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Effects of Sex Offenders' Residential Locations on Property Values Using both Parametric and Semiparametric Models

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Abstract The objective of this study is to assess the impact of sex offenders' residential locations on property values in Rochester, New York, by using 19,702 screened single residential housing sales data from 2000 to May 2013. This paper uses both fixed effects and semiparametric models and concludes that the impact from a sex offender's residential location on property values is only regional. Homeowners residing within 0.1 mile, between a 0.1 and 0.2 miles, and between a 0.2 and 0.3 mile radius of a nearby sex offender suffer about 7 %, 6 %, and 3 % property value drops, respectively. These percentage changes translate into $4617, $3731, and $1897 reductions for the average-priced house in the sample, respectively. This negative impact dissipates beyond the 0.3 mile radius.

Keywords Property values · Sex offenders · Semiparametric model · Fixed effects model · Spatial heterogeneity

Introduction

A sex offender (SO) is anyone who has perpetrated a sex crime, which can be categorized into rape, sexual assault, child molestation, child pornography, and attempt to commit any of these crimes. This study depicts how SOs' residential locations impact property values in Rochester, New York. The SO information is made publicly available due to public outrage over some notorious sex-related crimes. The Jacob Wetterling Crimes against Children and Sexually Violent Offender Registration Act is a

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law requiring states to keep and make available an SO and crimes-against-children registry after Jacob Wetterling's abduction in 1994.[1] In 1996, the federal government required states to pass legislation requiring public notification of personal information for SOs based on Megan's Laws.[2] In 2007, the Adam Walsh Child Protection and Safety Act was enacted, leading to the birth of a National Sex Offender Public Website that shares SO information nationwide.[3]

As of this writing, there are more than 800,000 registered SOs in the United States. New York has the third largest number of SOs lagging behind California and Florida. The New York State law prohibits level two and three offenders on parole or probation from living within 1000 feet of schools and day care facilities. Approximately 130 New York counties and communities have passed laws that restrict, to some degree, where registered SOs can live. Among them are the Town of Hamlin and the Village of East Rochester (Mule 2015). For the Village of East Rochester, the county law states that no adult SO shall be permitted to temporarily or permanently reside or live in the Village of East Rochester within 2000 feet of any school grounds, playgrounds, parks, recreational facilities, community center or day-care facilities (Town Village of East Rochester 2016). The question addressed here is how do the residential location choices from the SOs affect the property values in their neighborhoods, if at all? Do the residents care if one of their neighbors is a SO?

This study assumes that there is no information asymmetry among homebuyers or homeowners regarding the information about the neighborhood. Since the SO registry is easily accessible on the Internet, if people were indeed informed, their behaviors might be altered. For example, if their expected costs of living near an SO are higher than the expected benefits of living in that neighborhood, then people would be more likely to move away. The lower demand for houses due to fear or risk aversion could drive down the housing prices in SOs' neighborhoods. The purpose of this paper is to see how the vicinity of an SO could impact both the citywide and local housing prices.

Using house sales data from the Department of Assessment and Taxation and the Department of Neighborhood and Business Development, I conduct an analysis of the impact of SOs' residential locations on property values in the city of Rochester, NY. The findings indicate that there is no significant citywide distance impact from a SO's presence on property values. However, there are significant local effects: homeowners dwelling within 0.1 mile, between a 0.1 and 0.2 miles, and between a 0.2 and 0.3 mile radius of an SO suffer approximately 7.3 %, 5.9 % and 3 % drop in property values, respectively. Those are approximately \$4617, \$3731, and \$1897 reductions respectively for the average priced house in the sample. These negative impacts become insignificant beyond the 0.3 mile radius.

[1] Nobody knows what happened to Jacob Wetterling after his abduction in October 1989 in St. Joseph, Minnesota. His parents initiated the Jacob Wetterling Foundation and have been supporting Child Safety and Protection laws.

[2] Megan Kanka was killed by a prior SO in her neighborhood and Megan's Laws are named after her.

[3] Adam Walsh was murdered and decapitated after being abducted in July 1981 in Florida.

Literature Review

There are plenty of studies that find a negative relationship between housing prices and local crime rates. Thaler (1978) performs his analysis using Rochester, NY's data for 1971, and find that property values drop by 3 % for a one-standard-deviation increase in property crime. His method is just a simple hedonic pricing model and one year's data can easily lead to omitted variable bias. Gibbons (2004) studies the impact of domestic property crimes on housing prices using data containing 10,464 properties in the inner London area between December 2000 and July 2001. His crime data are from April 1999 to March 2001 and finds that property prices decrease by 10 % for a one-standard-deviation increase in the local density of criminal damage. Gibbons uses a semiparametric model to remove the spatial variation from his data before estimating the linear parameters in the hedonic model.

However, there are only a few studies investigating the relationship between SOs' residential locations and property values. Larsen et al. (2003) investigate the relationship between housing prices and proximity to the residence of a registered SO by using sales data in Montgomery County, Ohio in 2000. They find that houses located within a 0.1 mile radius of an offender sold for 17.4 % less, and the significant effect extends to 0.2 miles from the offender's residence with a smaller effect. Linden and Rockoff (2008) examines whether home prices fall when an SO moves into the neighborhood by using data in Mecklenburg County, North Carolina. They use a four-year window surrounding offenders' arrivals (two years prior and two years after) for their analysis. They use a difference-in-difference strategy to control neighborhood and time fixed effects and find that housing prices fall by 4 % within one-tenth of a square mile of the offender's residence location when the offender moves into a neighborhood. However, by combining data from the housing market with North Carolina SO Registry data, they find no statistically significant impact on housing prices further away from the offender's home. Pope (2008) finds evidence that housing prices fall by 2.3 % after an SO moves into a neighborhood and the housing prices rebound after an SO moves out of a neighborhood by using data from Hillsborough County, Florida. He uses a simple cross-sectional approach and spatial-temporal identification strategy to control for neighborhood and time-fixed effects. Caudill et al. (2015) uses a hedonic spatial error model and find that each additional SO 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 SO increases values by about 0.17 % in Shelby County, Tennessee.

This study contributes to the literature by using fixed effects and semiparametric models with extensive cross-sectional and time series city-level data rather than just county-level data. The more advanced semiparametric technique enables flexibility in the model fitting by including both the parametric components and the geographic coordinates as non-parametric parts. This flexibility helps address model misspecification problems and spatial parameters entered non-parametric help address spatial dependence problems.

Study Area and Data

As shown in Fig. 1 below, the study area in this paper is Rochester, New York. There are currently 631 SOs in this city. However, there are many SOs constantly moving

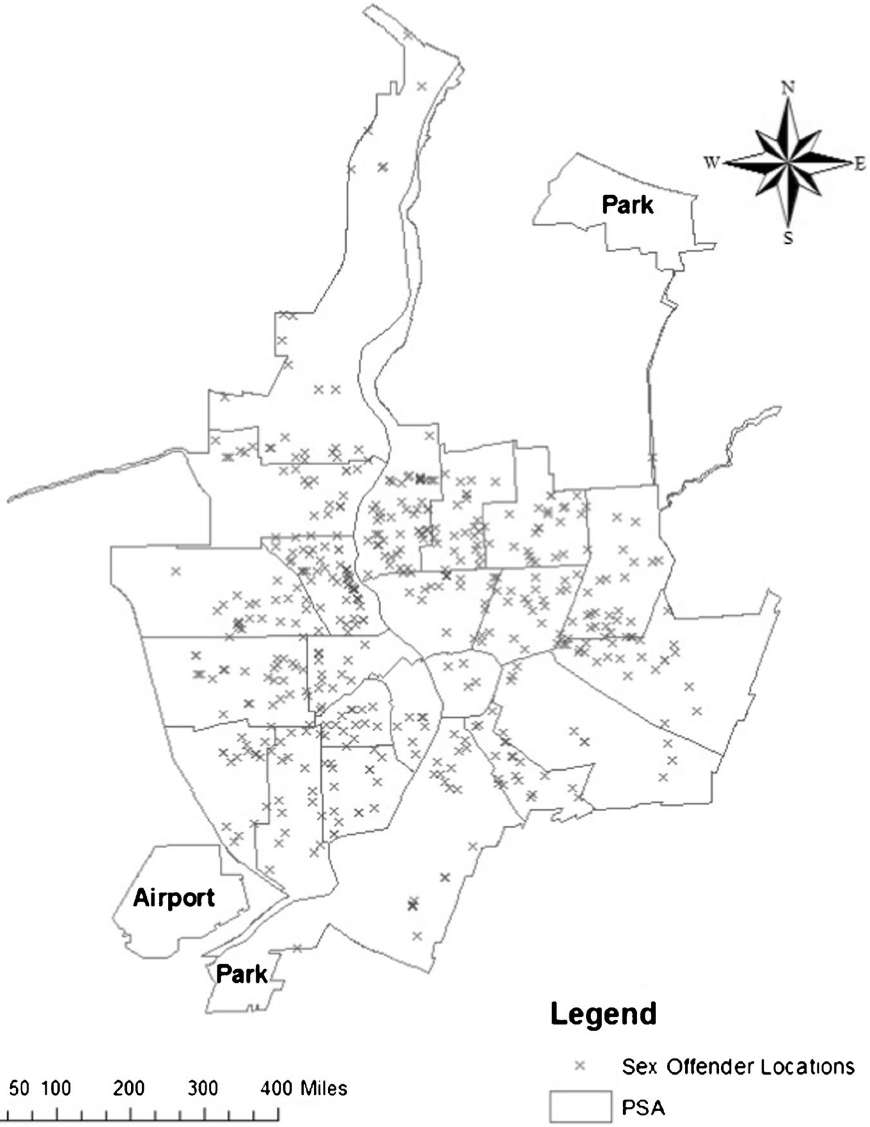

Fig. 1 Study area with geocoded sex offender addresses. Data source: Department of Neighborhood and Business Development – City Hall of Rochester, New York

during the study period. By excluding the highly transient SOs, since the police department of Rochester fails to provide detailed tracking data and the addresses cannot be geocoded by GIS, there are 332 SOs left for observations. The SO registries started on January 21, 1996. By May 11, 2000 the New York registries could be searched online. These housing sales data span from 2000 to May 2013. There are about five months of observations that the homebuyers cannot access via the internet, but can get the information by phone.

Several sources of data were needed to estimate the impact of the SOs' residential locations on property values. The primary dataset used in this analysis consists of single family-housing transactions occurring between 2000 and May 2013 in Rochester, New York. Data on sale prices and property characteristics were compiled from information provided by the Department of Assessment and Taxation. There were originally 27,154 observations, and 7425 of them were deleted because they were multi-families, land sales or commercial transactions. Thus, residential data for 19,729 single families remain. An additional 27 house addresses could not be geocoded. Finally, 19,702 observations remained for study. The recorded nominal housing prices were all converted to the prices in 2000 based on the annual Consumer Price Index (CPI). Various GIS shapefiles of schools, libraries, recreation centers and Central Business Districts (CBDs) were acquired from the Department of Neighborhood and Business Development. SOs' detailed information is from the official New York State Sex Offender Registry online.

Table 1 contains the descriptive statistic for the key variables of primary interest in this paper. The school district, library, recreation center, and CBD shape files are added to create distance variables by using the 'near' function of the ArcGIS. The distance to the nearest SO is created (*SO_DIST*) in the same manner. The dummy variable *SO0.1 m* is created to account for the houses sold within 0.1 mile radius of the nearest SO. *SO0.2 m* accounts for the houses sold between 0.1 and 0.2 miles radius of the nearest SO; *SO0.3 m* accounts for the houses sold between 0.2 and 0.3 miles radius of the nearest SO, and *SO0.4 m* accounts for the houses sold between 0.3 and 0.4 miles radius of the nearest SO. Latitude and longitude were generated through the geocoding processes to be used in both parametric and semiparametric analysis. The Appendix contains all the other characteristics of the houses excluding the house style dummies, exterior material dummies, and year dummies included in the regression. Based on the Moran's I test results, this dataset has a significant spatial dependence problem. Thus, spatial autocorrelation, spatial heterogeneity and omitted variable bias were addressed.

Models

Hedonic Pricing Model

The hedonic pricing model for this study is:

$$\begin{aligned} LnP_i = \alpha_0 + \alpha_1 SO\_\mathrm{DIST} + \alpha_2 SO0.1m + \alpha_3 SO0.2m + \alpha_4 SO0.3m \\ + \alpha_5 SO0.4m + \alpha_t Year_t\_d + \sum \alpha_p S_{ip} + \sum \alpha_q L_{iq} + \varepsilon_i \end{aligned} \quad (1)$$

where *SO_DIST* = the nearest distance to a sex offender for the houses sold after the SO moved in the neighborhood; *SO0.1 m*, *SO0.2 m*, *SO0.3 m*, and *SO0.4 m* are the dummy variables for houses located in the corresponding radius of an SO's residential location; $Year_t\_d$ = the dummy variables for each year controlling for annual housing market trend (t = 1, 2, … 14); S_{ip} = structural attribute p of property i; L_{iq} = locational variable q of property i; α_0 = constant term vector, α_1, α_2, α_3, α_4, α_5 = matrices of parameters;

Table 1 Descriptions and summary statistics of all the other variables

Variables	Descriptions	Mean	St Dev	Min	Max
PERSF	Price per square footage	50.8	28.1	0.0	692.1
Frontage	Width of the lot in meter	46.2	17.6	4.0	1040.0
Depth	Distance from the lot's front to its back in meters	119.0	34.4	9.0	1118.0
Age	Age of the house in year	81.9	25.5	0.0	211.0.
ST	Story height of the house	2.1	0.5	0.5	7.5
MLA	Main living area in square footage	1418.0	419.5	0.0	8948.0
ADDLA	Additional living area in square footage	43.4	123.3	0.0	1244.0
FB	Finished basement area in square footage	4.4	54.2	0.0	1850.0
FRR	Finished recreation room area in square footage	53.6	166.7	0.0	1892.0
BG	Basement garage or number of car spaces	0.02	0.2	0.0	4.0
RMS	Number of total rooms	6.4	1.3	0.0	16.0
BDS	Number of total bedrooms	3.1	0.8	1.0	32.0
AC	1 if the house has central air conditioner, 0 otherwise	0.2	0.4	0.0	1.0
FP	Number of fireplaces	0.2	0.5	0.0	7.0
Min_grade	1 if the construction grade is minimum, 0 otherwise	0.002	0.05	0.0	1.0
Economy	1 if the construction grade is economy, 0 otherwise	0.04	0.2	0.0	1.0
Ave_grade	1 if the construction grade is average, 0 otherwise	0.9	0.2	0.0	1.0
Good_grade	1 if the construction grade is good (omitted)	0.02	0.1	0.0	1.0
Poor_kitchen	1 if the kitchen quality is poor, 0 otherwise	0.1	0.3	0.0	1.0
Ave_kitchen	1 if the kitchen quality is average, 0 otherwise	0.7	0.5	0.0	1.0
Good_kitchen	1 if the kitchen quality is good, 0 otherwise	0.2	0.4	0.0	1.0
Poor_bath	1 if the bathroom quality is poor, 0 otherwise	0.1	0.3	0.0	1.0
Ave_bath	1 if the bathroom quality is average, 0 otherwise	0.7	0.4	0.0	1.0
Good_bath	1 if the bathroom quality is good, 0 otherwise	0.2	0.4	0.0	1.0
Poor_IC	1 if the interior condition is poor, 0 otherwise	0.006	0.1	0.0	1.0
Fair_IC	1 if the interior condition is fair, 0 otherwise	0.1	0.3	0.0	1.0
Normal_IC	1 if the interior condition is normal, 0 otherwise	0.8	0.4	0.0	1.0
Good_IC	1 if the interior condition is good, 0 otherwise	0.1	0.4	0.0	1.0
Excellent_IC	1 if the interior condition is excellent, 0 otherwise	0.01	0.1	0.0	1.0
Poor_EC	1 if the exterior condition is poor, 0 otherwise	0.0009	0.03	0.0	1.0
Fair_EC	1 if the exterior condition is fair, 0 otherwise	0.1	0.3	0.0	1.0
Normal_EC	1 if the exterior condition is normal, 0 otherwise	0.7	0.5	0.0	1.0
Good_EC	1 if the exterior condition is good, 0 otherwise	0.2	0.4	0.0	1.0
Excellent_EC	1 if the exterior condition is excellent, 0 otherwise	0.01	0.1	0.0	1.0
School_d	Nearest distance to a school in mile	0.4	0.3	0.03	3.36
Library_d	Nearest distance to a library in mile	0.7	0.4	0.02	3.57
CBD	Nearest distance to the CBD in mile	1.7	1.1	0.0	6.78
Recreation	Nearest distance to the recreation center in mile	0.7	0.8	0.01	5.35
Latitude	Latitude of the house in degrees	43.2	0.03	43.1	43.27
Longitude	Longitude of the house in degrees	−77.6	0.04	−77.7	−77.54

Data source: Department of Assessment and Taxation, City Hall of Rochester, New York

ε_i = vector of error terms. If the SOs' residential locations affect housing prices negatively both citywide and locally, the first-order relationships of the dependent variable with respect to the key variables are: $\partial LnP_i/\partial SO\_DIST > 0$, $\partial LnP_i/\partial SO0.1m < 0$, $\partial LnP_i/\partial SO0.2m < 0$, $\partial LnP_i/\partial SO0.3m < 0$, $\partial LnP_i/\partial SO0.4m < 0$.

Fixed Effects Model

The fixed effects model assumes that the neighborhood-specific effect (λ_n) in Eq. 2 is correlated with some of the independent variables, while the random effects model assumes that λ_n is not related to any of those regressors and it is part of the sampling errors. The Hausman Test indicates that the fixed effects model generates more consistent estimations than the random effects model for this dataset. This study uses the fixed effects model to remove the within-neighborhood invariant factors that affect the property values. The general fixed effects model is constructed as follows:

$$LnP_{nt} = \alpha + \beta_1 S_{nt} + \beta_2 L_{nt} + \beta_t Year_t\_d + \lambda_n + \varepsilon_{nt} for\ n = 1, 2, \ldots 130 \text{ and t } = 1, 2, \ldots 14 \quad (2)$$

where LnP_{nt} is the natural logarithm of housing price in the n_{th} neighborhood in the t_{th} year; S_{nt} is the structural variables for the home in the n_{th} neighborhood in the t_{th} year and L_{nt} is the locational variables for the home in the n_{th} neighborhood in the t_{th} year. The $\lambda_n + \varepsilon_{nt}$ is the error term that accounts for the variations between the same neighborhood and same year. The component λ_n represents all unobserved factors that vary across neighborhoods but are constant over time (neighborhood-specific effect). The component ε_{nt} represents all unobserved factors that vary across both neighborhoods and time. The component α is the constant in the regressions. This model helps deal with the omitted variable bias by removing unobserved constants within the neighborhood. This dataset includes 130 well-defined neighborhoods; therefore, many omitted variables can be accounted for in this study.[4] From the Moran I's test results, the generated P-value is extremely small, indicating a strong spatial dependence. The following model can help address the spatial heterogeneity and spatial autocorrelation problems.

Semiparametric Model

A semiparametric model is a combination of the parametric and nonparametric approaches. The benchmark model assumes a very strict functional form, in which the dependent variable is determined by the regressors and unobserved errors based on a fixed structure. A functional form misspecification generally means that the model does not account for some important nonlinearities. The disadvantage of parametric models including the fixed effects model is the requirement that both the structure and the error distribution are specified correctly. However, a fixed effects model can help address the omitting variable bias since omitting important variables is also a model misspecification. Functional form misspecification generally causes bias in the

[4] The city of Rochester divides the city into four quadrants (Northeast, Southeast, Northwest and Southwest). These quadrants are broken down into 130 neighborhoods, each with their own character.

remaining parameter estimators. Nonparametric models, on the other hand, impose very few restrictions on the functional form, so there is little room for misspecification. However, the precision of estimators which impose only nonparametric restrictions is poor (Powell 1994). Therefore, the semiparametric estimators are much more flexible than pure parametric models and at the same time do not suffer from the curse of dimensionality.

Locally weighted scatterplot smoothing (LOWESS), is a procedure for fitting a regression surface to data through multivariate smoothing: the dependent variable is smoothed as a function of the independent variables in a moving fashion analogous to how a moving average is computed for a time series (Cleveland and Devlin 1988). The smoothing degree varies usually falling between 0 and 1. For example, if the window size is 0.3, it indicates that the smoothing window has a total width of 30 % of the horizontal axis variable. A detailed application to the housing price functions is in McMillen and Redfern (2010). Let the target for the nonparametric estimator be a house with structural and locational characteristics given by the vector X. The LOWESS estimator is then derived by minimizing the following equation with respect to α and β:

$$\sum_{i=1}^{n}\left(LnP_i-\alpha-\beta'(X_i-X)\right)^2 K\left(\frac{X_i-X}{h}\right). \tag{3}$$

The kernel function $K(z)$ determines the weight for each house sold as an observation in estimating the housing price at target point X, with $X_i - X$ defined as the distance between the target point and the ith neighboring house and h is a smoothing parameter called the bandwidth. As the distance increases, the weight declines. Thus a kernel represents a decreasing function of a distance between two objects. This study uses a tri-cube kernel, but h is more important since it determines how many observations receive positive weight when constructing the estimate as well as how rapidly the weights decline with distance. By placing more weight on more distant observations, high values of h or larger bandwidth imply local regressions that produce more smoothing than do smaller bandwidths (McMillen and Redfern 2010). This study uses the Silverman's Rule of Thumb to determine the optimal bandwidth. Silverman proposes the rule-of-thumb bandwidth as $h = \widehat{\sigma}C_v(k)n^{-1/(2v+1)}$, where $\widehat{\sigma}$ is the sample standard deviation, v is the order of the kernel, and $C_v(k)$ is a constant depending on the type of kernel used. Since this study uses the tri-weight kernel, according to Silverman, the constant is 3.15 if the kernel order is 2. Since the latitude and longitude of each house are estimated in the nonparametric part, their average standard deviation is 0.063 given the Table 1. Plugging this number in the rule-of-thumb function, the optimal bandwidth for this study is 0.03 (rounded). This paper uses 25 % and 3 % bandwidths for comparisons since the choice of bandwidth is critical in nonparametric estimation.

Table 2 Full results for semiparametric model with the optimal bandwidth 3 %

Variables	Estimates	Variables	Estimates
SO_DIST	−0.067 (0.044)	Brick	0.048 (0.015)**
SO0.1 m	−0.073 (0.019)***	Alum/Vinyl	0.009 (0.005)
SO0.2 m	−0.059 (0.016)***	Composition	−0.011 (0.006)
SO0.3 m	−0.030 (0.012)*	Concrete	0.089 (0.034)**
SO0.4 m	−0.006 (0.009)	Stucco	0.013 (0.013)
Year 2000	0.339 (0.016)***	MLA	0.0005 (0.000009)***
Year 2001	0.291 (0.015)***	ADDLA	−0.00007 (0.00002)***
Year 2002	0.261 (0.015)***	FB	0.0001 (0.00004)**
Year 2003	0.243 (0.015)***	FRR	0.00002 (0.00001)
Year 2004	0.209 (0.015)***	BG	0.008 (0.013)
Year 2005	0.189 (0.015)***	RMS	0.010 (0.003)***
Year 2006	0.174 (0.015)***	BDS	0.005 (0.004)
Year 2007	0.137 (0.015)***	BTH	0.003 (0.01)
Year 2008	0.131 (0.015)***	AC	−0.020 (0.005)***
Year 2009	0.067 (0.015)***	FP	0.005 (0.005)
Year 2010	0.091 (0.015)***	Min_grade	−0.641 (0.057)***
Year 2011	0.036 (0.015)*	Economy_grade	−0.089 (0.020)***
Year 2012	−0.012 (0.015)	Average_grade	0.036 (0.015)
Year 2013	omitted	Poor_kitchen	−0.045 (0.009)***
Persf	0.018 (0.0001)***	Average_kitchen	−0.009 (0.006)
Frontage	0.0004 (0.0001)**	Average_bathr	0.049 (0.008)***
Depth	0.0002 (0.00006)**	Good_bathr	0.061 (0.010)***
Ranch_d	0.050 (0.035)	Poor_interior	−0.409 (0.063)***
Manshion_d	0.098 (0.038)*	Fair_interior	−0.004 (0.057)
Contemporary_d	0.071 (0.034)*	Normal_interior	0.111 (0.056)*
Splitlevel_d	0.047 (0.034)	Good_interior	0.119 (0.056)*
Capecod_d	−0.098 (0.070)	Poor_exterior	−0.607 (0.087)***
Bungalow_d	−0.394 (0.073)***	Fair_exterior	−0.244 (0.058)***
Colonial_d	0.039 (0.034)	Normal_exterior	−0.095 (0.058)
Cottage_d	0.095 (0.074)	Good_exterior	−0.089 (0.057)
Oldstyle_d	0.073 (0.056)	Nodriveway_d	−0.307 (0.255)
Row_d	−0.081 (0.052)	Unpaveddriveway_d	−0.057 (0.010)***
Logcabin_d	0.018 (0.036)	Paveddriveway_d	0.012 (0.008)
Townhouse_d	−0.112 (0.037)**	SchoolD	−0.0003 (0.024)
Age	−0.001 (0.0001)***	LibraryD	−0.036 (0.028)
ST	0.073 (0.006)***	CBD	0.086 (0.043)*
Extra_fixture	0.020 (0.012)	RecreationD	0.008 (0.026)

Standard errors in the parentheses; * 5 % significance, ** 1 % significance, ***0.1 % significance. $N = 19{,}702$
Data source: Department of Assessment and Taxation – City Hall of Rochester, New York

Empirical Results

Table 2 includes all the results for the key variables. The regression models include three general model specifications, model (1) is the benchmark OLS model, models (2) and (3) are the fixed effects models, and models (4) and (5) are the semiparametric models. Model (2) includes the geographic coordinates while model (3) does not. Model (4) uses the bandwidth of 25 %, while model (5) uses the optimal bandwidth of 3 %.

Model (1) indicates that there is a positive citywide distance impact from SOs' locations on property values. Being one mile closer to an SO, the housing prices increase by 7 %. However, the regional impacts are negative. Homeowners residing within a 0.1 mile radius of a SO suffer about a 17 % drop of in property values and a 15 % drop for homeowners living between a 0.1 and 0.2 mile radius of an SO. Homeowners residing between a 0.2 and 0.3 mile radius of an SO suffer about a 9 % drop of their property values and there is a 3 % drop in homeowners living between 0.3 and 0.4 miles radius of an SO. These negative regional results work against the positive average citywide results. The impacts from latitude and longitude are significant, the latitude being one degree larger, the housing prices drop by 89.6 %. When the longitude is one degree larger, the housing prices drop by 53.1 %. It seems that this OLS model is very sensitive to the geographic coordinates, but when excluding the coordinates, this model still generates a positive citywide distance impact and negative regional impact from the SO's location on property values. This is clearly a biased result.

Model (2) is the fixed effects model including the geographic coordinates. This model indicates that the housing prices drop by 9.4 % when they are located one mile further from an SO's location. This is a positive citywide distance impact from an SO's presence on property values. However, the local impacts are negative. Homeowners residing within 0.1 mile radius of an SO suffer a 6.2 % drop in their property values and a 4.5 % drop in property values for homeowners living between a 0.1 and 0.2 mile radius of an SO. These negative impacts disappear beyond a 0.2 mile radius. The unreasonable results are from the coordinates. When the latitude is one degree larger, the housing prices increase by 489 % and the longitude is not significant. It is obvious that this fixed effects model is way too sensitive to the absolute house location because the geographic coordinates are fixed, and they should be eliminated in the fixed effects model already.

Model (3) is the fixed effects model without geographic coordinates. This model indicates that the distance variable (*SO_DIST*) is not significant in explaining the average housing prices across the city. The presence of an SO has a negative local impact on property values until a 0.2 mile radius of an SO's location. Homeowners residing within a 0.1 mile radius of an SO suffer a 5.5 % drop in their property values. There is a 3.9 % drop for homeowners living between a 0.1 and 0.2 mile radius of an SO. All the other variables are very reasonable, such as when one year older, the housing prices drop by 0.1 %. If one story higher, the housing prices increase by 8 %. Using the minimum grade quality of construction, the housing prices drop by 51.4 %. If the kitchen quality is poor, the housing prices drop by 4.2 %. Good bathroom quality, results in a housing price increase of 5.8 %. A location mile closer to CBD, causes housing prices to drop by 9.9 %. The adjusted R-squared is 0.927, indicating that 92.7 % of the variation in the dependent variable is explained. The comparison between model (2) and model (3) indicates that including the geographic coordinates in the fixed effects model produces biased results.

Model (4) is the semiparametric model using 25 % bandwidth. When the bandwidth is larger than the optimal bandwidth (0.03), it produces over-smoothing results, making insignificant variables significant. This could be the reason why this model generates very similar parametric results as the OLS model does. It indicates that the housing prices drop by 9.7 % when the homeowners move one mile closer to an SO. This positive citywide distance impact contrasts with the negative local impact from an SO's presence in the neighborhood. The homeowners residing within 0.1 mile, between a 0.1 and 0.2 mile, between 0.2 and 0.3 mile and between 0.3 and 0.4 mile radius of a SO suffer 12.5 %, 11.1 %, 6.3 % and 2.3 % drops in property values, respectively.

Model (5) is the semiparametric model using the optimal bandwidth (0.03). It indicates that the distance to the nearest SO has no citywide impact on housing prices. Figure 2 plotted using LOWESS with the optimal bandwidth shows no spillover effects beyond 0.3 miles, only negative local effects. The presence of SOs in the neighborhood has an adverse local impact on property

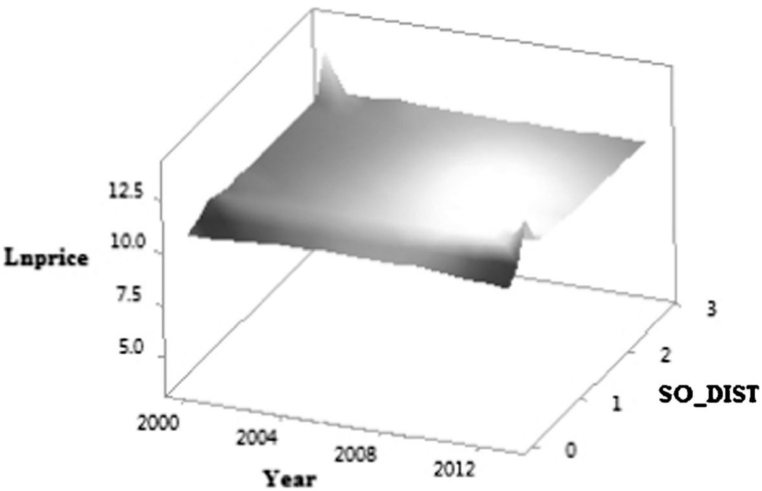

Fig. 2 Surface Plot of *Lnprice* vs *SO_DIST*, *Year*. Evidence of Spatial Heterogeneity in 3D. Data source: Department of Assessment and Taxation – City Hall of Rochester, New York

values: homeowners residing within a 0.1 mile radius of an SO suffer a 7.3 % drop in property values. There is a 5.9 % drop in property values for homeowners living between a 0.1 and 0.2 mile radius of an SO. Homeowners residing between a 0.2 and 0.3 mile radius of an SO suffer a 3 % drop in property values. All the other results are fairly standard. The housing prices have a 1.8 % increase when there is one more square footage of the house, a 0.1 % decrease when the house is one year older, a 7.3 % increase when the house is one level higher, a 1 % increase when the house includes one more room, and a 64 % drop when the grade quality of the construction is the minimum.

The key variables' results from model (5) are similar to model (3)'s but with larger significance and magnitudes. These magnitudes can also be revealed in dollar amounts. Homeowners living within a 0.1 mile radius of an SO suffer about a \$4617 reduction in property values from model (5) comparing to a \$3749 reduction in average property values in the sample from model (3). Similarly, homeowners living between a 0.1 and 0.2 mile radius of an SO suffer \$3731 and \$2467 reductions in average property values from models (5) and (3) respectively. The negative local impacts disappear after 0.3 mile radius while model (3) indicates that the negative local impacts disappear after a 0.2 mile radius of an SO. Homeowners living between a 0.2 and 0.3 miles radius of an SO suffer about \$1897 reductions in average property values in the sample. Both of these two models indicate an insignificant citywide distance impact from an SO's location on property values.

Conclusion

This study illustrates that SOs impose not only direct costs to their victim but also indirect costs to property owners and society at large. While some impacts of crime can be avoided (residents can install surveillance systems, avoid dangerous neighborhoods, go outside less or move elsewhere), this study shows that homeowners in Rochester city residing within an 0.3 mile radius of an SO suffer a reduction in the value of their homes (often a major source of their equity). Homeowners could lobby for more stringent policies to keep SOs out of their neighborhoods, vote for anti-crime policies or choose to move to other communities (i.e. "vote with their feet"). In this case homeowners selling their properties could lead to further changes in the housing market.

There is a large research literature on the connections between disamenities/crime and property values. However, it is notoriously challenging to isolate the specific variables and characteristics directly affected by crime. While many crime variables have been studied in the literature (robbery and aggravated assault crime per acre are known to exert some of the largest influences upon neighborhood housing values), this study shows that the location of

SOs also plays a critical role in influencing housing prices. This study makes a valuable contribution to the field by introducing a semiparametric model using the optimal bandwidth (0.03) to analyze the city-level data across ten years. The result indicates that there is no significant citywide distance impact from an SO's residential location on the housing prices. However, SOs' presence pose a strong negative externality in the local housing market. These results indicate that homebuyers or current residents are informed of the SO presence in the neighborhoods since their aversions or fears of living near one can alter their consumer behavior. The degree of aversion or fear has a negative relationship with the distance to an SO's residential location and dissipates quickly beyond the 0.3 mile radius. Within a 0.3 mile radius of an SO, the closer to his or her residential location, the stronger the aversions are from the households or consumers who are concerned about living in the proximity to an SO.

The association between the locations of SOs and property values will in different socio-economic communities, and by region or country. Future studies could emphasize the unique types of crimes and perceptions associated with registered SOs. Is there a need to modify Megan's Law? Is the impact on property values always proportionally higher in low-income neighborhoods? A difference-in-difference approach could be employed to compare with the semiparametric model in the future studies.

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Appendix

Table 3 Descriptive statistics for key variables

	Mean	Standard deviation	Minimum	Maximum
Lnprice	10.8	0.8	4.4	13.6
SO_DIST	0.5	0.5	0.0	4.0
SO0.1 m	0.1	0.3	0.0	1.0
SO0.2 m	0.2	0.4	0.0	1.0
SO0.3 m	0.2	0.4	0.0	1.0
SO0.4 m	0.1	0.3	0.0	1.0

Data source: Department of Assessment and Taxation, City Hall of Rochester, New York

Table 4 Regression results

Lnprice	Model (1) OLS model	Model (2) FE model	Model (3) FE model	Model (4) Semiparametric Model	Model (5) Semiparametric Model
Intercept	5.914 (8.28)	−120.218 (105.810)	8.738*** (0.212)		
SO_DIST	−0.072*** (0.011)	−0.094* (0.041)	−0.064 (0.037)	−0.097*** (0.016)	−0.067 (0.044)
*SO*0.1 m	−0.166*** (0.001)	−0.062** (0.023)	−0.055* (0.021)	−0.125*** (0.012)	−0.073*** (0.019)
*SO*0.2 m	−0.145*** (0.008)	−0.045** (0.016)	−0.013* (0.015)	−0.111*** (0.009)	−0.059*** (0.016)
*SO*0.3 m	−0.086*** (0.008)	−0.019 (0.012)	−0.013 (0.012)	−0.063*** (0.008)	−0.030* (0.012)
*SO*0.4 m	−0.033*** (0.007)	−0.004 (0.011)	0.002 (0.011)	−0.023*** (0.008)	−0.006 (0.009)
Latitude	−0.896*** (0.122)	4.893* (2.210)			
Longitude	−0.531*** (0.073)	1.060 (1.061)			
Adjusted R^2	0.860	0.875	0.927		
Time control	x	x	x	x	x
House control	x	x	x	x	x
# of observations	19,702	19,702	19,702	19,702	19,702

Standard errors in the parentheses; * 5 % significance; ** 1 % significance, *** 0.1 % significance

Data source: Department of Assessment and Taxation, City Hall of Rochester, New York

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