value) plus the crime variables. After the first estimation, three other sets of attributes are added in the model which include the residents' features in the neighbourhood (like a set of the population by cohort until 70 years old, female population, population density, level of education); the neighbourhood features (level of poverty, unemployment, mean income level) and, finally, adding a set of 22 distances to the main points in the area. The hedonic model is estimated step-by-step and calculating the Lagrange tests and Moran's I in every step to identify the spatial lag and/or error pattern existing on data in every step. Results reject the null of the non-existence of spatial autorregression (both lag and error with Lagrange multiplier and robust LM) in every intermediate regression. When the distances measures are added, the hedonic model with distance measures cannot reject the null of the non-existence of spatial error in data. Looking at Table 4, the results suggest that a hedonic OLS specification suffers from a multicollinearity problem. Moreover, as shown by the Jarque-Bera test, the data does not follow a normal distribution. Breusch-Pagan and Koenker-Bassett tests demonstrate heteroscedasticity and the Langrange Multiplier tests and Moran's I test advert that the model suffers from spatial correlation[10].

Table 4. OLS HEDONIC MODEL BETWEEN HOUSING PRICES AND CRIME REGRESSION DIAGNOSTICS OF SPATIAL AUTOCORRELATION*		
REGRESSION DIAGNOSTICS		
Jarque-Bera	130210,5	***
Breusch-Pagan test	13871,61	***
Koenker-Bassett test	4490,921	***
DIAGNOSTICS FOR SPATIAL DEPENDENCE		
Anselin-Kelejian Test		
Moran's I (error)	57,683	***
Lagrange Multiplier (lag)	3667,206	***
Robust LM (lag)	371,939	***
Lagrange Multiplier (error)	3295,71	***
Robust LM (error)	0,442	
Lagrange Multiplier (SARMA)	3667,648	***

* These results correspond to the equation (1) in Table 5

Following the endogeneity concerns in the literature, model (5) is recalculated using Spatial Weighted Two-Step Least Squared (SW2SLS) with total crime being considered as endogenously related with transaction prices; in this model, crime is the variable instrumented by other types of crimes. Results are in Table 5. Eleven models have been estimated. The first four contain crime as an aggregated variable with the crime as exogenous (OLS estimation) and equation 2 having it as endogenous (SW2SLS method); equation 3 introduces the spatial correction. Equation 4 estimates the crimes by type in an exogenous spatial functional form with variables accounting for the number of crimes in the radius distance of 500, 1000 and 2000 metres far from the house. From equation 5 to 11, the models include the crime types endogenously determined. Those models require instruments and other types of crimes (with the largest correlation) are used for this purpose. Equations 5 to 9 test the crimes separately while equations 10 and 11 examine the impact of crimes committed regarding whether they are within a 1000m and 2000m distance of the house transacted.

[10] The regressions have been calculated with both Queen and KNN matrices although only the results from the former are reported here. Anselin-Kelejian tests have also been calculated to check some remaining spatial association after to controlling for spatial lag. Test indicates in all cases that some spatial correlation still remains (see Table 5). All models have been re-estimated by including spatial errors. The parameters estimated for the crime variables are consistent and almost the same in both models. In the estimation with spatial lag and error coefficients both have very close value but with contrary sign. Having lag and error spatial effect similar values and with the opposite sign, suggest that both are measuring the same event. This paper includes the result of the model with spatial lag correction for extension limit issues. The complete set of results are available on request from the lead author.

5. Discussion of Results

The purpose of this section is to evidence the results obtained from the application of the different spatial modelling approaches and are broken down in to a number of key findings. First, results suggest that crime (aggregated) are statistically significant to determine the model's transaction price, explaining around 28% of the housing prices variability and with the crime effect having a consistent impact in both OLS a d SW2L2 MODELS. Regarding models (1) to (3), the effect of crimes is negative (as expected), suggesting a small effect on transaction prices (in places with 100 crimes more than average committed is associated with a -0.000489% lower transaction price, regarding equation 3 where housing prices and crime are endogenous).

Results for the type of crimes are closely consistent on both OLS and SW2SLS models[11]. Equation 4 presents the results where all crimes are treated as exogenous. The model suggests that the individual effect varies with the distance, with negative impact on transaction prices when the aggravated assault is committed at 2000 metres (with a reduction on housing prices in a 0.066% associated to 100 extra assaults). However, at 1000 metres in the case of burglary (a fall of 0.044% in transaction prices when an extra 100 burglary events appear) and substantial impact of narcotics crimes very close (at 500 metres with a reduction of 0.018%) and far from the property (-0.033% at 2000 metres). The model also gives a positive association suggesting that crimes increase in proximity to larger house prices. It happens in aggravated assaults at 500 metres (0.205% of increase) or burglary at 2000 metres (0.029%). Those results give an inconclusive interpretation which would result from the strong spatial correlation among crimes shown above.

Equations 5 to 11 treat the crime variables as endogenous, and from 5 to 9 each model includes one type of crime. As can be seen, aggravated assaults (agg), vandalism (van) and burglary (but) are not statistically significantly associated to the changes on transaction prices by themselves while narcotics and non-aggravated assaults (nar) are. Narcotic crimes seem to be strongly significant (with the larger statistically significant parameter) so as a reduction of housing transaction of 0.11% is associated to narcotic crimes when 100 extra cases are registered within 2000 metres far from the property; non-aggravated assault show weakly significant parameters (at 5% of confidence) within 1000 and 500 metres.

The last two equations (10 and 11) estimate the models focusing on a radio of 1000 metres and 2000 metres. Within 1000 metres, vandalism crimes seem not to impact housing transaction prices (the parameter is insignificant), while an increase in 100 aggravated assaults and narcotics crimes seems to strongly be related to a fall in house prices of 0.19% and 0.08%, respectively. Both results are confirmed in equation 11, estimated for 2000 metres of property radius-model, with lower parameters but the same negative sign and significance (-0.05% and -0.02%, respectively). The parameters for burglary and non-aggravated assaults show a positive association and are confirmed for 2000 metres in the latter: the larger the price increase is, the higher the crime accumulation within 1000 metres of distance. With 2000 metres distance, vandalism is also positively associated with the house price increase.

[11] This paper only reports the results of SW2SLS models. The OLS results are available on request to the lead author.

Those results suggest that prices react positively when those crimes happen far from the property.

The results suggest that crime and prices are endogenously generated depending on the type of crime and the distance they are committed. The model suggests that prices do not react to property crimes or non-aggravated assault when they are committed far from the house but when an aggravated assault or narcotics crimes happen, although they can be between 1 to 2 km away.

The findings also suggest that the effect of individual crimes on housing prices are not apparent. The strong association between crime types and the lack of individual significance in some of them suggests that the effect of crime is not straightforward. That is because crime types relate to each other spatially; their concentration exerts a negative externality that contaminates the neighbourhood's residents' feelings, negatively affecting the perception of their quality. This is an unobserved effect that is captured in the endogenous model when crime typology is included.

Finally, this research empirically shows that controlling for crime types separately is not sufficient to control for the unobserved heterogeneity with spatial effects. This can be interpreted as the insufficiency to control for the neighbourhood effect derived from the accumulation of crime where only one type of crime is included.

The accumulation of crime gives relevance to hotspots in the model affecting housing prices. The fact that hotspots are so widespread is consistent with the effects of crime on prices occurring in the middle distance, within a radius of 1000 metres, although the pattern for narcotics is different.

The general positive effect of those particular crimes reflects the owner (positive) reaction when seeing that crimes are further away –the further the crime, the larger the price.

In summary, the empirical exercise suggests several issues that allow understanding the complex crime and housing prices pattern. First of all, there is a close relationship between the housing transaction prices and the types of crimes, and findings support the idea that they are not independent.

Secondly, the type of crimes shows different patterns associated with housing transaction prices: positive and negative. The positive when the crime happens far away can be understood as the far the crime, the higher the price (in Non-aggravated assaults, burglary and vandalism) and the negative captures the discount on prices due to crime (in aggravated assaults and narcotics at all distances). The different reactions of housing prices to a type of crime and the robust relationship in the last two models support the idea of endogeneity.

Table 5. SPATIAL WEIGHTED 2STL RESULTS FOR HOUSING TRANSACTION PRICE MODEL AND CRIME

Dependent Variable : LN_PRICE

MODELS	OLS	2SLS	SW2SLS	SW2SLS	SW2SLS	SW2SLS	SW2SLS	SW2SLS	SW2SLS	SW2SLS	SW2SLS
	1	2	3	4	5	6	7	8	9	10	11
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
CONSTANT	3,249 ***	3,256 ***	2,340 ***	2,384 ***	2,266 ***	2,342 ***	0,294 ***	4,683 ***	4,683 ***	2,364 ***	2,344 ***
TOTCRIMES	**-0,000011** ***	**-0,000006** **	**-0,000005** **								
AGG0TO500				0,00205 ***	0,0016						
AGG0TO1000				0,00021	0,0003					-0,0019 ***	
AGG0TO2000				-0,00066 ***	-0,0001						-0,0005 ***
BUR0TO500				-0,00042		-0,0044					
BUR0TO1000				-0,00048 **		0,0015				0,0004 **	
BUR0TO2000				0,00029 ***		-0,0003					0,0000
NAR0TO500				-0,00136 **			0,0044				
NAR0TO1000				0,00055 **			0,0025 *			-0,0008 ***	
NAR0TO2000				-0,00030 ***			-0,0011 ***				-0,0002 ***
NAS0TO500				-0,00018				0,0016 **			
NAS0TO1000				-0,00014				-0,0005 **		0,0006 **	
NAS0TO2000				0,00023 ***				0,0001			0,0001 **
VAN0TO500				0,00028					0,0011		
VAN0TO1000				0,00077 **					-0,0003	0,0004	
VAN0TO2000				-0,00023					0,0001		0,0003 **
CONTROLS	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Crime variables	EXOGENOUS	ENDOGENOUS	SPATIAL-ENDOGENOUS	Spatial-EXOGENOUS	SPATIAL - ENDOGENOUS						
SPATIAL PARAMETERS											
W_LN_PRICE-ρ			**0,2878** ***	0,2706 ***	**0,2878** ***	**0,2955** ***	0,2938 ***	0,2893 ***	0,2907 ***	0,2747 ***	0,2779 ***
lambda											

REGRESSIONS TESTS											
R-squared	0,280										
Adjusted R-squared	0,280										
Pseudo R-squared		0,280	0,304	0,304	0,304	0,302	0,301	0,303	0,304	0,304	0,304
Spatial Pseudo R-squared			0,282	0,284	0,282	0,278	0,277	0,281	0,285	0,282	0,283
Σe2	96319,98										
F	1020,17 ***										
Num obs	128442	128442	128442	128442	128442	128442	128442	128442	128442	128442	128442
Nº Variables	50	50	51	65	53	53	53	53	53	55	55
Num Instruments		1	51+1	51	51+3	51+3	51+3	51+3	51+3	51+5	51+5
Anselin-Kelejian Test		3245,92 ***	43,268 ***	28,814 ***	43,291 ***	40,823 ***	37,554 ***	42,697 ***	46,31 ***	29,519 ***	34,395 ***
INSTRUMENTED VARIABLE-IV model		TOTCRIMES	TOTCRIMES, W*LN_PRICE	W*LN_PRICE	W_ln_price, agg0to1000, agg0to2000, agg0to500	W_ln_price, bur0to1000, bur0to2000, bur0to500	W_ln_price, nar0to1000, nar0to2000, nar0to500	W_ln_price, nas0to1000, nas0to2000, nas0to500	W_ln_price, van0to1000, van0to2000, van0to500	W_ln_price, agg0to1000, bur0to1000, nar0to1000, nas0to1000, van0to1000	W_ln_price, agg0to2000, bur0to2000, nar0to2000, nas0to2000, van0to2000

*** p-value>0.01, ** pvalue<0.05

The third finding is that the endogenous effect between housing prices and crime would be a mirage and the real impact comes from the negative externality in the neighbourhood created by the accumulation of crimes, increasing the unobserved heterogeneity affecting housing prices. The results of crime by distances suggest their relevancy when the crime typology is narcotics and aggravated assaults.

6. Conclusion

Our analysis identifies some interesting patterns concerning the effects of crime and housing transaction prices. It explores the behaviour of house prices in 2016 in Los Angeles County, US, by using a micro-data base of housing transactions to which a crime dataset has been merged. Using an endogenous modelling approach with spatial correction and Spatial Weighted Two Step Least Squares, the paper explores the relationship between different types of crime with housing prices at the spatial level.

First of all, the close relationship between the housing transaction prices and different types of crimes is put under doubt as paper findings suggest that estimated impact would be the result of the accumulation of crimes occurrences (as crime types are not independent spatially at least), which generates a negative externality in the neighbourhood, affecting housing price growth. Secondly, the type of crime shows different patterns in the association with prices: housing price reacts negatively to the commission of narcotics and aggravate assaults that are committed closer, and does not react to others, while the property crimes tend to be committed mainly in those areas where the house prices rise. The empirical exercise suggests that prices react positively when property, vandalism and non-aggravated assault crimes are committed far away.

Another relevant issue raised by this paper is the idea that the type of crimes, when isolated, has no direct impact on housing prices. In this case, when the concentration of crime happens (so crimes appear together), the negative effect is clearly captured by the endogenous models. The existence of hotspots of crime is the key issue for future analysis to understand the spatial pattern of crime and its effects on the housing market.

Crime has significant but quantitative small effects on LA housing transaction prices suggesting that the effect depends on the spatial scale as well as of lack on information about where the crimes are committed. Lack on information suggests low transparency in the market, affecting the transaction decision-taken process, affection the risk perception and with relevant implications over household welfare .

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