Article

Urban Studies

Urban Studies
2015, Vol. 52(13) 2425–2440

DOI: 10.1177/0042098014547368
usj.sagepub.com
SAGE

Registered sex offenders and house prices: An hedonic analysis

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Abstract
The sex offender registry system provides consumers with locations of registered sex offenders. This paper uses two methods to evaluate the impact of sex offender registries on house prices in Memphis. Using an hedonic spatial error model, we find that each additional sex offender in a one-mile radius results in a loss of about 2% of the property value and that a 10% increase in distance from the nearest sex offender increases value by about 0.17%. At the mean values of the independent variables we find a 7% loss of value within a one-mile radius and a 14% loss of value within a 0.1 mile radius.

Keywords
crime, hedonic regression, property values, urban economics

Received June 2013; accepted July 2014

Introduction

The murder of Megan Kanka, a seven-year-old girl in New Jersey, by a child molester who moved next to Kanka's family without notification, caused public concern for neighbourhood safety. In response to the death of Megan Kanka, Congress passed the Violent Crime Control and Law Enforcement Act of 1994, commonly known as 'Megan's Law', which required real estate agencies to disclose the location of nearby sex offenders to potential home buyers. Economic theory suggests that Megan's Law should have a measurable effect on property values. The goal of the present study is to use hedonic regression models to evaluate how the location of a registered sex offender in a neighbourhood affects house

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prices in Shelby County, Tennessee (the Memphis area). We use two measures of the presence of sex offenders in a neighbourhood: the distance from the house to the nearest sex offender and the number of sex offenders within a one-mile radius of the property. We estimate an hedonic regression model for house prices using OLS, but also estimate two additional models to allow for spatial dependence. In particular, we estimate a mixed regressive-spatial autoregressive model and a spatial error model. Information criteria indicate that the spatial error model is preferred. Based on the estimates from this model, we find that a 10% increase in distance from the nearest sex offender increases property values by about 0.17%, and that an additional offender with a one-mile radius lowers property values by about 2%.

Literature review

In their excellent survey on hedonic methods Follain and Jiminez (1985) conclude that the theoretical basis for hedonic regression models is sound but the econometric applications are weak. The theoretical basis is Rosen's (1974) study of a market for a single commodity with many characteristics and, in general, the function is non-linear. Follain and Jimenez also discuss several estimation techniques. The first method discussed they call the simple hedonic approach where the coefficients of the estimated regression model are interpreted as the marginal willingness to pay for a particular characteristic. Follain and Jimenez state that only under restrictive assumptions can the hedonic regression reveal underlying demand parameters. One possible set of assumptions is that all households in the sample are alike in terms of income and socioeconomic characteristics but supplies of characteristics vary. In this situation the hedonic coefficients represent marginal willingness to pay.

There are other criticisms of the hedonic approach. Citing work by Freeman (2003), Haab and McConnell (2002), Palmquist (2005) and Taylor (2003), Nelson (2009) details several frequent criticisms of empirical studies using hedonic methods. First, many home buyers are poorly informed about market conditions and, in particular, neighbourhood amenities and cannot make an informed evaluation. Second, residential properties are heterogeneous and trade infrequently. Third, market segmentation can lead to differences in hedonic prices by location. Fourth, some of the neighbourhood characteristics may be provided in relatively fixed bundles making estimation of separate hedonic prices difficult.

Despite the concerns with hedonic methods, they have been widely applied in the housing market. What follows is a sampling of the types of amenities and dis-amenties that have been examined using hedonic methods. Studies including Brasingtion (1999), Irwin (2002), Sunding and Swoboda (2010), Harrison and Rubinfeld (1978) and Gibbons and Machin (2008) have shown that house prices reflect the surrounding environment. Many features of the surrounding environment have been empirically investigated. For example, Siegel et al. (2013) estimate the impact of the Gulf oil spill on condominium prices in Alabama, Ready and Abdallah (2005) examine the dis-amenity effects of agriculture, Guignet (2013) examines the effects of underground storage tanks, and Agee and Crocker (2010) examine the impact of crematory operations. Ham et al. (2013) and Hite (2001) examine the impact of landfills and Eshet et al. (2007) examine the impact of waste transfer stations. The impact of noise has been examined by Pope (2008b), Clark (2006), Andersson et al. (2010), Franck et al. (2013) and Theebe (2004). Air pollution has been examined by Huang (2010) and overhead transmission lines by Harrison (2002).

A connection between crime rates and property values has been established in the literature through a subset of the literature on hedonic methods. Recent studies examining the impact of crime and illegal activities on property values have been conducted by Buonanno et al. (2013), Congdon-Hohman (2013) and Bishop and Murphy (2011). An early study by Thaler (1978) finds a strong negative correlation between crime rates and house prices in Rochester, New York. Specifically, Thaler finds that the cost of a property crime is, on average, about US$500 – this is the amount people are willing to pay to avoid crime. Gibbons (2004) finds that a one standard deviation increase in property crime results in a 10% decrease in house prices in the London area. He interprets the willingness to pay to avoid crimes as implicit in higher house prices. Ihlanfeldt and Mayock (2010) find evidence that homebuyers are willing to pay premiums for living in neighbourhoods with less aggravated crimes. Lynch and Rasmussen (2001) point out that 'although crime does not substantially affect the price of the average home, house prices decline dramatically in a high crime area'. In addition, Schwartz et al. (2003) discover that falling crime rates caused one-third of the post-1994 boom in property values. In this vein, this paper uses the hedonic pricing model to examine the relationship between house prices and sex offender location and concentration.

There have been few studies of the impact of registered sex offenders on property values for the simple reason that prior to 1994, few convicted sex offenders were required to register with the state. In 1994, the Jacob Wetterling Crimes Against Children and Sexually Violent Offender Registration Act required a sex offender registry for all states. Later, in 1996, 'Megan's Law', an amendment to the Act, called for public disclosure of sex offenders' information. More recently, a few studies have investigated the impact of registered sex offenders on property values.

There are at least two possible measures of the influence of sex offender location on house price: distance to closest offender and number of nearby offenders. Proximity should lead to a reduction in house price.[1] Three studies have taken this approach. The first, by Larsen et al. (2003), finds that house prices fall by 17% when the house is located within 0.1 miles of a registered offender labelled as a predator, while prices fall by only 8% when the offenders are not labelled as predators.[2] This study is based on data from Montgomery County, Ohio. Linden and Rockoff (2008) use data from Mecklenburg County, North Carolina to compare the house prices before and after an offender moves into a neighbourhood. They find that house prices fall by 4% when a sex offender moves nearby. Pope (2008a), using a similar method, concludes that house price falls by 2.3% when a sex offender moves within a tenth of a mile of a house.

The other measurement of offender presence in a neighbourhood is the density or number of sex offenders in the immediate area. The larger the number of sex offenders nearby, the lower the house price. We measure density as the number of registered sex offenders living within a one-mile radius. Because our hedonic model includes distance to nearest sex offender and density of offenders, we are able to separate the two effects and avoid possibly inflating the distance effect due to the presence of other nearby offenders. Furthermore, in contrast to the studies previously cited, our research also tests and controls for the presence of spatial correlation which is typical in hedonic modelling.

Many of the traditional criticisms detailed above on hedonic methods are less consequential in the present study. First, our housing sample is based around the location of the registered sex offenders. In this way we expect the households to be similar in terms of income and socioeconomic characteristics. However, there should be some variation in housing characteristics. The second is a legal obligation of real estate agents to inform potential buyers about the location of registered sex offenders. This is one characteristic about which buyers should not be poorly informed. The issue of market segmentation is likely to be less relevant because, once again, we use a fairly homogeneous group of houses. Although the provision of some neighbourhood characteristics in fixed bundles makes the estimation of hedonic prices difficult, this is not a problem in the present study. We use dummy variables for neighbourhoods, which is exactly the right solution to the problem. In addition, we incorporate spatial effects into our hedonic regression models.

The present study adds to the rather scant literature on the impact of sex offenders on property values in several respects. Ours is the only study based on data for Shelby County, Tennessee and we are the only study to include a density measure for sex offenders. We are also one of the few studies to incorporate spatial elements in our estimation.

Measuring the impact of sex offenders on property values is important for at least two reasons. First, the location of a sex offender into a neighbourhood will cause a loss in property value for all nearby owners. Second, if one is contemplating moving into an area in the vicinity of a sex offender, the value of the sex offender disamenities should be capitalised into the house price. Measuring these costs is an important task.

Data and model

There were 2125 registered sex offenders living in Memphis as of 2 November 2012. The ratio of residents to sex offenders in Memphis is 318 to 1 and Shelby County has a ratio 202 to 1, which is the highest in the state of Tennessee. Our data come from two sources: one providing the locations of registered sex offenders and the other providing details on nearby property sales. We use an automated script to scrape data from the Shelby County Assessor of Properties, which is an official local website and provides probably the most complete information on property transactions in Shelby County, and the Tennessee Bureau of Investigation, which is a governmental data base of registered sex offenders available online. After removing duplicates and missing data, we have 2036 unique house transactions within 1 mile of 1203 sex offenders from 2008 to 2012.[3] All observations represent single-family homes. The sample is constructed such that all included transactions take place after the location of a sex offender into the immediate neighbourhood. To the extent that registered sex offenders live in less desirable neighbourhoods, the use of very local housing transactions should reduce the impact of neighbourhood effects.

Our dependent variable, sales price, is adjusted to 2012 US dollars. As independent variables we have a full set of house characteristics. Our independent variables of interest are distance to the nearest sex offender (always less than one mile) and the density of sex offenders within a one mile radius of the housing transaction. We also include zip code fixed effects to incorporate average neighbourhood effects. Descriptive statistics of the variables used in our study are reported in Table 1.

Conceptual model

A house can be considered as a composite good whose price is a function of the characteristics of the bundle. Therefore, when the housing market clears, the equilibrium price is a function of house characteristics, neighbourhood characteristics and environmental characteristics. In other words the house price can be assumed to be the sum of the

Table 1. Descriptive statistics.

Variable	1st Q.	Median	Mean	3rd Q.	St. Dev.
Price	$46,912.21	$63,337.93	$74,535.31	$84,301.73	$54,010.28
Distance to sex offender	0.09	0.16	0.21	0.28	0.17
Density025 (0.25 mile radius)	0	1	1.32	2	1.41
Density050 (0.50 mile radius)	1	2	2.62	4	2.42
Density100 (1.00 mile radius)	1	2	3.43	5	3.23
Plot area	0.17	0.21	0.25	0.27	0.18
Centralised AC	1	1	0.75	1	0.43
Forced AC	0	0	0.12	0	0.33
Fireplace	0	0	0.18	0	0.39
GAS	0	0	0.1	0	0.3
Total square feet	1147.00	1396.00	1510.99	1728.00	555.79
Building age	38	51	49.88	61	21.05
Bedrooms	3	3	3	3	0.65
Half baths	0	0	0.17	0	0.38
Bathrooms	1	2	1.58	2	0.57
Stories	1	1	1.12	1	0.28
Distance to Allen Plant	0.15	0.21	0.21	0.26	0.08
Distance to Downtown	0.09	0.13	0.14	0.17	0.07
zip38114	0	0	0.04	0	0.2
zip38116	0	0	0.08	0	0.27
zip38117	0	0	0.03	0	0.16
zip38118	0	0	0.07	0	0.26
zip38119	0	0	0.04	0	0.2
zip38120	0	0	0.01	0	0.1
zip38122	0	0	0.08	0	0.27
zip38125	0	0	0.01	0	0.11
zip38126	0	0	0.01	0	0.1
zip38127	0	0	0.09	0	0.29
zip38128	0	0	0.08	0	0.27
zip38131	0	0	0	0	0.04
zip38132	0	0	0.01	0	0.09
zip38133	0	0	0.09	0	0.29
zip38135	0	0	0	0	0.05
zip38141	0	0	0.05	0	0.22
zip38157	0	0	0.01	0	0.11
Year 2009	0	0	0.08	0	0.28
Year 2010	0	0	0.15	0	0.36
Year 2011	0	0	0.24	0	0.43
Year 2012	0	0	0.43	1	0.49
Sample size $N = 2036$					

implicit or hedonic prices of each element of the bundle (Rosen, 1974). For example, in the USA the demand for housing is linked to the demand for local public services, so neighbourhood characteristics and environmental characteristics are capitalised in the house price (see, for example, Brunner et al., 2012). Consequently, it is plausible to assume that house prices at a distance from a registered sex offender reflect the implicit price of neighbourhood safety.

The model below is the result of an investigation of several independent variables in order to obtain a parsimonious model with very good explanatory power. We use the following hedonic price equation to measure the extent to which the social cost of location near sex offender(s) is capitalised in the housing market of Memphis, TN:

$$\begin{aligned}\ln(price)_i = {} & \beta_0 + \beta_1 \ln(dist2offender)_i + \beta_2 density100_i + \beta_3 \ln(lotsize)_i + \beta_4 central\,ac_i \\ & + \beta_5 forced\ air_i + \beta_6 fireplace\,prefab_i + \beta_7 gas_i \\ & + \beta_8 \ln(totlivarea)_i + \beta_9 building\ age_i + \beta_{10} bedrooms_i + \beta_{11} Half\ Bathrooms_i \\ & + \beta_{12} Bathrooms_i + \beta_{13} Stories_i + \beta_{16} \ln(dist2allen)_i \\ & + \beta_{14} \ln(dist2cc)_i + \sum_{j=15}^{31} \beta_j ZIP\ Code_{ji} + \sum_{j=32}^{35} \beta_j saleyear_{ij} + \varepsilon_i\end{aligned} \quad (1)$$

where *price* is the selling price of the house, *dist2offender*[4] is the distance to the closest sex offender measured in miles, and *density100* are the number of offenders in a one-mile radius, respectively; *lotsize* is the lot size measured in square feet, *central ac, forced air, fireplace prefab* and *gas* are dummy variables representing house heating and cooling characteristics. *Totlivarea* is the total housing area measured in square feet.

We also incorporate spatial elements in our model by including two variables: *dist2allen* and *dist2cc*. *Dist2allen* is the distance of each housing unit to the Allen Fossil Plant. We include *dist2allen* to capture the impact of environmental disamenities which are correlated with housing prices and, in general, uncorrelated with crime. The Allen Fossil Plant is managed by the Tennessee Valley Authority (TVA) and supplies electricity to 340,000 housing units by using three coal-fired units. In 2010 the TVA Allen Fossil Plant was the largest polluter in the Memphis Metropolitan area, releasing approximately 2.5 M lbs of chemical compounds into air and water pathways. The facility is located on the Mississippi River, five miles southwest of downtown Memphis (LON −90.1389, LAT 35.0704). *Dist2cc* is the distance from the property to the city centre (Downtown LON −90.04889, LAT 35.14981) expressed in miles (Tennessee Valley Authority, 2013).

In addition, we include 17 dummy variables representing the zip codes of each housing unit to capture unobserved neighbourhood heterogeneities and four dummy variables indicating the year the property was sold. These dichotomous variables refer to the years 2009, 2010, 2011 and 2012, with 2008 being the omitted year.

We add spatial elements to our hedonic analysis. The first law of geography states that ‘everything is related to everything else, but near things are more related than distant things’ (Tobler, 1970: 236). Ergo, spatial dependence is naturally expected to be in hedonic property price models (Anselin, 2003). LeSage and Pace (2008) argue that housing price depends on price of recently sold neighbouring houses. One explanation for this dependence is that real estate appraisers might be influenced by the value of neighbouring properties when making an appraisal. This issue must be addressed in the estimation in order to provide parameter estimates which are unbiased, efficient and consistent.

There are essentially two types of spatial dependence, one in the dependent variable and a second in the random error term. These two spatial processes are often represented in the linear regression model in compact form as:

$$\mathbf{y} = \rho \mathbf{W}_1 \mathbf{y} + \mathbf{X}\beta + \lambda \mathbf{W}_2 \boldsymbol{\varepsilon} + \mathbf{u} \quad (2)$$

where $\mathbf{y}$ is a 2036 $\times$ 1 vector of housing prices in log form, $\mathbf{W}_1$ and $\mathbf{W}_2$ are 2036 $\times$ 2036 spatial weight matrices, $\mathbf{X}$ is a 2036 $\times$ 39 matrix which includes the explanatory variables defined above, $\boldsymbol{\beta}$ is a 39 $\times$ 1 vector of parameters to be estimated, ρ and λ are the coefficients of spatial correlation and $\mathbf{u}$ is a vector of spatial white noise $\mathbf{u} \sim N(0,\sigma^2)$. Maximum likelihood is used to simultaneously estimate $\boldsymbol{\beta}$, ρ, λ and σ. However, noting that $\mathbf{u} = \boldsymbol{\varepsilon} - \lambda\mathbf{W}_2\boldsymbol{\varepsilon}$ an equivalent expression, factorising with respect to $\mathbf{y}$ and $\mathbf{u}$, is:

$$(\mathbf{I} - \rho\mathbf{W}_1)\mathbf{y} = \mathbf{X}\beta + (\mathbf{I} - \lambda\mathbf{W}_2)^{-1}\mathbf{u} \qquad (3)$$

here $\mathbf{I}$ is a 2036 $\times$ 2036 identity matrix. Because the joint distribution of $\mathbf{u}$ is not observed, the log-likelihood function must be based on the joint distribution of $\mathbf{y}$. Thus, we can also maximise the following log-likelihood function:

$$\begin{aligned} LL(\beta, \rho, \lambda, \sigma|\mathbf{y}) = &-0.5N \ln \pi - 0.5N \ln \sigma^2 \\ &+ \ln|\mathbf{I} - \lambda\mathbf{W}_2| + \ln|\mathbf{I} - \rho\mathbf{W}_1| - 0.5\sigma^{-2}\mathbf{u}'\mathbf{u} \end{aligned} \qquad (4)$$

where $N = 2036$ is the sample size; $\mathbf{u} = (\mathbf{I} - \lambda\mathbf{W}_2)(\mathbf{I} - \rho\mathbf{W}_1)\mathbf{y} - (\mathbf{I} - \lambda\mathbf{W}_2)\mathbf{X}\beta$ and $(\ln|\mathbf{I} - \lambda\mathbf{W}_2| + \ln|\mathbf{I} - \rho\mathbf{W}_1|)$is the log-Jacobian of the transformation from $\mathbf{u}$ to $\mathbf{y}$, i.e. $\ln\det(\partial\mathbf{u}/\partial\mathbf{y})$.

In applied work two special cases of (3) are considered; the mixed regressive – spatial autoregressive model (SAR), for which $\lambda = 0$ and the spatial error model (SEM) with $\rho = 0$ (Anselin, 1988). We assume the same geographic relationships implied by the spatial weight matrices so that $\mathbf{W}_1 = \mathbf{W}_2 = \mathbf{W}$, which is a row standardised spatial weight matrix. Such matrices define neighbours as the k closest property units to the observational unit.

The spatial matrix was constructed using the Delaunay triangulation algorithm available in the spatial statistics toolbox of Pace (http://www.spatial-statistics.com/software_index.htm). The algorithm creates a network of Voronoi triangles where each set of housing coordinates represents a triangle node. Nodes connected by a triangle edge are natural neighbours. We choose $k = 3$ closest neighbours, where a neighbour is house that has recently sold. This spatial relationship is used to model the previous assumption that real estate agents use information on the value of immediate neighbouring houses to determine the asking price.

For example, if house i is a close neighbour of house j, then the element w_{ij} of $\mathbf{W}$ will equal 1, if there is no such relationship (i.e. house i and j are not connected nodes of a Voronoi triangle) w_{ij} will equal 0. It is obvious that if i and j are neighbours then w_{ji} will also equal 1, thus $\mathbf{W}$ is a symmetric matrix.

As we mention previously, the spatial weight matrix is row standardised for computational reasons to facilitate the maximisation of (4), that is, the elements of each row must sum to 1. This procedure ensures that the absolute values of ρ and λ will be less than 1 (Anselin, 1982: 1025, 1988: 63; Ord, 1975). In Figure 1 we provide an illustration of the sparsity pattern of the spatial weight matrix $\mathbf{W}_{2036\times2036}$ of 4,145,296 entries. The figure shows the evident symmetry of the matrix where the ‘ + ’ symbols represents non-zero elements of $\mathbf{W}$. We also note that a large proportion of these non-zero elements are found near the main diagonal of the spatial weight matrix. This is typical and is noted in other studies (Pace and Barry, 1997). Finally, we apply Moran’s I test for spatial dependence in the error term. For a row standardised matrix, Moran’s I statistics can be computed from the OLS residuals of (1) as $I = \boldsymbol{\varepsilon}'\mathbf{W}\boldsymbol{\varepsilon}/\boldsymbol{\varepsilon}'\boldsymbol{\varepsilon}$ which is asymptotically normal, that is, $I/\mathrm{Var}(I)^{0.5} \sim N(0,1)$. For a large sample, as in our case, if $Z_I = [I - E(I)]/\mathrm{Var}(I)^{0.5} > 1.96$, then the null hypothesis of no spatial dependence is rejected. Following this procedure

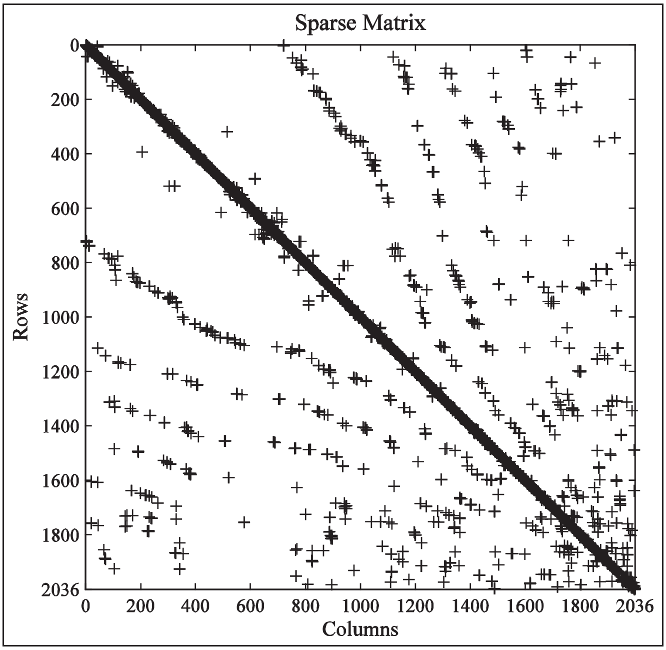

Figure 1. Sparsity pattern of the spatial weight matrix (W).

we computed Moran's *I* statistic, obtaining a value of 24.94, allowing us to reject the null of no spatial dependence in the model.

Estimation results

In Table 2 we present our estimation results. To save space we do not report the parameter estimates of the zip code dummy variables. However, this information is available from the authors upon request. Column 2 of the table contains the OLS estimation results. The R^2 for the model is 0.63, which is of appropriate magnitude in this type of cross-sectional study. Coefficients of all explanatory variables except *Fireplace, Building Age, Stories* and *log(dist2allen)* are statistically significant at the $\alpha = 0.05$ level, or better. We believe this finding is due to the fact that there is little variation in these density measures.

As expected, the hedonic prices of the heating and cooling house characteristics are positive and they would increase the average housing value between 18% and 28% approximately. A 10% increase in the total living area of the house would increase the average price of the property by 7.3%, ceteris paribus. The coefficient of *log(dist2offender)*, which is of primary interest in our study, indicates that a 10% increase in distance from the nearest offender increases house price by about 0.23%. The coefficient of *density* indicates that an additional nearby sex offender decreases house price by just over 3%. It is noteworthy that after the subprime mortgage crisis (2008) the average value of the property dropped between 20% and 30% in the following four years.[5]

Column three of Table 2 gives the results from estimating the spatial autoregressive model. Coefficient estimates and statistical significance mirror the OLS results. Column four of Table 2 gives the results from estimating the spatial error model. These results are slightly different from the OLS and SAR

Table 2. Estimation results.

Parameter	OLS	SAR	SEM
log(Distance to Sex Offender)	0.023*** (2.790)	0.024*** (3.018)	0.017** (2.242)
Density100 (1.00 mile radius)	−0.033*** (−12.150)	−0.031*** (−11.586)	−0.020*** (−5.046)
log(Plot Area)	0.047** (2.400)	0.046** (2.369)	0.084*** (4.550)
Centralised AC	0.281*** (10.000)	0.277*** (10.024)	0.165*** (7.379)
Forced AC	0.181*** (5.810)	0.174*** (5.689)	0.142*** (5.912)
Fireplace	0.033 (1.240)	0.029 (1.092)	0.010 (0.433)
GAS	0.053** (1.970)	0.054** (2.061)	0.065** (3.027)
log(Total Square Feet)	0.727*** (17.070)	0.715*** (17.125)	0.527*** (15.178)
Building Age	0.000 (0.510)	0.000 (0.485)	−0.002*** (−4.546)
Bedrooms	−0.033** (−2.190)	−0.030** (−2.034)	0.002 (0.159)
Half Baths	0.103*** (4.640)	0.079*** (3.806)	0.056*** (3.415)
Bathrooms	0.084*** (3.970)	0.100*** (4.596)	0.057*** (3.316)
Stories	0.006 (0.170)	0.003 (0.106)	0.045* (1.744)
log(Distance to Allen Plant)	0.050 (1.570)	0.040 (1.270)	0.099* (1.873)
log(Distance to Downtown)	−0.164*** (−5.370)	−0.152*** (−5.056)	−0.161** (−3.088)
Y2009	−0.194*** (−5.510)	−0.199*** (−5.757)	−0.229*** (−8.715)
Y2010	−0.305*** (−9.650)	−0.313*** (−10.102)	−0.337*** (−14.163)
Y2011	−0.334*** (−11.140)	−0.342*** (−11.636)	−0.395*** (−16.731)
Y2012	−0.218*** (−7.570)	−0.230*** (−8.128)	−0.376*** (−15.955)
Constant	5.627*** (19.710)	5.698*** (19.773)	7.537*** (27.378)
P		0.036*** (6.497)	
Λ	–	–	0.622*** (34.928)
σ^2	0.112	0.107*** (31.906)	0.069*** (30.443)
R^2	0.630	–	–
Log-Likelihood	−637.7	−691.10	−446.02
AIC	1351	1385.80	895.65
BIC (Schwarz)	1565	1648.80	1158.70
Sample size (*N*)	2036	2036	2036

Notes:
***99%, **95%, *90% confidence interval. T-ratios in parentheses. Dependent variable: log(Housing Price). Parameter estimates of the zip codes are not reported to save space. These estimates and related statistics are available from the authors upon request.

estimates. For example, SEM estimates of *log(dist2offender)* and *Density100* are 26% and 65% smaller compared with the OLS. In particular, the coefficient of *log(dist2offender)* indicates that a 10% increase in distance to the nearest offender decreases house price by approximately 0.17% and an additional offender nearby decreases house price by about 2%.

We now turn our attention to model selection. As previously mentioned, Moran's *I* test indicated the presence of spatial dependence in our study. Following Osland's (2010) suggestions, we conduct the Lagrange Multiplier (LM) test of Burridge (1980) for spatial dependence in the random error, and the LM test of Anselin (1988) to test for spatial dependence in the dependent variable. These tests provided the following results: $LM_\lambda = 563.00$ $LM_\rho = 41.28$ ($p = 0.00$ for both) indicating the presence of spatial correlation. Florax and de Graaf (2004) suggest that when both hypotheses are rejected, then one should assess the magnitude of the tests statistics. The test with the largest statistic should be preferred. Using this criterion, $LM_\lambda > LM_\rho$ therefore the SEM model should be selected.

In addition, Anselin et al. (1996) proposed a set of simple robust LM tests for spatial dependence. These tests correct the previous tests by accounting for the presence of local spatial misspecification. We use these robust LM tests as our second set of spatial diagnostic tests for our hedonic model and we found that $RLM_\lambda = 485.90$ (p-val 0.00) and $RLM_\rho = 3.38$ (p-val 0.06), indicating the presence of spatial correlation in the random error but not in the dependent variable (at $\alpha = 0.05$ level). Consequently, the SEM model is preferred to the SAR model. Although redundant, for completeness we also conducted a bidirectional LM test, following Anselin et al. (1996). The results of this test and the other spatial diagnostic tests implemented in the current study are summarised in Table 3.

Table 3. Diagnostic tests for spatial dependence.

Statistics	Value
Moran's *I*	0.41
Z_I	24.94*** (0.00)
$LM_{\rho\lambda}$	572.20*** (0.00)
LM_ρ	41.28*** (0.00)
LM_λ	563.00*** (0.00)
RLM_ρ	3.38* (0.06)
RLM_λ	485.90*** (0.00)
Λ_{SAR}	43.70*** (0.00)
Λ_{SEM}	620.54*** (0.00)
LL_{SAR}	−615.85
LL_{SEM}	−305.58
AIC_{SAR}	1237.40
AIC_{SEM}	614.82
BIC_{SAR}	1648.80
BIC_{SEM}	1515.60

Notes:
***99% confidence interval. *P*-values in parentheses. Λ are log-likelihood ratio statistics for SAR and SEM model; LL is the maximised value of the log-likelihood function; AIC and BIC are Akaike and Bayesian (Schwarz) information criteria. All the test statistics follow the χ^2 distribution with one degree of freedom except $LM_{\rho\lambda}$ that follow χ^2 distribution with zero degree of freedom.

Also, the results of two likelihood ratio tests indicated the existence of spatial dependence in the hedonic model. In particular, our results indicate the SAR and SEM models are preferred to OLS (unrestricted model with spatial nuisances set to zero) $\Lambda_{SEM} = 624.54 > \Lambda_{SAR} = 43.70 > \chi^2(1) = 10.83$ with p-value = 0.001. Furthermore, the likelihood ratio statistic of the SEM is greater than that of the SAR. An analysis of the information criteria, Akaike (AIC) and Bayesian (BIC), also confirms the SEM represents real processes with minimum information loss compared with the SAR model. Finally, by comparing the values of the log-likelihood functions for the two models, it appears that SEM fits the data better than SAR ($-305.58 > -615.85$), therefore we have very good evidence that the SEM is preferred to the SAR.

Because the OLS estimates are inefficient, we focus our discussion on the estimation results of the SEM model.[6] As expected, this model reveals that the total living area is the variable that is of greatest economic significance. In fact, a 10% increase in the total dwelling area would increase the housing price by approximately 5.3%, on average. The variable *lot size*, which is statistically significant at the 1% level, has a lower economic impact on the average property value. Unexpectedly, *Building Age*, has a negligible impact on housing price and even more surprising is the fact that *Bedrooms* and *Stories* have no impact on property value.

However, other housing characteristics (heating and cooling, bathrooms and half bathrooms) have good explanatory power. The marginal prices of housing characteristics are associated with a change of from approximately 6% to 17% of the average property price. As expected, the geographic location of the property with respect to the city centre influences the dwelling price. Furthermore, based on the coefficient of *log(dist2allen)*, we note that lower environmental quality of a neighbourhood is capitalised in the property values of Shelby County.

Spatial analysis of the social cost of sex offender

We now carefully examine the impact of sexual offender location on house prices based on the SEM model. As expected, an additional sex offender within a one-mile radius decreases house value by about 2%. Distance to the nearest sex offender is also important. We find that, on average, a 10% increase in distance from the nearest sex offender increases property value by 0.17%. We further explore the impact of this elasticity by simulating the expected value of the housing price for different values of the variable *dist2offender*, ceteris paribus. We use the following equation:

$$(price) = \exp[11.27 + 0.017 \log(dist2offender)] \quad \text{for } 0 \leq dist2offender \leq 1 \text{ and}$$
$$(price) = \exp[11.34] \text{for} dist2offender = 1 + \varepsilon\backslash \tag{5}$$

where 11.27 is obtained by evaluating the SEM regression model at the means of all variables except *dist2offender* while 11.34 is obtained by evaluating the SEM regression model at the means variables except *dist2sex-offender* (evaluated at 1 + ε) and *density100* at 3.43 – the sample mean. A graphical illustration of this relationship is given in Figure 2. Figure 2a shows the impact of proximity to a registered sex offender within a one-mile radius and Figure 2b shows the impact with a 0.10 mile radius.

In order to make the calculations we make two assumptions: (1) that the urban

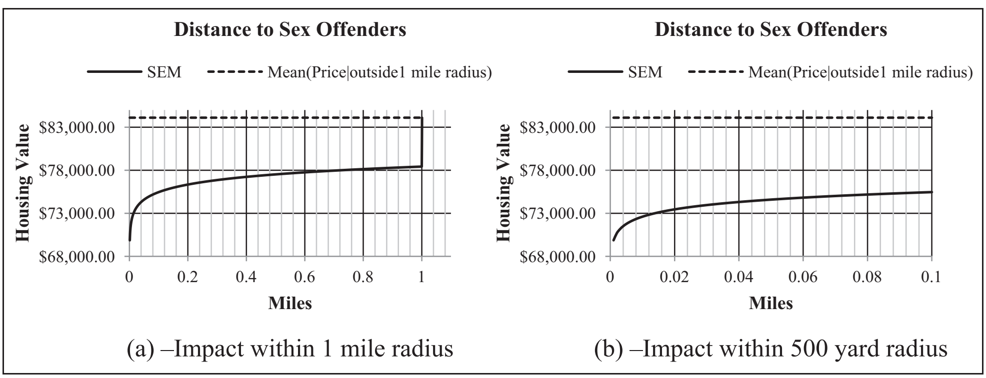

Figure 2. Impact of sex offender proximity on housing price.

area affected by the presence of the sex offender is circular; (2) outside the one-mile radius, the impact of a sex offender on housing value is negligible. The use of the sample average density of sex offenders within one mile and (2) explain the discontinuity at one-mile distance illustrated in Figure 2.

Based on an expected house value of approximately US$84,120 (outside the sex offender area), the figures show that a household's welfare is severely affected by the presence of offenders in the form of a lower house price, particularly for those who live within 0.10 of a mile of an offender. On average, the value of a house at a distance of 0.10 of a mile from a sex offender falls by US$8653.95.[7]

We wish to calculate the total welfare loss in the area affected by the sex offenders (1 mile radius) and in closer proximity to the sex offender (0.10 mile radius). If we label the price variable as y and *dist2sexoffender* as x, by the property of logarithms and exponential functions we can rewrite (5) as:

$$y = exp(11.27)x^{0.017} \text{ for } 0 \leq x \leq 1 \text{ and} \\ y = exp(11.34) \text{ for } x = 1 + \varepsilon \tag{6}$$

We need to rotate this function around the y axis. This function consists of two parts. The top is a cylinder owing to the discontinuity associated with being within the one-mile radius circle containing an average of 3.43 sex offenders. The bottom part of the figure can be integrated by adding circles together to obtain the volume.

To set up the integral we first define some notation. Let B equal the house price in the absence of the offender effect. In our sample this is US$84,120. Let A be the house value immediately upon entering the one-mile radius. In our sample this value is US$78,543. Let y = price, let x = distance, let α indicate the price gradient (0.017), and let $\beta \leq 1$ be the cutoff associated with the radius under study which is always less than or equal to 1 mile, meaning the highest house price in the presence of sex offenders is always some fraction of A. To complete our calculations, we need distance as function of price, solving yields:

$$y = Ax^{\alpha} \xrightarrow{yields} x = \left(\frac{y}{A}\right)^{\frac{1}{\alpha}}$$

The volume of the top is then given by

$$V_T = \pi r^2(B - \beta A) \tag{7}$$

and the volume of the bottom is given by

$$V_B = \pi \int_0^{\beta A} \left(\frac{y}{A}\right)^{\frac{2}{\alpha}} dy = \frac{\beta^{\frac{2}{\alpha}+1} \alpha \pi A}{2 + \alpha} \tag{8}$$

The volume of interest is the sum of these two, and we wish to express this volume as a percentage of house value with no sex offenders present. This value is $V^* = \pi r^2(84{,}120)$. We ultimately calculate $(V_T + V_B)/V^*$.

Using the values for our parameters, in a one-mile radius $\beta = r = 1$, and V_T = 17,521, V_B = 2080 and V^* = 264,271 implying 7.4% of value lost. At one-tenth of a mile, the implied house price falls to 96% of A, indicating that $\beta = 0.96$. Thus, with $r = 0.10$ and our parameter values, $V_T = \pi(0.12)[84{,}120-(0.96)78{,}543] = 274$, $V_B = 96$, and $V^* = 2642$, implying 14% of value lost. These values of 7.4 and 14% might be underestimated for two reasons. First, as one moves closer to the offender the density of sex offenders is also going to increase and, second, the offender effect is not exactly zero at a distance of one mile.

Conclusion

The Sexual Offender Act of 1994, informally known as the Megan's Law, requires that individuals who have been convicted of sex crimes must notify local law enforcement of their current address. Real Estate agencies are required to disclose the location of nearby sex offenders to potential buyers. The goal of our study was to measure the extent to which the social cost of sex crime is capitalised in the housing market. For this purpose, we have performed a cross-sectional hedonic analysis using data on property sales from Shelby County Assessor of Properties and sex offenders' data from the Tennessee Bureau of Investigation.

Our econometric results indicate that a spatial error model should be used to estimate the hedonic equation. Based on the estimates of this model, we find that an additional offender within a one-mile radius lowers property values by about 2%. Additionally, we find that the total housing value loss in a 0.1 of a mile from a sex offender residence is approximately 14% of house value and about 7% of value within a one-mile radius.

Although our empirical results are consistent with other findings in other studies direct comparisons are complicated by the fact that we use two measures of sex offender presence in a neighbourhood. The first is the distance to the nearest sex offender and the second is the density of sex offenders in a one-mile radius visit. The complication arises from the fact that if one begins at a distance of 1 mile and moves toward the nearest sex offender the concentration of sex offenders is likely to increase as well. In fact, our empirical results indicate that the concentration effect, which is not present in other studies, tends to be much larger than the distance effect. With this difference in measurement as a caveat, we find that 14% of the house value is lost if one is within one 0.1 of a mile of a registered sex offender. This value is comparable with a value of 17% found by Larsen et al. (2003) for the case in which the offender was labelled as a 'predator'. In our study there is likely more than one registered sex offender in the radius. The study by Pope (2008a) finds a fall in house price of 2.3% when an offender moves within 0.1 of a mile. This estimate is much smaller than our estimate but we also include a density measure. Pope's estimate is more in line with our findings if we consider the density in a one-mile radius to equal 1, rather than our sample mean of 3.23. Of course, the difference may also be due to the fact that the studies are undertaken for different cities.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Notes

1. Prescott and Rockoff (2011) conclude that the registered offenders system deters first-time sex offenders but increases recidivism due to a change in utility provided by legal and illegal behaviours. Agan (2011) finds no evidence that sex offender registries are effective tools for increasing public safety. If sex offender registries do not reduce crime, the proximity to sex offenders must be troubling to prospective buyers and this concern should be reflected in house prices.
2. A predator is defined as 'a person who has been convicted of, or pleaded guilty to, a sexually oriented offense and who is considered likely in the future to commit additional sexually oriented offenses'.
3. Home sales are matched in time such that no recent locations of offenders can affect past house prices. We have about 14 houses that were sold more than once during the period. We elected to keep them in the sample because the number is small, all transactions occur after the sex offender was in the immediate vicinity, and real estate sales people are required to tell prospective buyers of the location of nearby sex offenders.
4. Note that in our hedonic regression model we use the natural logarithm of *dist2offender* which allows for a non-linear, diminishing-with-distance effect. Non-linear effects have been found in other studies of disamenities by Skaburskis (1989).
5. At the suggestion of a referee, we split our sample by year and re-estimated our basic

model. Either the coefficient of *log(dist2offender)* or the coefficient of *Density100*, or both were statistically significant for every year in the sample except for 2008, which is one of the smaller samples.

6. For the SEM model the effects presented are total effects.
7. The Tennessee Ann. Code § 40-39-[2]11(a)-(b) (2004 Supp. 2012) forbids sex offenders from living within 1000 feet of schools, childcare facilities and victims' residences. Based on our results, living 1000 feet ($\approx$0.19 miles) from a sex offender would appreciate the housing value by US$6410.21. The presence of this effect might be to artificially spread out sex offenders, leading to a possible underestimation of the effect we seek.

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