REAL ESTATE DECISION-MAKING IN A WORLD OF INCREASING UNCERTAINTY ABOUT SECURITY: THE IMPACT OF CRIME ON RESIDENTIAL PROPERTY VALUES

Professor Alastair Adair
Dr David McIlhatton
Professor Stanley McGreal
Professor Paloma Taltavul de la Paz
Ulster University, Built Environment Research Institute
Coventry University, Securing Society Research Group
Universidad de Alicante, Applied Economics Department
All correspondence to be addressed to as.adair@ulster.ac.uk

A fuller version of the paper, in particular the statistical analysis, is contained in McIlhatton, D, McGreal, S, Taltavul de la Paz, P and Adair, A (2016) Impact of Crime on Spatial Analysis of House Prices: evidence from a UK city, accepted for publication by *International Journal of Housing and Market Analysis*

ABSTRACT

Security is playing an increasingly important role in decision making across many aspects of life including decisions about real estate. Since the last IRERS conference in 2014 political uncertainty and instability has increased in various parts of the world and the threat of crime, political instability and terrorist activity has been heightened in the conscience of government, corporate and individual decision-making. Such uncertainty is highlighted in the Safe Cities Index 2015 (EIU, 2015) and the Global Terrorism Index 2015 (IPE, 2015) measuring the direct and indirect impact of terrorism across 162 countries in terms of the effect on lives lost, injuries and damage to property and recording an 80% increase in incidents over the previous year the highest level ever recorded. In order to examine the impact of crime and fear of crime on property values we have to turn to the literature in particular those studies examining the influence of crime and fear of crime on property values globally. Much of this research has identified that crime has a negative pricing effect on residential property, although to varying degrees. However, there is little literature examining the impact of crime on property value and the role which government can have in managing such impact. Building on previous work, this paper seeks to add to the current knowledge base through an understanding the impact of crime on house prices and areas at risk in the future. The latter is designed to enable decision-makers to have an understanding of where potential interventions may need to go in the future in order to maintain and enhance economic and social vitality in real estate decision-making.

1.0 INTRODUCTION

The real estate literature indicates that the impact of crime or the fear of crime is an externality that is perceived to have a detrimental influence on the way neighbourhoods are regarded with a consequential negative impact on property values. While such perceptions are widely held and are supported by the literature the reality is much more complex with such pricing effects being more variable than uniform.

In addition much of the literature focuses on wider socio-economic relationships including measures of multiple deprivation consequently masking the impact of property value and performance. Nevertheless the international spread of the literature indicates the global significance of this area of research.

The current study seeks to extend the current knowledge base on the impact of crime on residential property values utilizing a comprehensive data set of property, neighbourhood/ location, socio-economic and crime variables for Belfast, Northern Ireland. Belfast provides a laboratory where submarkets historically have been segmented on the basis of religious belief, especially in the north and west of the city whereas in the south and east of the urban 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.

The following hypothesis is tested namely that spatial effects due to religious segregation that have persisted historically should be marked and how these relationships are related to the incidence of crime and vary by type of crime. A further question is do segregated housing markets show greater sensitivity to crime or is the impact of crime reduced by more homogeneous resident groups within submarkets?

The structure of the paper comprises a critical review of key issues in the relevant literature in section 2 drawn from an international perspective. In particular there is an examination of how spatial analysis, spatial lag and spatial error, have been used in previous studies. The database, variables and models that underpin the analysis are outlined in section 3 followed by an examination of the models and results in section 4. The final section draws conclusions.

2.0 RISK, UNCERTAINTY AND IMPACT OF CRIME ON HOUSE PRICES

The Global Risks Survey (WEF, 2015) identifies a series of risks that in the estimation of the World Economic Forum global regions are least prepared for. In the case of East Asia and the Pacific, Latin America and the Caribbean, and South Asia failure of urban planning is among the first three risks. In such regions, urbanization is especially rapid and the failure of urban planning can lead to a wide range of catastrophic scenarios from social unrest to pandemic outbreak. The other two regional risks are terrorist attacks and water crises.

In the case of Europe the risks are high structural unemployment or underemployment followed by large-scale involuntary migration and profound social instability. Both unemployment and migration flows into Europe are expected to remain high on the agenda going forward and are driving factors of social instability.

The impact of a recent wave of 190,000 immigrants into Sweden during 2015 has seen Stockholm as one of Europe's fastest growing cities with house prices rising by 14% over the year and apartment prices increasing by 150% over the decade (Economist (2015, November 7th). It is this social instability that creates uncertainty and poses a threat to real estate markets. Uncertainty is highlighted in the Global Terrorism Index published in 2015 measuring the direct and indirect impact of terrorism across 162 countries in terms of the effect on lives lost, injuries and damage to property and recording an 80% increase in incidents over the previous year the highest level ever recorded.

The threat to life and property is now very real at a macro level but it is at the micro or local level that the threat posed to real estate is often measured. There is a significant evidence base of the adverse impact of crime of house prices but most of this work remains in the academic field as professional bodies are concerned that publishing such statistics could have an unnecessarily detrimental effect on property prices.

Indeed evidence exists that freely available information on hospital and school league tables can have an undue influence on local house sale prices. In the UK the Home Office has committed to making public statistics relating to burglary, street robbery, vehicle crime and anti-social behaviour in specific neighbourhoods. Contrary to the RICS the Home Office claims that there is no proven link between published crime figures and house prices.

Finding definitive proof of the link between local crime rates and property values is difficult as it is felt that deprived neighbourhoods are more susceptible to crime and often already suffer from lower than average house prices. But even this statement is contested.

Evidence from the Economist (2015, January 31st) cites research in Leicester UK in one of the poorest neighbourhoods primarily occupied by immigrants. The local unemployment rate is three times the national average yet school performance and educational attainment among children is high. Indeed levels of crime and anti-social behaviour are higher in the more wealthy areas.

Further evidence from the Economist (2014, April 8th) indicates that gentrification of certain boroughs in London has seen a marked reduction in crime and a corresponding rise in property values. Twenty years ago few middle-class people wished to live in Hackney due to high crime rates, severe congestion and pollution and poorly performing schools.

In the academic literature there is a large volume of research on the impact of externalities on house prices. Crime or perception of crime is included amongst those factors considered to lower property prices in a neighbourhood yet in comparison to other externalities 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.

Nevertheless the literature acknowledges that the impact of crime can be complex. For example Taylor (1995) while showing that high crime levels result in weaker attachments of residents to and satisfaction with their neighbourhood, the desire to move and lower house prices simultaneously suggests that crime neither spurs mobility nor necessarily decreases local involvement.

Tita et al (2006) take a slightly different perspective and 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 capitalised into local housing markets quickly and provides an early indicator of neighbourhood transition. 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.

There is a larger literature on the impact of externalities such as urban parks which are generally perceived as beneficial environmental amenities and hence should have a positive impact on house price. However the propensity of parks to attract specific types of crime may also have negative impacts on house price (Troya and Grove, 2008). In a study in Baltimore they show 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 showed 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, in those circumstances park proximity has a negative impact on property values.

At a macro-level, Pope and Pope (2012) compiled information on changes in property values and crime during the 1990s in nearly 3000 urban zip codes throughout the US. Their analysis shows strong statistical significance between crime and property values, with estimated elasticities of property values ranging from –0.15 to –0.35 and notably, zip codes in the top decile in terms of crime reduction saw property value increases of 7–19%.

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 utilize 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. In relation to the distinctive social geography of Belfast, McCord et al (2013) show how "peace walls" that cut across segregated communities has resulted in a decline in value of 29.6 per cent for properties located within 250m of a peace wall, which is still a feature of divided communities, notably in the north and west of the city.

In terms of research into the design of real estate, Mohit, Mohammad Abdul and Kulliyyah, Hanan Mohamed Hassan Elsawahli (2010) focus on the "Safe city program" adopted by Malaysia aimed at creating violence and crime free cities. Their research indicates that changes in the built environment and modifications in space design can impact residents' and offenders' perceptions of criminality.

[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).

Baharon, AH and Muzafar Shah Habibullah (2009) examine the causality between income inequality and crime in Malaysia over the period 1973-2003. They found that income inequality had no meaningful relationship with any category of crime and were not cointegrated. They conclude that there is ambiguity in the empirical studies of crime economics regarding various income variables leading to often mixed and contradicting results.

A critical review of the literature indicates an increasing focus upon spatial analytics reflecting the growth of geographically referenced databases 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).

Overall 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 in Belfast (section 3) and the techniques employed (section 4).

3.0 RESEARCH DESIGN

The research design is based on a robust data set of property, location, socio-economic, neighbourhood and crime variables for Belfast as outlined in the fuller paper (McIlhatton et al, 2015). There is a historic pattern of housing submarkets segmented on the basis of religion, catholic and non-Catholic, in the west and north of the city whereas in remaining parts of Belfast they are structured more on the basis of income and socio-economic status (Adair et al, 1996). Property variables are sourced primarily from the Northern Ireland Quarterly House Price Index containing sales transactions across a wide network of selling agents over twelve quarters from the first quarter of 2012 to the final quarter of 2014. The sample size (n=4325 properties) includes properties for which specific address was available thereby facilitating the geo-coding of each property. For each property, house type is categorized as one of terraced house, semi-detached house, detached house, semi-detached bungalow, detached bungalow or apartment. Age band contains six categories (from pre-1919 to new development), the floor area of the property, number of bedrooms, and number of reception rooms, heating type and whether the property has a garage. Each property also has a location variable in the form of local X and Y coordinates.

Seven neighbourhood/location variables are included namely: distance to bus stop, distance to retail centres, distance to open space/parks, distance to interface areas, distance to police stations and distance to train stations. The spatial distance of these variables was calculated in a proprietary GIS using a Euclidean distance calculation tool.

The focus of the research is the impact of crime on property values between 2012 and 2014. The paper utilizes six specific crime variables, namely violence against the person, criminal damage, drugs offences, burglary, theft and other crime. The crime data was sourced from police.uk which is published by the United Kingdom Home Office and provides X and Y coordinates of individual crime. Socio-economic variables are captured through a multiple deprivation index, sourced from the Northern Ireland Statistics and Research Agency.

There are two stages to the analysis, firstly an exploratory examination of crime variables with the objective of identifying univariate/bivariate spatial patterns in the data and establishing the nature and direction of relationships between crime variables and house prices. Secondly the application of spatial auto-regression models (SAR) seeks to estimate the role of crime on house prices in Belfast controlling by spatial association. More specifically a SW2SLS (HET) (Spatial Weighted Two Stage Least Squares with Kelejian and Prucha (2010) robust standard errors) method is employed for the house price model specification.

Spatial patterns in house prices and crime variables are determined using Moran's I and Local Indicator Spatial Association (LISA) models enabling variation of spatial dependence between two variables to be examined. In determining Moran's I, the analysis utilizes the Queen contiguity matrix (GAL), based on actual contiguity of properties. For each of the crime variables, the analysis is consistent revealing high positive values. There is little variation in univariate Moran's I 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 Belfast. LISA analysis identifies the location of these clusters (Figure 1) representing the local clusters for the total crime variable with two main clusters identified. One cluster of a high and increasing incidence of high order crimes (H-H) is located in the centre/ inner city area. 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.

In general 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 records a Moran's I value of 0.45 suggesting a degree of spatial association of price data inferring that when the prices of neighbouring properties are likely to be high, the price of a particular property is high.

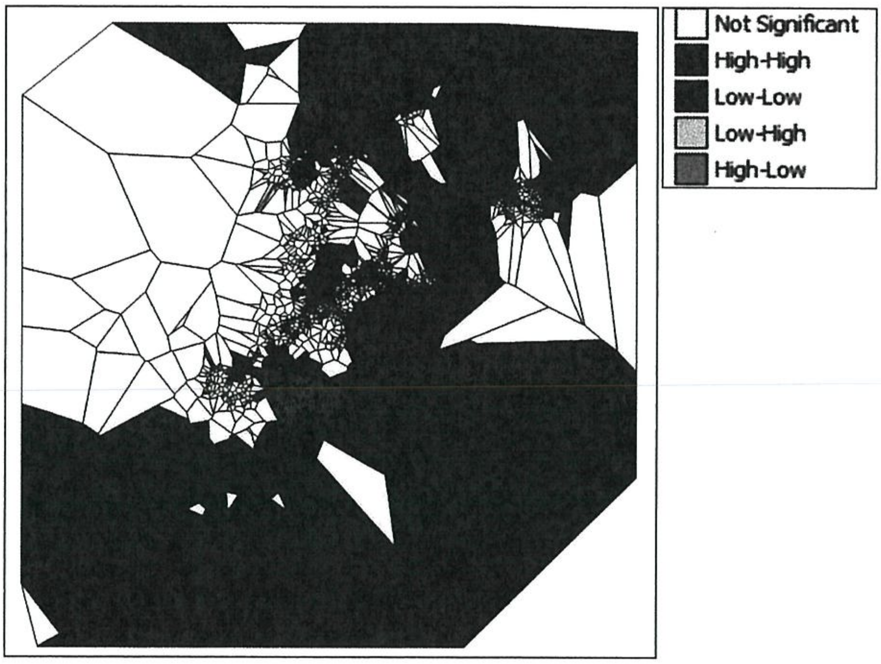

Figure 1: Total Crime Univariate Analysis LISA Clusters

Of particular interest is how spatial lagged crime variables could affect house prices, the power of such association and the existence of clusters. In this regard the Morans' I tests are undertaken in levels and in logs format (Table 1). The analysis, revealing low and negative Moran's I, is indicative of the relative non-existence of spatial association at an aggregate level. The outcome of no spatial association at a general level, while surprising, is apparent for all crime variables.

Table 1: Spatial analysis of crime variables, Moran's I and LISA

	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 -%
R14	0.907	-0.095	-0.178	45.76	54.24
VAP 14	0.888	-0.110	-0.249	44.72	55.28
BURGL14	0.936	-0.035	-0.041	45.83	54.17
THEFT14	0.896	-0.073	-0.103	45.16	54.84
CD14	0.928	-0.121	-0.179	47.77	52.23
DO14	0.868	-0.107	-0.235	39.82	60.18
AO014	0.883	-0.105	-0.182	41.06	58.94
		*Total observations		4325	

LISA analysis indicates 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 city as illustrated in Figure 2 (total crime variable). In central/inner city locations, an L-H cluster indicates that the lower crime is in a neighbourhood the higher are the 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.

Figure 2: Price – Total Crime Bivariate Analysis LISA Clusters

In relation to SAR model of house prices and crime the paper utilizes a hedonic perspective with prices explained through the property, location and crime variables. 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 hence avoiding aggregation bias. 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. The bivariate analysis demonstrates that crime types are spatially related to house prices defining clusters at a local level. Hence endogenous relationships between crime and housing characteristics were tested, no statistically significant association (no causal, nor spatial) was found to exist. 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, and that price and crime are endogenous.

The model for Belfast needs to adapt the hedonic model to include property characteristics, neighbourhood features and spatial association derived from both spatial continuity influence (spatial lag) and from the unobservable features (spatial error), and, as endogenous, the crime component. The latter is estimated using a set of instrumental variables (z) capturing their spatial association (z*W) within the model. The analysis is cross-sectional based on a panel of data as defined in Equation 2.

(2) $$Pi = \alpha + \rho WPi\text{-}j + \Sigma\ [\beta'1kxki] + \Sigma\ [\beta'2fNfi] + \Sigma\gamma'dCdi + \lambda W\varepsilon i + \mu i$$

Where,

C	are a set of the six endogenous crime variables.
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
Y'	is the IV estimated parameters measuring the association between crime and house prices.
P	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

μi 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 on variables and the parameter interpretation is pseudo-elasticity. The functional form described in the Equation is estimated using a General Spatially Weighted Two Stage Least Square (GSWTSLS) with robust estimators as described in Kelejian and Prucha (2010).

4.0 RESULTS

Model results (Table 1) show high levels of association between the dependent, the independent and endogenous variables. Pseudo R^2 with values greater than 0.6 in all models suggests a high level of association. 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 Belfast, an outcome in line with expectations. 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.

Table 2: General Spatially Weighed 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	
	a	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	***
b1	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	***
	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	**
b2	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	**
	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	***
g	**LVAP14**	**-0.046**	**0.050**		**-0.056**	**0.015**	***																		
	LBURG14	**0.138**	**0.023**	***				**0.15**	**0.02**	***															
	LTHEF14	**0.084**	**0.028**	***							**0.110**	**0.020**	***												
	LCD14	**-0.010**	**0.040**											-0.035	0.015	**									
	LD014	**0.013**	**0.027**														**-0.075**	**0.018**	***						
	LA0014	**-0.152**	**0.037**	***																**-0.056**	**0.019**	***			
r	**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**	***
l	**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, LD014, LA0014, W_LPRICE			LVAP14, W_LPRICE			LBURG14, W_LPRICE			LTHEF14, W_LPRICE			LCD14, W_LPRICE			LD014, W_LPRICE			LA0014, W_LPRICE			W_ LPRICE		
Instruments Used:		MDMRANK, LBURG13, LTHEF13, LCD13, LD013, LA0013, 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																			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

The effect of individual crime variables (Models 2 to 7) highlights subtle changes in spatial association. The spatial lag parameter increases in each of the 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. Presence of crime variable theft (Model 4) 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 addition of crime variables, either all variables as in Model 1 or individual crime variables (Models 2 to 7) does not fundamentally change the relationship.

The coefficients for property type (relative to apartments, omitted case) are generally negative across the respective crime specific models. 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).

The neighbourhood/location effects are less consistent than property variables regarding impact on house price. Proximity to a bus stop is 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 and proximity to a bus stop ie theft is higher with distance and house price is also higher but from an opposite perspective the probability of violence against the person increases with distance from a bus stop and hence serves to have a negative impact on house price.

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 been identified by previous hedonic studies considering the proximity of transport modes on house price.

Distance to open space (OSP) is often hypothesized as enhancing value however 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. Some previous studies have shown that crime increases in parks and other public spaces. The Belfast analysis 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.

Peace walls are a specific characteristic of Belfast and these divide segregated communities notably within inner city areas in west and north Belfast (McCord, et al, 2013). Proximity to a peace wall (PEACE) as expected shows a positive association with house price change, namely higher price with distance from a peace wall. 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.

Distance to a police station is statistically significant across all models and is 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.

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, 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 types of crime are associated with higher priced, higher income neighbourhoods whereas other types of crime namely 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.

6.0 CONCLUSIONS

Political uncertainty and instability has increased in various parts of the world and the threat of crime, political instability and terrorist activity has been heightened in the conscience of government, corporate and individual decision-making. 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.

This study extends the body of knowledge by using an innovative approach to statistical modelling to draw out the complex interrelationships between type of crime, housing attributes, locational variables and house price. 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 insight are provided by the analysis. Overall the research 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 t o 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. An important finding is the sensitivity of certain types of crime to distance to the CBD.

In relation to open space, the analysis shows house price increasing with distance from open space, a finding that concurs 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.

More generally a criticism of hedonic pricing 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.

REFERENCES

Adair, A S, Berry, J N and McGreal, W S (1996) Hedonic modeling, housing submarkets and residential valuation", *Journal of Property Research,* **13**, pp67-83.

Anselin, L (1988) Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity, *Geographical analysis*, Vol 20 (1), pp1-17

Baharon, AH and Muzafar Shah Habibullah (2009) Crime and Income Inequality: The Case of Malaysia, *Journal of Politics and Law*, Vol 2 (1), pp55-70.

Ceccato, V and Wilhelmsson, M (2011) The impact of crime on apartment prices: evidence from Stockholm, Sweden, *Geografiska Annaler: Series B*, 81-103.

Economist (2014, April 8th) *Chasing Cool, Gentrification in London*, The Economist, London

Economist (2015, January 31st) *The paradox of the ghetto, poverty, crime and education*, The Economist, London

Economist (2015, November 7th) *Home is where the heartache is, property in Sweden*, The Economist, London

EIU (2015) *Safe Cities Index 2015 White Paper*, The Economist Intelligence Unit, London

Gibbons, S and Machin, S (2008) Valuing school quality, better transport, and lower crime: evidence from house prices, *Oxford Review of Economic Policy*, Vol24, No1, pp99–119.

Home Office https://www.gov.uk/government/uploads/system/uploads/attachment _data/file/1164

IPE (2015) *Global Terrorism Index 2015*, Institute for Economics & Peace, Sydney.

Kelejian, HH and Prucha, IR (2010) 'Especification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances', *Journal of Econometrics*, Vol 157, pp 53-67.

Matthews, SA, Yang, TC, Hayslett-McCall, KL and Ruback, RB (2010), *Environment Planning A*, Vol 42 (6), 1403-1420.

McCord, J, McCord, M, McCluskey, W, Davis, P, McIlhatton, D and Haran, M (2013) Belfast's iron(ic) curtain: "Peace walls" and their impact on house prices in the Belfast housing market, *Journal of European Real Estate Research*, Vol 6 (3) pp333-358.

McIlhatton, D, McGreal, S, Adair, A and Tultaville De La Paz, P (2015) Crime, House Prices and Policy: A Case Study of a UK City, paper presented at 31st *American Real Estate Society* Meeting, Fort Meyers.

Mohit, Mohammad Abdul and Kulliyyah, Hanan Mohamed Hassan Elsawahli (2010) Crime and Housing in Malaysia: Case Study of Taman Melati Terrace Housing in Kuala Lumpur, *Asian Journal of Environment Behaviour Studies*, Vol 1,(3), pp25-36.

Mueller, H and Besley, T (2012) Estimating the Peace Dividend: The Impact of Violence on House Prices in Northern Ireland, *American Economic Review*, Vol 102 (2), pp810–833.

Pope, DG and Pope, JC (2012) Crime and property values: Evidence from the 1990s crime drop, *Regional Science and Urban Economics*, Vol 42, pp177-188.

Taylor, RB (1995) The Impact of Crime on Communities, ANNALS of *American Academy of Political and Social Science,* 539.

Tita, GE, Petras, TL and Greenbaum, RT (2006) Crime and Residential Choice: A Neighborhood Level Analysis of the Impact of Crime on Housing Prices, *Journal of Quantitative Criminology,* Vol 22, pp299–317.

Troya, A and Grove, JM (2008) Property values, parks, and crime: A hedonic analysis in Baltimore, MD, Landscape and Urban Planning, Vol 87, pp233–245.

WEF (2015) *Global Risks 2015*, 10th Edition, World Economic Forum, Geneva