Attempting to Measure the effect of “Justified Homicides” on Home Values

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INTRODUCTION

Using rich microdata on home sales and geographic data on the occurrence of so-called “justified homicides” from the Fairfax County government in Virginia, we construct an implicit market measure of the effect of these non-criminal homicides on nearby home values. After controlling for land parcel fixed effects, time fixed effects, and home age, we find that homes that fall within 0.3 miles of a justified homicide and are sold within a year of the incident have sale prices that are more than 3.3% lower than other homes, on average. However, we note that our test cannot distinguish between the causal effect of the “justified homicide” and the events which precipitated it. Consequently, we cannot conclude that justified homicides cause declines in nearby home values.

BACKGROUND

A negative externality is a cost imposed on society by some action such that the cost is not borne or considered by any of the participants in the action. One of the ways economists seek to quantify the magnitude of externalities (or at least prove its existence) is through implicit market measures. For example, it is well understood that *all else equal*, areas with high murder rates tend to have lower property values than safer areas. However, it is not clear whether homicides which are not deemed criminal have a similar effect on home values. For example, if a police officer fatally shoots a citizen, and this action is not deemed criminal by the justice system, does society still bear a negative externality? An econometrician can use multiple regression to estimate the effect of such a shooting on local home values. But mathematical statistics has an essential role to play in economic research when distinguishing between misleading correlation and plausible causation.

ASSUMPTIONS FOR REGRESSIONS WITH PANEL DATA

To be sure that our point estimates of regression coefficients are unbiased and that our confidence intervals around those estimates are reliable, the following assumptions should be addressed - an extension of the Gauss-Markov assumptions for OLS (Taboga 2021; Stock and Watson 2007).

Assumptions:

1. Regressors do not have perfect multicollinearity
2. Observations for different homes are i.i.d (random sampling);
3. E[error | X]=0; the error is uncorrelated with the independent variables and has mean 0
4. Large outliers are unlikely
5. Errors are homoscedastic and uncorrelated over time

Most of these assumptions are met easily enough. Assumption five is not met for housing sales data, which is why we calculate heteroskedasticity- and autocorrelation- consistent (HAC) standard errors. Assumption three is the main source of problems in this field of research. When errors are correlated with independent variables due to omitted variables, simultaneity, selection, certain types of measurement error, or other pitfalls, point estimates of regression coefficients may be biased (Yezer 2021). We focus on reducing omitted variable bias (OVB), which arises when the regressor, X, is correlated with an omitted variable. OVB prevents the estimator from converging in probability to the true parameter value. Strength and direction of the bias are determined by ρX_u , the correlation between the error term and the regressor.

INSPIRATION

Pope (2007) examines the causal effect of sex offenders moving in and out of an area on nearby home values. They looked at 0.1, 0.2, and 0.3 mile "closeness" bands around where the offender moves and found that the closest homes suffered price drops of over 2 percent when an offender moved in. We are aware of the housing data we rely on thanks to Professor Carrillo.

DATA

We extracted all of our data from the open geospatial data website maintained by the government of Fairfax County in Virginia.[1] In particular, we downloaded Parcel ID data on location, sales, and physical characteristics (the raw or prepared data and the do-files can be made available, though consultation with the authors about how to edit the files to work on your computer is recommended). An FCPD dataset on the time and location of 17 justified homicides was also downloaded from Fairfax County; however, this data only contained address information on the block where the justified homicide occurred. Latitude and longitude coordinates were calculated manually and added to the data using a geolocation web service.[2] We then merged all housing datasets to the sales panel and identified the distance from each parcel to the nearest justified homicide. Importantly, we consider only detached single family homes and townhomes in ownership developments in our analysis. We use data on sales between 1967 and April 17th, 2021. Sales with a price less than $5,000 or more than $10,000,000 are omitted. This leaves over 700,000 observations.

METHODOLOGY

The distance of a home sale to a justified homicide incident has both a time and space dimension. Therefore, we use a difference-in-difference design to estimate the pure effect of the justified homicide on home prices, net of any other effects driving a secular trend over time.

Table 1. Differences in Differences Illustration

	Sold Before Incident	Sold after Incident	Difference
Houses within 0.3 miles of an incident location (Treated Group)	P1A	P2A	P2A - P1A
Houses more than 0.3 miles from the nearest incident location (Untreated Group)	P1B	P2B	P2B - P1B
Difference in Differences			**(P2A-P1A) - (P2B-P1B)**

We define the treated group to include houses within 0.3 miles of an incident location. We consider three time periods: the period before the nearest incident occurred; the first 365 days after that incident; and the time period after that. This enables an estimation of both short- and long-term effects. We estimate the "B" values in the parsimonious model and the fixed effects models below, respectively.

$$\mathbf{log(price)_{it} = B_0 + B_1{}^kX_i{}^{(k)} + B_2{}^jG_{it}{}^{(j)} + B_3C_i + B_4S_t + B_5F_t + B_6C_iS_t + B_7C_iF_t + B_8Y_t + e_{it}} \quad (1)$$

$$\mathbf{log(price)_{it} = B_0 + B_1{}^jG_{it}{}^{(j)} + B_2S_t + B_3F_t + B_4C_iS_t + B_5C_iF_t + B_6Y_t + B_7Z_t + e_{it}} \quad (2)$$

B_0 is the constant, $X_i^{(k)}$ refers to a set of k time-invariant regressors, $G_{it}^{(j)}$ refers to a set of j regressors that vary across time and parcel, C is the "within 0.3 miles of incident" dummy, S is the "sold within 365 days" dummy, F is the "sold more than 365 days after the incident" dummy, Y represents year fixed-effects (with 2021 as the base), Z represents land parcel fixed effects, and e is the error term. Price refers to sale price. The coefficients on the interaction terms are

[1] https://www.fairfaxcounty.gov/maps/open-geospatial-data
[2] https://www.latlong.net/convert-address-to-lat-long.html

intended to represent the pure effect of the incident on logged home prices. Due to inflation, it makes sense to make the dependent variable logged home prices, as this enables coefficients to be interpreted in terms of percentages.

Table 2 shows the distribution of observations across the dummy variable categories of interest (1 = yes, 0 = no). We observe 324 home sales that are within 0.3 miles of a justified homicide and occured within 365 days of the incident. This should be a large enough sample for the regression analysis.

Table 2

Within 0.3 mi of Justified Homicide	Sale within 365 days of justified homicide 0	1	Total
0	674,423	15,110	689,533
1	12,466	324	12,790
Total	686,889	15,434	702,323

RESULTS

Table 3

VARIABLES	Parsimonious ln (sale price)	Fixed Effects ln (sale price)
Home Age in years	0.00209***	0.0483***
	(0.000129)	(0.000444)
Home Age^2	-3.06e-05***	-3.05e-05***
	(2.32e-06)	(2.45e-06)
log sq ft living area	0.517***	
	(0.00224)	
log acres of land	0.0803***	
	(0.000724)	
Bedroom Count	0.00406***	
	(0.000800)	
Full Bathrooms	0.0522***	
	(0.000804)	
Sold within 365 days after Justified Homicide	0.105***	0.0241***
	(0.00319)	(0.00373)
Sold over 365 days of Justified Homicide	0.177***	0.00495
	(0.00310)	(0.00325)
Close to justified homicide location (<0.3 mi)	0.0166***	
	(0.00283)	
Close * Sold within 365 days	0.0343**	-0.0337**
	(0.0149)	(0.0163)
Close * Sold after more than 365 days	0.00867	-0.0332***
	(0.00582)	(0.00639)
Constant	8.634***	11.47***
	(0.0175)	(0.00943)
Year Fixed Effects (Base year 2021)	Yes	Yes
Parcel ID individual fixed effects	No	Yes
Observations	690,910	702,135
R-squared	0.842	0.948

Robust standard errors in parentheses. Fixed Effects standard errors are also clustered at Parcel ID
*** p<0.01, ** p<0.05, * p<0.1
Source: Fairfax County Government

In our fixed effects model (which best reduces omitted variable bias), we find that homes that fall within 0.3 miles of a justified homicide and are sold within a year of the incident have sale prices that are more than 3.3% lower than other homes, on average (see Table 3). The effect is statistically significant at the 5% level, and the effect appears to remain for over one year (both interaction terms are significant). Standard errors in the fixed effects model are robust to heteroskedasticity, and they are clustered at the Parcel ID level to account for autocorrelation.

LIMITATIONS

We cannot differentiate between the effects of the justified homicide and other events that occurred near the same time, such as if the justified homicide was a response to a serious crime in progress. These crimes, whose occurrences are correlated with justified homicides, are left to be part of the error term in our regression model, violating the Gauss-Markov assumption that the error term is uncorrelated with the independent variable (omitted variable bias). To illustrate the consequences, consider the simple model $P = \sigma J_{it} + \omega C_{it} + v_{it}$, where P_{it} is home price for house i at time t, J_{it} is an indicator of a nearby justified homicide, C_{it} is an indicator for a crime occurring near house i at time t, and v_{it} is the error term. Suppose $\omega < 0$. Assume that as it stands, this model is correct and the error is uncorrelated with the independent variables. If, in our regression model, we disregarded C_{it}, the equation becomes: $P = \sigma J_{it} + \acute{v}_{it}$. With crime left out, the error term changes (Yezer 2021). We now have $v' = \omega C_{it} + v_{it}$. So $E[v'|J] = E[\omega C_{it} + v_{it}.|J]$. But crime events are positively correlated with justified homicides. In terms of notation, we have $C = \varphi J + e$, where $\varphi > 0$ because crime and justified homicides are are directly related (one follows the other), and so we find that $E[\omega C+v| J] = \omega\varphi J < 0$. So what will our estimated coefficient on J look like? We have $E[P|J] = \sigma J + E[v'|J] = \sigma J + \omega\varphi J = (\sigma + \omega\varphi)J$. So our estimate σ^* of σ will be $\sigma^* = \sigma + \omega\varphi < \sigma$. So we would systematically estimate that σ is more negative than it actually is, possibly leading to a false confirmation that justified homicides cause reductions of home prices. While our model is more complex, the omission of crime from the model may similarly induce bias on our estimates.

CONCLUSION

We constructed an implicit market measure of the effect of these non-criminal homicides on nearby home values in Fairfax County. We found that homes within 0.3 miles of a justified homicide that are sold within a year of an incident have sale prices that are more than 3.3% lower than other homes, on average. However, due to the violation of Gauss-Markov assumption that the errors should be uncorrelated with the independent variables, we cannot conclude that justified homicides are the causal force behind declines in nearby home values. Further research might look into ways to separate effects of justified homicides from that of crime.

References

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