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Impact of crime on spatial analysis of house prices: evidence from a UK city

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1. Introduction

Crime is an externality that is perceived to have a detrimental impact across many activities and sectors including the property market. The expectation is that crime has a negative pricing effect on residential property, although in reality greater complexity is apparent and the extent to which impact occurs is variable. Frequently the literature has focused on crime, the relationships to deprivation measures and wider socio-economic characteristics, separately from property market considerations thus implications on performance and value/price, are not always sufficiently developed. Whilst there is a growing interest in the impact of crime on house price, the literature base is relatively embryonic but nevertheless international in flavor highlighting the relevance of understanding these relationships in different markets.

Previous research has shown that spatial autocorrelation effects exist in terms of house price but there is a lack of understanding on how such spatial effects impact on the property market. This paper seeks to develop the literature in this area through an analysis of spatial relationships between a range of crime variables and achieved house price. The hypothesis underpinning this paper is that spatial effects in the housing market are strong but how these are related to the incidence of crime and whether the effects vary by type of crime are key research questions to be addressed in this research.

This study contributes to the current knowledge base in several ways. Firstly, the paper shows with spatial-point detail how crime acts are distributed across space and how they are related to each other - thus highlighting crime models with spatial dimensions. Secondly, the research utilises new econometric methodologies to estimate house prices through spatial analysis while controlling for endogeneity. Thirdly, it estimates the direct impact of crime on house prices and includes the analysis of housing and neighbourhood features.

The paper is structured as follows. Section two provides a consideration of 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 that are utilized in this paper. Section five brings forward the results across a range of models examining different types of crime. Section six draws conclusions.

2. Literature Review

Stemming from the seminal studies by Lancaster (1966) and Rosen (1974) there has been a rich flow of literature generally based around hedonic analyses. These studies have sought to examine the impact of an array of externalities upon house price and whether these have had negative consequences, such as air quality and pollution, or positive impacts, such as accessibility to open space or view (Hui et al, 2007). Crime or perception of crime is included amongst those factors considered to lower property prices in a neighborhood and while there is an emerging body of literature, the impact of crime has received significantly less attention than other variables possibly arising from the potential high correlation and multicollinearity between crime and socio-economic variables. For example in the UK, Craglia et al (2001) showed that high intensity crime areas are characterized by high density, deprived populations and that high levels of violent crime fosters social disorganization with an inferred spatial effect.

The literature acknowledges that the impact of crime can be complex. Taylor (1995) while showing that high crime levels results in weaker attachment of residents to and satisfaction with their neighborhood, the desire to move and lower house prices simultaneously suggests that crime neither spurs mobility nor necessarily decreases local involvement. Taylor argues that different crimes influence different aspects of the housing market and that the impact of crime and related problems on neighborhood viability may be contingent on personal, historical, and locale-specific factors. Similarly, a study by Lynch and Rasmussen (2001) also casts doubt upon the extent to which the crime rate influences house prices. From an analysis of data on over 2800 house sales in Jacksonville, Florida they found that the cost of crime has virtually no impact on house prices at an overall level, though houses were significantly discounted in high crime areas.

Tita et al (2006) taking a slightly different perspective argue that crime is an important catalyst for change in the socioeconomic composition of communities, while such change is considered to occur gradually over time, crime is seen to be capitalized into local housing markets at different rates for poor, middle class and wealthy neighbourhoods. In a similar vein, Gibbons and Machin (2008) demonstrate that prices within urban areas exhibit highly localised variations that cannot be explained solely by differences in the physical attributes of dwellings but also reflect the role of local amenities and disamenities in generating price variation within cities, in particular, the role of transport accessibility, school quality and crime.

The literature also demonstrates that certain local amenities may have differing impacts on house price. Urban parks for instance are generally perceived as beneficial environmental amenities and hence should have a positive impact on house price though the propensity of parks to attract specific types of crime may also have negative impacts on house price. In this respect, the study by Troya and Grove (2008) in Baltimore is particularly illuminating showing that park proximity is positively valued by the housing market where the combined robbery and rape rates for a neighborhood are below a certain threshold rate[1] but negatively valued in locations above that threshold. Their analysis shows that the further the crime index value is from the threshold value for a particular property, the steeper the relationship is between park proximity and house price. Similarly, Matthews et al (2010) in an analysis of property crime in Seattle show that theft crimes are 23% higher for those census tracts with a public park. In relation to Stockholm, Ceccato and Wilhelmsson (2011) argue that if local crime levels are above the national average, park proximity has a negative impact on property values. Andresen and Malleson (2013) observe how the northern downtown peninsula of Vancouver, an area containing the city's largest park, has an increased concentration of all types of crime during the summer months highlighting that

[1] Depending upon model construction, the threshold occurs at a crime index value of between 406 and 484 that is, between 406% and 484% of the national average (the average rate by block group for Baltimore is 475% of the national average).

crime is mobile and not necessarily focused on deprived communities.

The literature suggests that the type of crime has differential impact on property prices. According to Gibbons (2003) in the UK, notably in London, crimes in the criminal damage category have a significant negative impact on prices, whereas burglaries have no measurable impact on house price. More specifically, Gibbons shows that a 0.1 standard deviation decrease in the local density of criminal damage adds 1% to the price of an average property in inner London. Pope (2008) employing a dataset that tracks sex offenders in Hillsborough County, Florida, found that after a sex offender moved into a neighbourhood, nearby housing prices fell by 2.3% ($3500 on average). However, once a sex offender moved out of a neighbourhood, housing prices appear to immediately rebound.

In Northern Ireland, Mueller and Besley (2012) assessed the impact of civil unrest on house prices and sought to estimate the peace dividend resulting from the cessation of violence. They utilized data on the pattern of violence across regions and over time to estimate the impact of the peace process. Their research indicates a negative correlation between murders and house prices. Also from Northern Ireland and reflecting the distinctive social geography of Belfast, McCord et al (2013) show how “peace walls” that cut across segregated communities, have resulted in a decline in value of 29.6 per cent for properties located within 250m of a peace wall.

From a methodological perspective, a key facet of the literature has been the increasing focus upon spatial analytics reflecting the growth of geographically referenced datasets for both housing markets and the spatial incidence of crime. Such analysis is characterized by complexity arising from the potential presence of spatial auto-correlation in data and the existence of spatial dependence or spatial lag (spatial autoregressive parameter), and spatial interaction arising from heterogeneity, the variation of relationships across space, or spatial error (Anselin, 1988). Vilalta (2013) observes that by not modelling spatial dependency and spatial heterogeneity the analysis of crime data may conceal valuable spatial information.

Within the literature, research from different cities demonstrates that the analysis of spatial structure of crime is an important consideration in the interpretation of housing markets. Matthews et al (2010) in an analysis of the distribution of property crime in Seattle, US, shows that spatial relationships vary depending upon the type of crime with spatial clustering of property crime apparent. Their analysis highlights that circa 80% of residual residential burglaries are due to variation of spatial structure. In Sydney, Australia, Abelson et al (2013) show that a propensity for violent crime significantly reduces property values. In their analysis a doubling of crime rate from 1.1% to 2.1% brings about a fall in the price of detached houses by 5.6%. A study from Stockholm, Sweden, by Ceccato and Wilhelmsson (2011) highlight that interpretation varies depending on the form of the model with both OLS and spatial lag models showing that crime rate had no significant impact on apartment prices, though in a spatial error model both crime and crime rate in neighbouring areas are negatively related to apartment price. According to their analysis a 1 per cent increase in crime rate leads to an expected fall in price by 0.04 per cent though if burglary increases by 1 per cent the expected fall was higher at 0.21 per cent. In relation to different types of crime, Ceccato and Wilhelmsson (2011) consider that different processes can produce varying perceptions contrary to expectations. For example thefts and vandalism in neighbouring areas were positively correlated with price. Their analysis also suggests that households in different parts of the city may have different tolerance levels towards crime leading to added complexity on price impact. Similarly Tita et al (2006) show that total crime has a negligible effect on house prices but violent crime is associated with a significant decrease in property values. Boggess et al (2013) articulate the same message in terms of the impact of violent crime on the volume of transactions.

In summary, the literature indicates that a complex set of factors may influence the relationship between crime, the location of crime and impact on house price requiring both robust datasets and the application of spatial modelling techniques to measure the effect of spatial lag and spatial error. The next sections of the paper review the dataset and variables utilized for this research (section 3) and the modelling techniques employed (section 4).

3. Data

The data for this paper relate to the Belfast Metropolitan Area (BMA) for which a rich set of property, neighbourhood/location, socio-economic and crime variables have been assembled across a range of sources. The choice of case study is particularly illuminating as the BMA provides a laboratory where submarkets notably in the west and north of the city are segmented on the basis of religious belief, catholic and non-catholic, whereas in the south and east of the city and the greater metropolitan area housing submarkets are structured more on income and socio-economic status (Adair et al, 1996) and in this respect are similar in structure to other major UK cities. Indeed, Belfast is also an interesting city to analyse as historically, organised crime and terrorism were the predominant crime types present. Post-Good Friday Agreement in 1998[2], Belfast has seen a distinct evolution of its crime typology and as a consequence, a greater understanding of the impact of crime must be achieved, particularly in relation to socio-economic impacts. Thus the BMA presents a tapestry in which housing markets have an overlay of segregation that has persisted historically and which is still evident. While the choice of case study has particular local nuances this is not unique with many cities worldwide characterized by segregated markets. Hence the contribution that this paper makes to the spatial analysis of the impact of crime on housing markets has wider application and relevance. Furthermore, the analysis and modelling is facilitated by a comprehensive dataset comprising three sets of variables: property characteristics including transaction price, locational factors and crime statistics.

The property variables are sourced primarily from the Northern Ireland Quarterly House Price Index[3] (NIQHPI) with data on characteristics cross-tabulated against evidence from Land and Property Services, the government agency responsible for valuation services in Northern Ireland. The NIQHPI accesses information on sales transactions across a wide network of selling agents, including major and smaller practices in Northern Ireland. The paper utilizes a subset of this database for sales within the BMA over twelve quarters from the first quarter of 2012 to the final quarter of 2014. The sample size (n=4325 properties) includes only those properties for which specific address was available thereby facilitating the geo-coding of each property. Property price is the actual transacted price[4] and for each property the following characteristics are known: type in terms of six categories (terraced house, semi-detached house, detached house, semi-detached bungalow, detached bungalow, apartment, (dummy variable for each type range, called Type#), age band again six categories (pre-1919, 1919-1939, 1940-1959, 1960-1980, Post-1980, new development), the floor area of the property, number of bedrooms, number of reception rooms, heating

[2] The Good Friday Agreement or Belfast Agreement saw a settlement between the different political parties in Northern Ireland leading to a power sharing Executive
[3] The Northern Ireland Quarterly House Price Index is a quarterly survey of the housing market conducted by Ulster University since 1984.
[4] Mean price of £175,986 and a standard deviation of £140,699.

type (electrical, oil, gas, solid fuel) and whether the property has a garage. Each property also has a location variable in the form of a local X,Y coordinate.

Seven neighbourhood/location variables were incorporated in this study and consisted of distance to bus stop, distance to retail centres, distance to open space/parks, distance to interface areas, distance to police stations and distance to fire train stations. The spatial distance of these variables was calculated in a proprietary GIS using a Euclidean distance calculation tool. This was achieved through utilising the absolute location of each property sales transaction (X, Y coordinate) and calculating distance in metres to the nearest facility (interface, police station, train station). Through this approach, the analysis captures the neighbourhood effect (Table 1).

Insert Table I Neighbourhood Variable Descriptions

The core of this paper is concerned with the impact of crime on property values between 2012 and 2014. To measure this effect, the paper utilizes six specific crime variables, namely violence against the person, criminal damage, drugs offences, burglary, theft and other crime[5]. The crime data was sourced from police.uk which is published by the United Kingdom Home Office and provides X, Y coordinates of individual crime events are categorized using the crime typology[6] set by the UK Home Office. The data specific to this paper relates to the police force area of the Police Service of Northern Ireland who provides this data to the Home Office and was made available through an Open Government License[7]. A description of each of these crime variables is illustrated in Table 2. The crime data are the total number of events that occurred in each neighborhood. Crime effect on the neighbourhood is captured by the number of crime events by year. However, any remaining unobserved variables affecting prices is also captured by the spatial error term in the spatial model.

Insert Table II Crime Variable Descriptions

Descriptive statistics relating to the property, neighborhood and crime data are presented in Table 3.

Insert Table III Basic Statistics

The literature has identified strong correlation between crime and socio-economic variables. This analysis captures the latter through a multiple deprivation index, sourced from the Northern Ireland Statistics and Research Agency[8], and used in this research as an instrumental variable (Section 4).

4. Methods and model development for spatial analysis

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5 The aggregate of these individual variables gives a total crime figure.

6 For Crime Typology Mapping between police.uk and Home Office see: https://www.police.uk/about-this-site/faqs/#what-do-the-crime-categories-mean

7 For information on Open Government License see: http://www.nationalarchives.gov.uk/doc/open-government-licence/version/3/

8 For an explanation of the deprivation measurement in Northern Ireland, please see http://www.nisra.gov.uk/deprivation/nimdm_2010.htm

The analysis follows two stages[9]. The first is an exploratory analysis of crime variables with the objective of identifying and analysing univariate/bivariate spatial patterns in the data and establishing the nature and direction of relationships between crime variables and house prices in the dataset. The second is the application of spatial auto-regression models (SAR) to estimate the role of crime on house prices in the BMA controlling by spatial association. More specifically a SW2SLS (HET) (Spatial Weighted Two Stage Least Squares with Kelejian and Prucha robust standard errors) method is employed for the house price model specification, defined with a hedonic shape to analyze the joint impact of crime variables on house prices.

4.1 Spatial analysis of crime variables

Spatial patterns in house prices and crime variables arguably are best established using Moran's I and Local Indicator Spatial Association (LISA) models which enable variation of spatial dependence between two variables to be studied. More widely in the real estate sector, (McGreal et al., 2015) have the benefits of utilizing these techniques and specifically in the crime sector Zhang and McCord (2014) provide a useful illustration of the application of this type of spatial analysis in establishing relationships between foreclosures and crime rates in the Louisville Metro (Kentucky, USA). In the case of Seattle, Matthews et al (2013) utilizing Moran's I identified localized spatial effects for different types of crime.

In determination of Moran's I, our analysis utilizes the Queen contiguity matrix (GAL), based on actual contiguity of properties (Table IV). For each of the crime variables, the analysis is consistent revealing high positive values with little variation in univariate Moran's I apparent, ranging from 0.936 for burglary to 0.868 for drugs offences. The results infer the strong existence of spatial autoregressive patterns in the crime variables and clusters in the BMA. LISA analysis identifies the location of these clusters. For example, Figure 1 represents the local clusters for the total crime variable with two main clusters apparent. One of these clusters (H-H) is located in the centre/inner city area where a high number of offences in the neighbourhood are associated with the higher and increasing number of crimes in a particular location. The second cluster (L-L) is where a low numbers of crimes at a location are associated with lower crimes in the neighbouring area thereby creating a cluster in which the number of crimes is reducing. Strong L-L clusters are in suburban and out of town locations. Broadly the same pattern is evident across each of the crime variables with only a small difference spatially, notably in relation to the H-H central location. For house price, univariate analysis yields a Moran's I value of 0.45 suggesting a spatial association of price data at a local level and inferring that when the prices of neighbouring properties are likely to be high, the price of a particular property is high.

Insert Figure 1: Total crime univariate analysis LISA clusters

[9] The analysis is run on an annual basis and in this paper we present the results for 2014. The previous are available from the authors on request.

The univariate analysis is important in identifying the presence of clusters, whereas bi-variant Moran's I statistics allow the analysis of the spatial pattern between house prices and crime. Central to this paper are questions concerning how spatial lagged crime variables could affect house prices, the power of such association and the existence of clusters. For this aspect of the analysis the Morans'I tests are undertaken in levels and in logs format (Table 4). The analysis, revealing low and negative Moran's I, is indicative of the relative non-existence of spatial association at an aggregate level and seemingly distributed randomly. The outcome of no spatial association at a general level, while surprising, is apparent for all crime variables.

Insert Table IV: Spatial analysis of crime variables, Moran's I and LISA

In contrast to the global Moran's I, LISA analysis shows that a spatial pattern exists for all of the crime variables at a local level with the number of significant observations varying between 39.83% for drugs offences to 47.77% for criminal damage. Various clusters are apparent across the BMA as illustrated in Figure 2 (total crime variable). In central/inner city locations, a L-H cluster indicates that the lower crime is in a neighbourhood, the higher are house prices. This area also includes neighbourhoods where high crime in the form of burglary (BURG) is associated with high house prices (H-H). Of particular interest is the occurrence of a number of H-L clusters and where these overlap with existing high priced locations the effect of increasing crime will be to act as a dampening effect on house price. The bilateral LISA analysis captures the marginal effect and highlights neighbourhoods that are price sensitive to changes in crime rates. In consequence, such relationship between crime and house prices suggests that prices could be affected by the crime at neighborhood level revealing that crime and housing prices have an endogenous relationship. As a result, endogeneity should be considered in the model to avoid biased estimations.

Insert Figure 2: Price – total crime bivariate analysis LISA clusters

4.2 SAR model of housing prices and crime

This paper analyses the impact of crime on house price following a hedonic perspective with prices explained through the characteristics discussed (property, location, crime). Equation 1 establishes the general form of the model which is subsequently modified to include spatial terms.

(1) $$P_i = \alpha + \Sigma[\beta_{1k}x_{ki}] + \Sigma[\beta_{2f}N_{fi}] + \Sigma\gamma_d C_{di} + \varepsilon_i$$

where,

X.. is a set of seven (*k*) housing characteristics of which six are categorical (age, bedrooms, garage, heat, type of heat and type of house) and one is continuous, size, measured in square metres

N… are another seven (*f*) neighborhood features which capture location characteristics through distance (in metres) to relevant points in the neighbourhood

C … is a set of six (*d*) of crime variables measured in terms of the number of offenses, VAP (violence against the persons), BURGL (burglary), theft, CD (Criminal Damage), DO (drugs offences) and AOO (all other offences).
$\beta 1$ and $\beta 2$ .. are the marginal effect of housing features and neighbourhood characteristics in prices, to be estimated
α .. is a parameter to be estimated
γ .. quantify the association between crime and house prices.
ε .. is the error measure

The model includes the six different measures of criminal offences as individual variables in order to capture their association with house prices rather than their summation into a total number of crimes to avoid aggregation bias in the model. In this analysis, the crime data used refer to 2014 only.

As house prices show a spatial pattern (univariate Moran's I) and spatial auto regression, a SAR functional form was utilized in the model (Equation 1). The existence of spatial correlation suggests that the dependent variable follows the expression of Anselin (1999) $Y = \rho Wy + X\beta + \lambda W\varepsilon + \mu$ with W being the nxn spatial weights matrix, resulting in the spatial lag term (Wy) and ρ being the spatial autoregressive parameter. The spatial error autocorrelation where individual errors are spatially related is defined as $E[\varepsilon_i\ \varepsilon_j]=\Sigma = W\varepsilon_I$, with λ being the spatial error parameter. In panel data, ε incorporates spillover across properties defined through W and μ is a vector of specific location errors, with $E[\mu\mu']=\sigma^2\Omega$ to allow for heteroskedasticity.

The bivariate analysis demonstrates that crime types are spatially related to house prices defining clusters at a local level. Endogenous relationships between crime and housing characteristics were tested in the LISA analysis and no statistically significant association (no causal, nor spatial) was found to exist at the global level. However, high correlations are apparent between crime variables suggesting some simultaneous determination of crime types. Furthermore crime variables show strong clusters that are spatially associated with price suggesting that crimes are more likely to be committed in some areas rather than in others.

Thus the model for the BMA needs to adapt Equation 1 to include property characteristics, neighbourhood features and spatial association derived from both spatial continuity influence (spatial lag) and from the unobservable features (spatial error), with the crime endogenous. The latter is estimated using a set of instrumental variables (z) capturing their spatial association (z*W) within the model.

The analysis is essentially cross-sectional based on data for the period 2012-2014 and is re-defined as Equation 2

$$(2) \qquad P_i = \alpha + \rho WP_{i-j} + \Sigma[\beta'_{1k}x_{ki}] + \Sigma[\beta'_{2f}N_{fi}] + \Sigma\gamma'_d C_{di} + \lambda W\varepsilon_i + \mu_i$$

Where,

C … are a set of the six endogenous crime variables[10].
W … is the spatial weight matrix which allows estimation of the spatial association.
β'_1 and β'_2 .. are the robust parameters estimators for housing features and neighborhood characteristics in the spatial framework
γ' .. is the IV estimated parameters measuring the association between crime and house prices.
ρ .. is the spatial price autoregressive parameter to be estimated, capturing the effect on prices due to the proximity of other houses
λ is the spatial error parameter measuring the spatial association affection housing prices related to unobservable characteristics in the neighborhood
μ_l is a vector of specific location error which are uncorrelated and normal distributed.

The continuous variables (price, size and distance variables) are measured in log terms, thus the model measures changes in variables and the parameter interpretation is pseudo-elasticity. The functional form described in Equation 2 is estimated using a General Spatially Weighted Two Stage Least Square (GSWTSLS) with robust estimators as described in Kelejian and Prucha (2010). Two types of instrument are used. One includes calculation of the IV estimator for C, the instruments (zi) used are the variable MDMRANK which measures the deprivation rate associated to each neighborhood and the lagged crime variables, all of which are strongly correlated to the six crime measures. The second instrument is used to estimate W*Pi-j, in this case, the spatial methodology uses the spatial lagged exogenous variables (W*Xi).

5. Results and findings

Model results (Table 5) show high levels of association between the dependent, the independent and endogenous variables. Pseudo R^2 [11] with values greater than 0.6 in all models suggests a high level of association. Likewise the spatial pseudo R^2 in excess of 0.68 across all models indicates that spatial relationships are strong in explaining house price variations in the BMA, an outcome in line with expectations given the segmentation in the housing sector notably in the city of Belfast. The overall model which includes all crime variables (Model 1) confirms that a spatial autoregressive pattern exists with both the spatial lag parameter rho (0.28) and the spatial error parameter lambda (0.27) having positive signs suggesting that circa 28% of the variation in house price arises from the price of adjacent properties and a further 27% is attributable to unobserved variables in the neighbourhood.

Insert Table V General spatially weighed two stage least squares model

[10] As C is engoneous to P, the model estimates the latter using instrumental variables to approach C in the first step, that is, doing C = $\Phi(z_i, W)$ with z_i being the matrix of instruments used in the analysis for endogenous control of C variables and Φ the endogenous functional form.
[11] Pseudo R^2 is a standard measure of goodness of fit

Assessing the effects of individual crime variables (Models 2 to 7) leads to subtle changes in spatial association. The spatial lag parameter increases in each of these respective models suggesting that changes in the neighbourhood having increasing influence in determining changes in observed house prices. In contrast, the value of the spatial error parameter diminishes appreciably inferring that changes in house prices arising from unobserved variables reduces when the effects of a specific type of crime are considered. Crime variable theft (Model 4) is particularly relevant; its presence in the model is associated with a null spatial error effect on house price change with lamba being insignificant suggesting that no unobservable effects are influencing house price.

The hedonic price model (Model 8) captures the effects of only housing characteristics and neighbourhood/location variables on house price change. The results reflect expected signs and impact with a one percent increase in house size leading to a house price rise of 0.75%; an inelastic relationship that is in accordance with previous research on non-linearity between size and prices (Palmquist, 1984). The addition of crime variables, either all variables as in Model 1 or individual crime variables (Models 2 to 7) does not fundamentally change this relationship. Age of property shows expected depreciation with negative coefficients apparent relative to new build property, though not statistically significant for houses in the oldest age categories (AGE1 and AGE2). This relationship is consistent across most of the individual crime models, with the exception of Model 3 (burglaries) and the overall model (Model 1) with all crime variables considered. Price also increases with the number of bedrooms, one extra bedroom indicating an increase of 6.3% (the parameter equals 0.06%) that is consistent across all the models. Similarly a garage is strongly significant in all estimated models, the strongest coefficients being observed for Models 3 and 4 inferring that the incidence of burglary or theft provides an additional price enhancement. The coefficients for property type (relative to apartments, omitted case) are generally negative across the respective crime specific models suggesting a lower price though whether this is attributable to crime is debatable as negative coefficients are also apparent in Model 8 (no crime variables added). Detached property, houses in particular (Type 3), have positive coefficients across the models which may simply be measuring a price differential with apartments though this observation is consistent with literature which suggests that certain types of crime, notably burglary, are associated with higher price property (Model 3, significant positive coefficient for detached houses and detached bungalows - Type 5).

A number of neighbourhood/location effects are considered; these are shown to be less consistent than property characteristics regarding their impact on house price. For instance, proximity to a bus stop is not statistically significant when all crime variables are omitted measure (Model 8) and equally so is not significant when all crime measures are included (Model 1). However this variable becomes statistically significant in a number of the crime-specific models. In the models violence against the person (VAP), criminal damage (CD), drugs offences (DO) there is a negative relationship between house price and distance to a bus stop whereas the model that includes the incidence of theft shows the reverse effect namely higher house price with distance from bus stops. These varying relationships suggest that house prices may be influenced to a subtle extent by the type of crime. Similar negative, significant relationships are apparent with the variable distance to train station in Model 2 (VAP), Model 5 (CD) and Model 6 (DO) suggesting that crime effect (type of crime) has an element of consistency across transport modes an effect that has not be identified by previous hedonic studies considering the proximity of transport modes on house price.

Many hedonic studies on house price have modelled distance to CBD as a standard variable. The analysis suggests that this relationship may be sensitive to the perception of certain types of crime. Model 8, which excludes consideration of crime, infers a positive association across the BMA. While all models have the same sign for this variable several models (1, 2, 3 and 5) are not significant suggesting that type of crime is impacting on assumptions regarding the effect of distance on house price. Similarly, various hedonic studies (de Roisiers, 2002) have shown that proximity to job location (JBO) has an important effect on house price. The models generated in this paper based on crime variables suggest differing outcomes with several models (2, 5, 6, 7, 8) demonstrating a significant negative effect whereas models 3 and 4, burglary and theft, have a positive but insignificant effect between house price and job location.

Distance to open space (OSP) provides a further indicator of the effect of crime on property prices. While it may be hypothesized that open space may enhance value this analysis suggests the contrary. The model excluding crime variables (Model 8) shows a positive but not statistically significant effect whereas Model 1, which includes all the crime variables, has the same sign but becomes statistically significant with the inference that house price increases with distance from open space. A number of studies reviewed in the literature section of this paper have shown the crime increases in parks and other public spaces. In this respect the analysis from the BMA is consistent with the literature in terms of perception of crime and impact on house price with models 3 (burglary), 4 (theft), 6 (drug offences) and 7 (other crimes) having significant positive coefficients for the association between price and open space.

A specific characteristic of Belfast as articulated in section 2 of the paper is the continuing presence of peace walls that divide segregated communities notably within inner city areas in west and north Belfast (McCord, et al, 2013). The models generated in this paper demonstrate that proximity to a peacewall (PEACE), in accordance with expectations, shows a positive association with house price change, namely higher price with distance from a peacewall. The value of the coefficient for PEACE is appreciably higher in Model 1 and significant (includes all crime variables) relative to Model 8 (no crime variables included) inferring an added effect when crime measures are taken into consideration. However, and indicative of complexity posed by the impact of crime and local geography within Belfast's segregated communities, some of the specific crime models have negative coefficients for the peacewall variable. For example, the model that includes drugs offences (Model 6) suggests that this variable is associated with a negative (though not significant) association between house price and distance from a peacewall which may be reflective of local circumstances in these communities in controlling drug offences.

Across all models, distance to a police station is statistically significant and negatively associated to house prices. This suggests that the closer properties are to a police station the higher the price due to the perception of greater security and lower incidence of crime. This inference is supported by the larger coefficient for the variable distance to a police station in Model 1 (includes all crime variables) indicating that for every 1% reduction in the distance from a house to the police station there is a 0.06% increase in price. In Model 8 (no crime variables) this translates into a 0.036% increase in price. Of the individual crime specific models the strongest effect is for Model 3 (burglary) for which the effect of a 1% reduction in distance is a 0.05% increase in price.

The overall model (Model 1) shows a statistically significant association with house price and crime variables: two with positive relationships (burglary and theft) and one negative (other offences). Burglary is strongly significant and suggests that a 1% increase in such attacks is associated with a 0.138% increase in house prices inferring that in more dynamic and higher priced neighbourhoods, the greater the incidence of burglary. Theft has a similar relationship although lower effect (1% increase in theft is associated with a 0.084% price increase). In the case of other offences (AOO), the association is strongly significant but negative with a 1% increase associated with a reduction in house prices of 0.152% suggesting that such crimes are connected with less dynamic locations. In Models 2 to 7 the respective individual crime variables are all significant and as discussed are associated with a reduction in the spatial error parameter. The single crime variable models confirm the positive coefficients for burglary (Model 3) and theft (Model 4) lending support to the inference that these type of crime are associated with higher priced, higher income neighbourhoods whereas violence against the person (Model 2), criminal damage (Model 5), drug offences (Model 6) have negative coefficients and are associated with a reduction in house price[12].

6. Conclusions

A key conclusion of this research is that the general expectation of crime having a negative pricing impact on residential property is in reality much more complex and varies in its influence by type of crime, type and location of property. In this respect an original contribution of this paper is highlighting the nuances of various types of crime on house price. The paper by seeking to differentiate the impact of crime provides an analysis of the pricing effect masked in many earlier studies by high correlation and multicollinearity between crime and socio-economic variables.

[12] The consistency of the results across the different reduced crime models, together with the comprehensive range of variables included in the analysis, is indicative in that omitted variable bias is not an issue in this analysis.

This study extends the body of knowledge on the impact of crime, an under-researched externality, by using an innovative approach to statistical modelling to draw out the complex interrelationships between type of crime, housing characteristics, locational variables and house price. The paper shows that the addition of crime variables in their entirety or as individual variables does not fundamentally change the primary relationship of house size as the principal variable impacting on house price. The study also confirms earlier work that certain types of crime notably burglary is associated with higher priced property namely detached houses and bungalows and in this regard a number of interesting nuances are provided by the analysis namely, the incidence of burglary and theft results in a higher price premium for presence of a garage. Overall the analysis shows that burglary and theft are associated with higher income neighbourhoods whereas other types of crime namely, violence against the person, criminal damage, drug offences are mainly found in lower priced neighbourhoods.

Neighbourhood/locational influences on price are shown to have a lesser impact than property characteristics, a finding common to other studies, yet in this analysis there are subtle differences. The findings indicate that the probability of violence against the person increases with distance from a bus stop with a negative impact on house price. Indeed the consistency of this finding across other transport modes (distance to train station) is an important consideration. Distance to a police station is negatively associated to house prices with proximity showing higher prices inferring greater security with the strongest effect for burglary where a 1% reduction in distance shows a 0.5% increase in price. The analysis shows sensitivity of certain types of crime to distance to the CBD. Proximity to job location has been shown to be an important influence on house price in other studies, however in this paper several models indicate different outcomes with a significant negative effect. In relation to open space, the analysis shows house price increasing with distance from open space. In this respect the findings concur with earlier studies and specific models including those for burglary, theft, drug offences and other crimes support this outcome.

Overall the analysis shows that crime does not have a uniform impact across the housing market but is highly differentiated with impact varying by property type. The study confirms that spatial information is essential in the analysis of the variation of property price with extension in to other housing market characteristics. Univariate Moran's I indicates spatial autoregressive patterns in crime data however spatial association between price and crime variables is less apparent at a global level though LISA models indicate in circa 45% of cases, that local spatial clusters are apparent. The results show that spatial lag (rho) suggests that 28% of the variation of house price arises from the price of adjacent properties and 27% is attributable to unobservable effects. A key finding is the reduction in the spatial error effect in models based on individual crime variables. More generally a criticism of hedonic pricing and its application has been the influence of the unexplained error effects, the significance of this paper suggests that greater use of crime data and spatial analytics may enhance models and reduce error effects.

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Figure 1: Total crime univariate analysis – LISA clusters

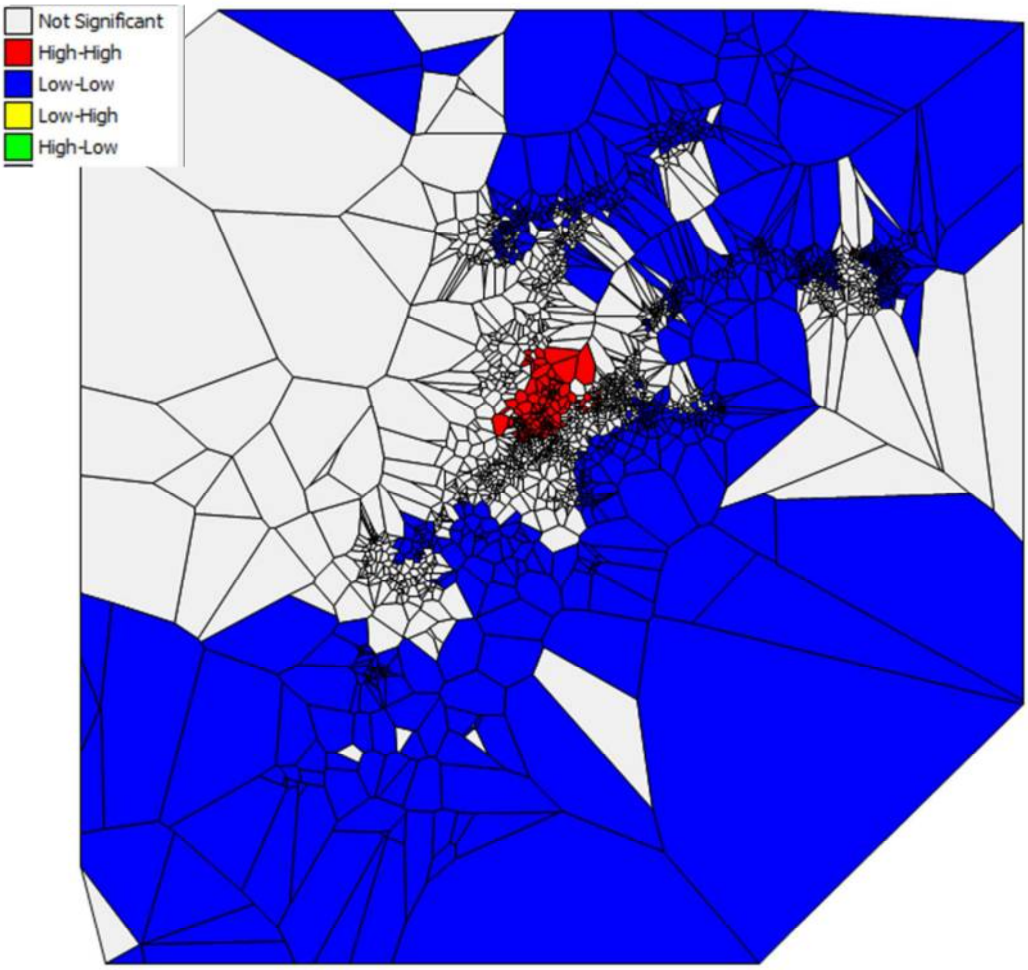

Figure 2: Price - total crime bivariate analysis, LISA clusters

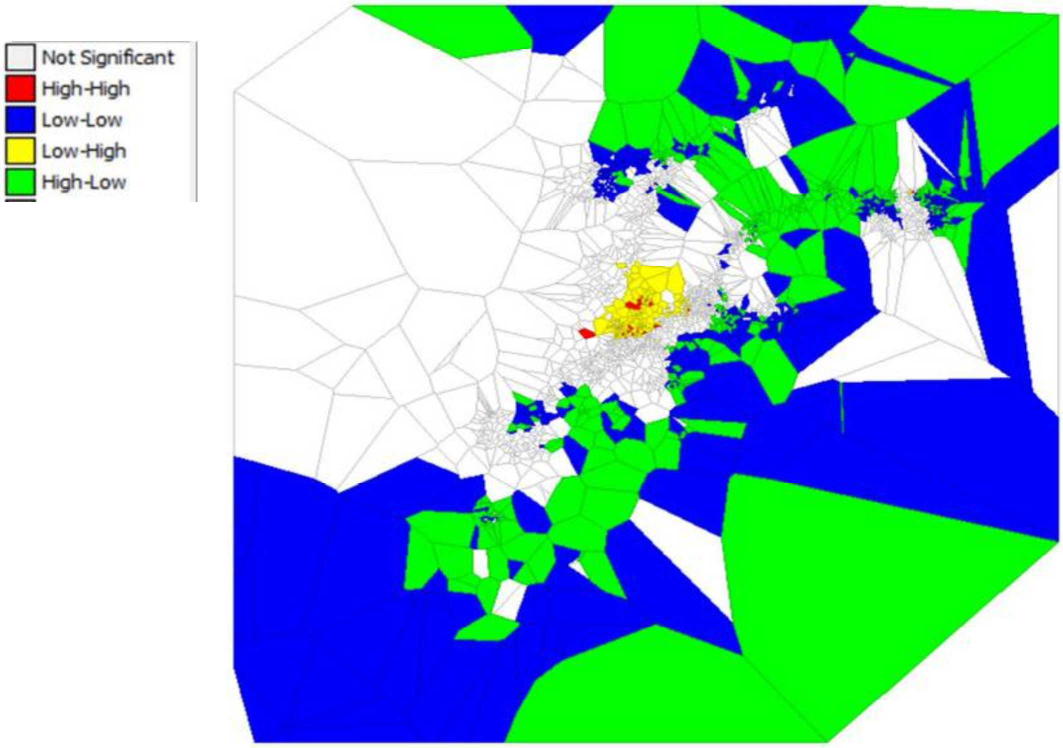

Table 1: Neighbourhood Variable Descriptions

Neighbourhood Variable	Measurement Description
Distance to bus stop	Distance to nearest bus stop
Distance to CBD	Distance to nearest central business district
Distance to retail centres	Distance to nearest major retail facility
Distance to open space/park	Distance to nearest park or open recreational space
Distance to interfaces	Distance to nearest interface between Loyalist and Republican areas
Distance to police station	Distance to nearest police station
Distance to train	Distance to nearest train station

Table 2: Crime variable descriptions

Crime Variable	Measurement Description
Violence Against the Person (VAP)	Includes offences against the person such as common assaults, Grievous Bodily Harm and sexual offences
Burglary (BURG)	Includes offences where a person enters a house or other building with the intention of stealing
Theft	Includes crimes that involve theft directly from the victim (including handbag, wallet, cash, mobile phones) but without the use or threat of physical force; Includes theft by an employee, blackmail and making off without payment and also bicycle theft
Criminal Damage (CD)	Includes damage to buildings and vehicles and deliberate damage by fire
Drug Offenses (DO)	Includes offences related to possession, supply and production
Other Crime	Includes forgery, perjury and other miscellaneous crime

Table 3. Basic Statistics

Variables	#	Mean	Median	Mode	Standard Dv.	Varianze	Assymettry	Kurtosis	Min	Max
RC14	4376	301,724	130	84	575,611	331328,044	5,728	37,915	0	4758
VAP14	4376	93,114	37	28	196,079	38447,043	6,499	48,831	0	1726
BURG14	4376	31,351	14	14	54,513	2971,655	4,866	27,885	0	403
THEFT14	4376	95,422	39	11	218,307	47657,860	6,326	46,168	0	1885
CD14	4376	54,764	33	53	84,167	7084,075	4,157	19,114	0	539
DO14	4376	10,586	6	0	21,171	448,195	5,832	39,134	0	176
AOO14	4376	16,487	10	6	27,547	758,852	6,393	49,122	0	247
PRICE	4376	175881,7	141000	125000	140621,5	19774417242,1	5,054	53,158	1000	2820000
Type1	4376	0,223	0	0	0,416	0,173	1,331	-0,228	0	1
Type2	4376	0,293	0	0	0,455	0,207	0,908	-1,177	0	1
Type3	4376	0,239	0	0	0,426	0,182	1,226	-0,498	0	1
Type4	4376	0,020	0	0	0,140	0,020	6,840	44,800	0	1
Type5	4376	0,065	0	0	0,246	0,061	3,541	10,545	0	1
Type6	4376	0,160	0	0	0,367	0,134	1,856	1,445	0	1
AGE1	4376	0,005	0	0	0,067	0,005	14,695	214,050	0	1
AGE2	4376	0,011	0	0	0,106	0,011	9,197	82,627	0	1
AGE3	4376	0,255	0	0	0,436	0,190	1,126	-0,733	0	1
AGE4	4376	0,474	0	0	0,499	0,249	0,105	-1,990	0	1
AGE5	4376	0,179	0	0	0,384	0,147	1,672	0,795	0	1
AGE6	4376	0,076	0	0	0,265	0,070	3,199	8,234	0	1
BEDS	4376	3,132	3	3	0,944	0,891	0,435	0,831	1	7
GARAGE	4376	0,313	0	0	0,464	0,215	0,805	-1,352	0	1
HEAT	4376	0,996	1	1	0,060	0,004	-16,453	268,812	0	1
HEATTYPE	4376	2,496	3	3	0,572	0,327	-0,380	-0,628	1	4
SIZE	4376	1263,54	1000,00	1000,00	640,46	410194,48	1,869	4,317	400	6931
DIST_Peace	4376	7543,41	5636,54	2462,90	6274,88	39374117,71	1,356	3,804	3,88	62733,01
DIST_BUS	4376	4737,62	4205,62	7830,18	2835,02	8037335,21	0,891	1,726	23,45	31058,94
DIST_POLICE	4376	2071,29	1614,09	152,47	1779,09	3165163,32	3,028	22,847	10,64	30742,83
DISTCBD	4376	3961,13	3055,97	2071,61	5403,63	29199225,22	8,546	104,593	33,15	106268,12
DIST_JBO	4376	4647,67	2959,12	1863,63	3983,41	15867594,94	1,358	2,116	35,28	31510,48
DIST_TRAIN	4376	2436,70	1662,61	348,21	2766,52	7653651,68	5,881	79,607	38,19	63550,67
DIST_OSP	4376	757,12	599,15	930,75	789,50	623305,47	13,977	412,836	10,98	28673,08
MDMRank	4376	407,74	470,0	407	168,37	28347,87	-0,95	-0,263	0	582
RC13	4376	275,28	135,0	66	527,64	278399,89	5,77	38,240	0	4367
VAP13	4376	80,55	41,0	16	172,60	29789,21	6,24	45,024	0	1487
BURG13	4376	28,79	16,0	7	41,10	1689,10	4,28	22,141	0	291
THEFT13	4376	88,69	39,0	11	205,72	42321,62	6,50	48,251	0	1792
CD13	4376	53,72	30,0	28	81,89	6706,00	4,30	20,256	0	517
DO13	4376	9,55	5,0	1	20,08	403,13	5,25	30,645	0	154

Table 4. SPATIAL PATTERN in Crime variables

Spatial model of crime	Spatial association between Price and Crime (using Gal Weight matrix)			
Moran's I	Moran's I		LISA*	
GAL (contiguity) Weight Matrix	levels	in logs	Statistically significant obs- %	No statistically significant obs -%
0.907	-0.095	-0.178	45.76	54.24
0.888	-0.110	-0.249	44.72	55.28
0.936	-0.035	-0.041	45.83	54.17
0.896	-0.073	-0.103	45.16	54.84
0.928	-0.121	-0.179	47.77	52.23
0.868	-0.107	-0.235	39.82	60.18
0.883	-0.105	-0.182	41.06	58.94
	*Total observations		4325	

TABLE 5. General Spatially weighted two stage least squares model (GSW2SLS-HET) OF HOUSING PRICES IN BELFAST

Dependent Variable:	Log (housing prices)…	LPRICE			LPRICE			LPRICE			LPRICE			LPRICE			LPRICE			LPRICE			LPRICE		
	MODEL	1			2			3			4			5			6			7			8		
	Variable	Coef	Std.Error		Coef	Std,Error		Coef	Std,Error		Coef	Std,Error		Coef	Std,Error		Coef	Std,Error		Coef	Std,Error		Coef	Std,Error	
	α	2.780	0.294	***	3.155	0.350	***	1.06	0.27	***	0.697	0.324	**	2.595	0.302	***	3.205	0.355	***	2.716	0.316	***	2.310	0.241	***
	AGE1	-0.165	0.062	***	-0.045	0.061		-0.17	0.06	**	-0.078	0.060		-0.048	0.061		-0.052	0.059		-0.037	0.061		-0.052	0.061	
	AGE2	-0.155	0.075	**	-0.064	0.072		-0.17	0.07	**	-0.081	0.073		-0.069	0.072		-0.073	0.073		-0.062	0.072		-0.066	0.072	
	AGE3	-0.290	0.026	***	-0.199	0.020	***	-0.29	0.02	***	-0.210	0.020	***	-0.199	0.020	***	-0.216	0.021	***	-0.180	0.019	***	-0.194	0.020	***
	AGE4	-0.214	0.022	***	-0.162	0.017	***	-0.23	0.02	***	-0.163	0.016	***	-0.165	0.017	***	-0.173	0.017	***	-0.150	0.017	***	-0.159	0.017	***
	AGE5	-0.144	0.024	***	-0.103	0.021	***	-0.16	0.02	***	-0.110	0.020	***	-0.109	0.021	***	-0.119	0.020	***	-0.101	0.020	***	-0.101	0.021	***
	BEDS	0.062	0.010	***	0.059	0.010	***	0.05	0.01	***	0.054	0.010	***	0.057	0.010	***	0.057	0.010	***	0.054	0.010	***	0.057	0.010	***
β'_1	GARAGE	0.053	0.011	***	0.050	0.011	***	0.07	0.01	***	0.073	0.011	***	0.053	0.010	***	0.042	0.011	***	0.050	0.010	***	0.060	0.010	***
	HEAT	0.081	0.082		0.106	0.091		0.11	0.08		0.113	0.087		0.113	0.090		0.104	0.086		0.096	0.092		0.110	0.089	
	HEATTYPE	0.053	0.010	***	0.046	0.009	***	0.05	0.01	***	0.044	0.009	***	0.047	0.009	***	0.049	0.009	***	0.048	0.009	***	0.043	0.009	***
	LSIZE	0.725	0.027	***	0.765	0.027	***	0.74	0.03	***	0.746	0.028	***	0.769	0.027	***	0.770	0.027	***	0.771	0.027	***	0.769	0.027	***
	TYPE1	-0.092	0.024	***	-0.144	0.023	***	-0.11	0.02	***	-0.134	0.023	***	-0.145	0.023	***	-0.150	0.023	***	-0.156	0.023	***	-0.144	0.023	***
	TYPE2	0.034	0.023		-0.047	0.021	**	0.02	0.02		-0.009	0.022		-0.047	0.021	**	-0.050	0.022	**	-0.061	0.021	***	-0.039	0.022	***
	TYPE3	0.146	0.027	***	0.053	0.026	**	0.12	0.03	***	0.081	0.026	***	0.049	0.026		0.044	0.026		0.037	0.025		0.059	0.026	**
	TYPE4	0.004	0.035		-0.085	0.034	**	0.02	0.03		-0.001	0.034		-0.081	0.033	**	-0.076	0.034	**	-0.098	0.034	***	-0.067	0.033	**
	TYPE5	0.128	0.030	***	0.056	0.029		0.12	0.03	***	0.097	0.030	***	0.056	0.028		0.043	0.029		0.040	0.028		0.067	0.028	**
	LD_BUS	-0.019	0.014		-0.044	0.012	***	0.01	0.01		0.038	0.014	***	-0.032	0.011	***	-0.055	0.014	***	-0.037	0.011	***	-0.019	0.010	
	LD_CBD	0.025	0.015		0.013	0.010		0.02	0.01		0.017	0.008	**	0.016	0.009		0.033	0.010	***	0.022	0.009	**	0.020	0.010	**
	LD_JBO	-0.016	0.013		-0.041	0.012	***	0.00	0.01		0.006	0.010		-0.032	0.011	***	-0.048	0.011	***	-0.036	0.010	***	-0.025	0.011	**
β'_2	LD_OSP	0.040	0.009	***	0.015	0.008		0.03	0.01	***	0.021	0.008	***	0.013	0.008		0.016	0.008	**	0.017	0.008	**	0.014	0.008	
	LD_PEACE	0.047	0.017	***	-0.002	0.014		0.08	0.01	***	0.059	0.015	***	-0.001	0.015		-0.010	0.014		-0.004	0.014		0.015	0.012	
	LD_POLICE	-0.060	0.011	***	-0.031	0.009	***	-0.05	0.01	***	-0.039	0.008	***	-0.035	0.008	***	-0.022	0.009	***	-0.036	0.008	***	-0.036	0.009	***
	LD_TRAIN	0.017	0.010		-0.020	0.007	***	0.01	0.01		-0.006	0.007		-0.020	0.007	***	-0.036	0.008	***	-0.021	0.007	***	-0.021	0.007	***
	LVAP14	**-0.046**	**0.050**		**-0.056**	**0.015**	***																		
	LBURG14	**0.138**	**0.023**	***				**0.15**	**0.02**	***															
γ'	**LTHEF14**	**0.084**	**0.028**	***							**0.110**	**0.020**	***												
	LCD14	**-0.010**	**0.040**											**-0.035**	**0.015**	**									
	LDO14	**0.013**	**0.027**														**-0.075**	**0.018**	***						
	LAOO14	**-0.152**	**0.037**	***																**-0.056**	**0.019**	***			
ρ	**W_LPRICE**	**0.280**	**0.023**	***	**0.354**	**0.019**	***	**0.35**	**0.02**	***	**0.376**	**0.018**	***	**0.376**	**0.018**	***	**0.350**	**0.019**	***	**0.370**	**0.018**	***	**0.363**	**0.018**	***
λ	**lambda**	**0.271**	**0.040**	***	**0.205**	**0.038**	***	**0.11**	**0.04**	***	**0.076**	**0.043**		**0.179**	**0.036**	***	**0.124**	**0.044**	***	**0.113**	**0.041**	***	**0.211**	**0.033**	***
Tests																									
Pseudo R^2		0,6003			0.7568			0.7438			0.6003			0.7601			0.7517			0.7577			0.7621		
Spatial Pseudo R^2		0,7361			0.7095			0.6891			0.752			0.7136			0.702			0.7097			0.7198		
Instrumented Variables :		LVAP14, LBURG14, LTHEF14, LCD14, LDO14, LAOO14, W_LPRICE			LVAP14, W_LPRICE			LBURG14, W_LPRICE			LTHEF14, W_LPRICE			LCD14, W_LPRICE			LDO14, W_LPRICE			LAOO14, W_LPRICE			W_LPRICE W_AGE1, W_AGE2, W_AGE3, W_AGE4, W_AGE5, W_BEDS, W_GARAGE, W_HEAT, W_HEATTYPE, W_LD_BUS, W_LD_CBD, W_LD_JBO, W_LD_OSP, W_LD_PEACE, W_LD_POLICE, W_LD_TRAIN, W_LSIZE, W_TYPE4, W_MDMRANK, W_TYPE1, W_TYPE2, W_TYPE3, W_TYPE4, W_TYPE5		
Instruments Used:		MDMRANK, LBURG13, LTHEF13, LCD13, LDO13, LAOO13, W_AGE1, W_AGE2, W_AGE3, W_AGE4, W_AGE5, W_BEDS,W_GARAGE, W_HEAT, W_HEATTYPE, W_LD_BUS, W_LD_CBD, W_LD_JBO, W_LD_OSP, W_LD_PEACE, W_LD_POLICE, W_LD_TRAIN, W_LSIZE, W_TYPE4, W_MDMRANK, W_TYPE1, W_TYPE2, W_TYPE3, W_TYPE4, W_TYPE5			MDMRANK+, W_AGE1, W_AGE2, W_AGE3, W_AGE4, W_AGE5, W_BEDS, W_GARAGE, W_HEAT, W_HEATTYPE, W_LD_BUS, W_LD_CBD, W_LD_JBO, W_LD_OSP, W_LD_PEACE, W_LD_POLICE, W_LD_TRAIN, W_LSIZE, W_TYPE4, W_MDMRANK, W_TYPE1, W_TYPE2, W_TYPE3, W_TYPE4, W_TYPE5																					

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

[+] MDMRANK is a variable used as instrument for every Crime variable due to it is highly related with every one with correlation larger than 0.8. The variable measure the deprivation rank for each house