SCARE OR SPREAD: Spill-over Effect of High Crime Rates on Nearby Cities' Housing Prices

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Abstract

We illustrate the spill-over effect of high crime rates on nearby cities' housing prices, by decomposing it into a direct effect ("SCARE") and an indirect effect ("SPREAD"). We use the fixed-effect regression model with city- and time-invariant and data from some Bay Area cities centered at Oakland. Our results support the negative indirect effect and partly the positive direct effect. As for the combined effect, we conclude that higher violent crime rates will decrease the nearby cities' housing prices mainly due to the indirect effect, while higher property crime rates will increase the nearby cities' housing prices mainly due to the direct effect.

Keywords: Housing Prices; Crime Rates; Spill-over Effect;

1 Introduction

Oakland has owned the bad reputation of insecurity for a long time. The high crime rates in this city will reduce its own housing price, for that people enduring the insecurity need to be compensated. Meanwhile, the fear of crimes may also drive citizens away to nearby cities, pushing up the local housing prices and creating a housing price gap.

Comparing to the stream of literature on the effect of crime rates on local housing prices, little attention has been paid to the spill-over effect of crime rates on nearby cities' housing prices. As an intuitive inference, the gap of housing prices shall increase along with the gap of crime rates. However, when crime rates get even higher, the marginal benefit of committing a crime declines, and criminals may spread to nearby cities, raise the crime rates and reduce the housing prices there, which makes the combined effect more complicated.

This paper tries to illustrate the whole picture of this question. Not only do we want to show a combined effect, but we will also decompose the effect into a direct part of how people scared away push up the housing prices(”SCARE”), and an indirect part of how crime rates in nearby cities raised by spreading criminals reduce the housing prices(”SPREAD”).

In order to show the direct effect, we assume unilateral moving out from the high crime rates city and that housing prices are always in equilibrium. This helps us to derive the identity relating the housing price gap with the crime rates. We also take into consideration the role played by distance between the two cities. By introducing a time-invariant and a city-invariant, we can rewrite the identity into a fixed-effect regression model.

As for the indirect effect, similarly, we assume unilateral spreading of criminals from high crime rates city and that crime rates are always in equilibrium. Following the step in the direct part, we may come to another fixed-effect regression model.

Combining the two regression models gives us a naive regression of housing prices on crime rates and some intersection items of crime rates and distance, which shall give away the combined effect.

We will use data from the Bay Area of California, taking advantage of the high crime rates city Oakland. The panel data of crime rates and housing prices will be in the city-level, containing Oakland and 76 other cities from the nearby counties of Alameda, Contra Costa, Bolano, Napa, Sonoma, Marin, San Francisco, San Mateo and Santa Clara, from the year 2001 to 2013. The crime rates are calculated in two different measures: The Area measure is crimes comitted per square foot, and the Population measure is crimes comitted per 10,000 people. FBI publications 'Crime in the US' provide us with the raw data of crimes known to law enforcement as well as the population data. For housing prices, we use the Zillow Home Value Index in the city-level. We refer to the website Travelmath for driving distance between cities. The area data come from 'Population, Housing Units, Area, and Density: 2010' and we assume that the area of each city has only negligible changes among these years.

Results from the regressions partly support the existence of both effects: The indirect effect is significant for both types of crimes and both measures, indicating that criminals are actually on the move. The direct effect is ambiguous for violent crime rates, and ambiguous but increasing in distance for property crime rates, which we interpret as that citizens hardly move away for fear of violent crimes but they tend to move far away for fear of property crimes. Finally, combining this two part gives us the combined effect, that higher violent crime rates will decrease the nearby cities' housing prices mainly due to the indirect effect, but higher property crime rates will increase the nearby cities' housing prices mainly due to the direct effect.

The rest of the paper is organized as follows: Section 2 briefly reviews the stream of literature on the mutual relationship of crime rates and housing decisions. Section 3 explains the economic intuition for us to derive the fixed-effect regression model, and provides more details about the data. Section 4 gives away the regression results along with the interpretations. The final section concludes the paper and offers some suggestions on future research.

2 Literature Review

It has been commonly acknowledged that high crime rates have a negative effect on neighborhood housing prices. One stream of literature regards crime rates as an exogenous variable. Lynch and Rasmussen (2001) develop a crime index based on the costs associated with the severity of different offenses; using this index as an independent variable, they suggest that house values decline dramatically in high crime areas. Tita, Petras, and Greenbaum (2006) correct the potential underreporting of crimes with homicide as an instrumental variable, and they find a significant negative effect of change in crime on housing values as well.

However, another stream of literature, tracing back to Becker (1968), realizes that crime rates may be endogenous in the housing price model, i.e. not only the housing prices are affected by crime rates, but criminals make crime decisions according to neighborhood housing prices as well, especially for property crimes. Ihlanfeldt and Mayock (2010) also point out this problem of endogeneity, and in addition to the basic time series model, they introduce different commercial land uses that exist within each neighborhood as instrumental variables to avoid the problem, since different commercial land uses favor specific types of crime, but are barely correlated with the property values. The result suggests that people are willing to pay nontrivial premiums for less aggravated assault and robbery crime neighborhood. Buonanno, Montolio, and Raya-Vilchez (2013) also present that crime exerts relevant costs beyond its direct costs, and houses in districts perceived as being less safe than average are highly discounted, even after accounting for the possible endogeneity of crime and housing prices.

In spite of continuing to accumulate papers on the topic of unilateral or mutual relationships between crime rates and housing prices in the neighborhood context, we turn to the spill-over effect of one cities' high crime rates on nearby cities in this paper, and the problem of endogeneity vanishes immediately in this new context, since the housing prices in one city shall not affect the crime rates in another. Yet, the reverse relationship may still hold true, mainly in the following two ways.

On the one hand, criminals can spread to nearby cities. This argument is supported by a series of papers concerning crime activities with convenient transportation systems. Poister (1996) studies the newly built MARTA system in Atlanta, suggesting that a new rail station encourages a one-shot increase in the incidence of crime. Although transportation systems usually benefit the local area, which is consistent with studies in Buffalos light rail system (Hess & Almeida, 2007) and the highways in the east of the Netherlands (Levkovich, Rouwendal, & Van Marwijk, 2015), the reality may be more complex than it appears, as Bowes and Ihlanfeldt (2001) conclude that stations may raise the value of nearby properties by reducing commuting costs or by attracting retail activity to the neighborhood, while there exists negative externality emitted by stations and the access to neighborhoods that stations provide to criminals. The decomposition of these effects requires them to estimate a hedonic price model as well as two auxiliary models for neighborhood crime and retail activity, and by doing so, the authors outstand the negative crime effects found mainly close to downtown, especially where the station has parking. That criminals prefer not travelling too far away from the station is largely due to that they are afraid of being considered an outsider, as the authors suggest.

The other way of thinking is that residents can vote by feet. Driven by fear of crime, they may move away to nearby cities if they can afford it. As Ihlanfeldt and Mayock (2010) conclude, the best option that can offer protection against most acts of violence may be to self-select peaceful living environments. To examine this, Smolders, Burssens, and Goeminne (2012) focus on how crime affects the tax capacity of local communities. Inspired by the Tiebout model, they suggest insecurity may drive out the wealthy as well as keep them from moving in, leaving the poor, unemployed, elderly citizens in the high crime communities. This may result in income sorting and, consequently, lead to changes in the tax base of the local communities. The empirical results turn out that crime has a depressing effect on average per capita income in the small cities, but surprisingly does not affect the tax capacity, which is interpreted as more less wealthy people are attracted to rent a place in this community. What we are more interested in is that, insecurity in surrounding municipalities significantly increases the tax base. Localities facing increasing levels of crime in the neighboring communities become an attractive heaven for the citizens moving out of those communities. Although the study is done in community-level, the same results shall still hold when we raise it to the city-level.

Both explanations are reasonable, but no such literature has taken both explanations into consideration, as we are going to do in this paper. Since crime rates play different roles in these two ways of thinking, we are expecting the direction of combined effect to be ambiguous, and we may have to run several regressions to separate the two kinds of effects.

Besides crime rates, housing prices are also determined by some other social factors. Koramaz and Dokmeci (2012) investigate spatial determinants, including distance to CBD, sub-centres, main transportation arteries and the coast, as one of the major explanatory domains for housing price values in Istanbul. De Bruyne and Van Hove (2013) study the housing prices in Belgium, Flanders and Wallonia. They investigate the impact of geographical elements, as well as the social and real estate determinants, such as average income level, unemployment, green areas, population and, maybe surprisingly, share of foreigners living in the community, all of which have shown a significant effect. Moreover, Wen, Zhang, and Zhang (2014) suggest that educational facilities have a positive capitalization effect on housing prices as well. But since these factors are rather irrelevant in our context, we won't pay much attention to them, and use a time-invariant as well as a city-invariant to represent them all in our model.

To sum up, besides the local social factors, which are rather trivial, the high crime rates in one city may also affect nearby cities' housing prices in two ways: either the criminals can travel to nearby cities, or residents moving out driven by fear of crime, both of which are revealed indirectly by previous literature. To further infer the magnitudes of these two effects, a fixed-effect regression model must be introduced, as we will discuss in the next section.

3 Model Setup

We will formally analyze the two explanations of how one city's crime rates affect nearby cities' housing prices. The first part, which is more direct, is that people tend to move away from high crime rates communities and into a low crime rates community at the cost of a higher housing prices(”SCARE”). If we assume that rate of compensation is the same for all cities, we could write this down as the following equations:

$$H_h = \mu_h - \beta_1 V_h - \beta_2 P_h$$

$$H_l = \mu_l - \beta_1 V_l - \beta_2 P_l$$

$$H_l = H_h + (\mu_l - \mu_h) + \beta_1(V_h - V_l) + \beta_2(P_h - P_l)$$

Here, H_h is the housing prices in the high crime rates city and H_l is the housing prices in the low crime rates city. μ_h and μ_l denote the part of price determined by social factors other than crime rates, such as income, unemployment rate, education level and etc. V_h and V_l are the violent crime rates in both cities, while P_h and P_l are the property crime rates in both cities.

Intuitively, we assume that residents only move from the high crime rates city to low crime rates cities. In this case, distance shall serve as a main factor of concern, since moving too far away brings about inconvenience to people's life. Thus it's better for us to put the distance and some intersection items into the equation:

$$H_l = H_h + (\mu_l - \mu_h) + \beta_1(V_h - V_l) + \beta_2(P_h - P_l) + \beta_3 D_{hl} + \beta_4(V_h - V_l)D_{hl} + \beta_5(P_h - P_l)D_{hl}$$

On the other hand, the crime rates may have an indirect effect on housing prices through the spreading of criminals(”SPREAD”). Intuitively, we write

$$V_l = \mu_l^V + \phi_1 V_h + \phi_2 D_{hl} + \phi_3 V_h D_{hl}$$

$$P_l = \mu_l^P + \psi_1 P_h + \psi_2 D_{hl} + \psi_3 P_h D_{hl}$$

Notice that μ_l^V and μ_l^P are the part of crime rates determined by social factors other than the housing prices. Again we assume that criminals only spread from the high crime rates city to low crime rates cities.

The combined effect is therefore,

$$\sigma^V = (\beta_1 + \beta_4 D_{hl})[1 - (\phi_1 + \phi_3 D_{hl})]$$

$$\sigma^P = (\beta_2 + \beta_5 D_{hl})[1 - (\psi_1 + \psi_3 D_{hl})]$$

where in the second brackets, 1 denotes the direct effect part and $(\phi_1 + \phi_3 D_{hl})$ or $(\psi_1 + \psi_3 D_{hl})$ denotes the indirect effect part. We can observe from the signs that these two effects go different ways. We can also learn from these equations that we shall include intersection of crime rates with squared distance item when capturing the combined effect.

To further avoid the endogenity problem that the higher housing prices may in some way attract or scare away criminals, resulting in the decrease or increase in another city’s crime rates, it will be better for us to use the housing prices in the next year rather than this year as the dependent variable, since the changes in next year’s housing prices cannot affect this year’s crime rates in another city.

On data collection, we will focus on the Bay Area of California. Oakland, a city with significantly high crime rates among the neighborhood, will be used as the center city with high crime rates. For the low crime rates cities, we choose 76 cities from the nearby counties of Alameda, Contra Costa, Bolano, Napa, Sonoma, Marin, San Francisco, San Mateo and Santa Clara. We include only the cities that have complete data of crime rates from the year 2001 to 2013, and appear in both the Area data and Housing Price Index data. We use driving distance rather than others mainly due to that driving serves as the most convenient way for criminal mobility. Note also that generally the concept of crime rates refers to the number of crimes committed over population, but sometimes it's more useful to use the number of crimes committed over area. We'll run the regression on both measures respectively for robustness check.

Data	Variable	Time	Source
Violent Crimes		2001$\sim$2013	FBI Crime in the U.S.
Property Crimes		2001$\sim$2013	FBI Crime in the U.S.
Population		2001$\sim$2013	FBI Crime in the U.S.
Area		2010	Population, Housing Units, Area, and Density: 2010
Violent Crime Rates	V_{it}	2001$\sim$2013	(Calculated)
Property Crime Rates	P_{it}	2001$\sim$2013	(Calculated)
Housing Price Index	H_{it}	1996/4$\sim$2015/2	Zillow Real Estate Research
Distance	D_i		Travelmath / Driving Dsitance

Table 1: Data Sources

Variable	Mean	Std. Dev.	Min	Max
$H_{i(t+1)}$	668777.3	401133.4	164625	3096383
D_i	32.59211	17.52891	3	90
V_{it}(Area)	17.98499	26.33537	0	170.9163
V_{it}(Pop.)	32.09755	26.4875	0	203.9416
P_{it}(Area)	149.2528	168.2515	12.34568	1388
P_{it}(Pop.)	290.6564	172.8959	59.1716	1682.995

Table 2: Data Summary

We will mainly use the fixed-effect model for all regressions, and in every regression we will include a city-invariant factor μ_i and a time-invariant factor ν_t. Therefore, most of the social factors' influences will be absorbed into these two factors. Besides, the distance D_i and housing price index in the center city $H_{0(t+1)}$ that appear in the equations are absorbed as well, since they are respectively invariant in time and between cities.

We will first do the naive regressions as a preview of our results,

$$H_{i(t+1)} = \beta_0 + \mu_i + \nu_t + \beta_1 V_{0t} + \beta_2 P_{0t}$$

$$H_{i(t+1)} = \beta_0 + \mu_i + \nu_t + \beta_1 V_{0t} + \beta_2 P_{0t} + \beta_3 V_{0t} D_i + \beta_4 P_{0t} D_i + \beta_5 V_{0t} D_i^2 + \beta_6 P_{0t} D_i^2$$

which shall give us an illustration of how the combined effect varies over distance.

To further separate the direct and indirect effect, we have to run three more regressions according to the equations we have come to. For direct effect, the regression model should be

$$H_{i(t+1)} - H_{0(t+1)} = \beta_0 + \mu_i^H + \nu_t^H + \beta_1 (V_{0t} - V_{it}) + \beta_2 (P_{0t} - P_{it}) + \beta_3 D_i + \beta_4 (V_{0t} - V_{it}) D_i + \beta_5 (P_{0t} - P_{it}) D_i$$

according to the equation, but since $H_{0(t+1)}$ and D_i are absorbed into the invariant factors, the regression model we actually run is

$$H_{i(t+1)} = \beta_0 + \mu_i^H + \nu_t^H + \beta_1 (V_{0t} - V_{it}) + \beta_2 (P_{0t} - P_{it}) + \beta_4 (V_{0t} - V_{it}) D_i + \beta_5 (P_{0t} - P_{it}) D_i$$

Similarly, for indirect effect, the regression model omits the distance item D_i, and therefore it turns into

$$V_{it} = \phi_0 + \mu_i^V + \nu_t^V + \phi_1 V_{0t} + \phi_3 V_{0t} D_i$$

$$P_{it} = \psi_0 + \mu_i^P + \nu_t^P + \psi_1 P_{0t} + \psi_3 P_{0t} D_i$$

4 Main Results

As we have talked about, we will run the following naive regressions first to capture the whole picture of the combined effects.

$$H_{i(t+1)} = \beta_0 + \mu_i + \nu_t + \beta_1 V_{0t} + \beta_2 P_{0t}$$

$$H_{i(t+1)} = \beta_0 + \mu_i + \nu_t + \beta_1 V_{0t} + \beta_2 P_{0t} + \beta_4 V_{0t} D_i + \beta_5 P_{0t} D_i + \beta_6 V_{0t} D_i^2 + \beta_7 P_{0t} D_i^2$$

The first regression implicitly assumes that the effect of crime rates is constant over distance. In other words, it can be treated as an average or overall effect. The second regression, including the intersection of crime rates and distance, and the intersection of crime rates and squared distance, assumes the effect of crime rates is quadratic over distance.

Measure	(1) Area	(2) Area	(3) Population	(4) Population
V_{0t}	-288.9147	-1171.955	-319.2547**	-917.9043*
	(213.0723)	(714.08)	(149.5279)	(501.0422)
P_{0t}	1223.35***	1091.279***	929.9714***	834.2401***
	(91.80947)	(307.6857)	(65.30203)	(218.8158)
$V_{0t}D_i$		68.26476*		46.44231*
		(39.28666)		(27.56592)
$P_{0t}D_i$		8.514247		62.08161
		(16.928)		(12.03863)
$V_{0t}D_i^2$		-0.9800467**		-.6682899**
		(0.484091)		(.3396679)
$P_{0t}D_i^2$		-0.1062154		-.0778615
		(0.2085871)		(.1483402)
N	912	912	912	912
Overall R^2	0.0154	0.0271	0.0173	0.0292

$^{***}p < 0.01;^{**} p < 0.05;^{*} p < 0.1$

Table 3: Combined Effect

For violent crime rates, results from the Area measure show that the effect is ambiguous, although it does appear to be somewhat quadratic. Results from the Population measure tell another story: the overall effect is quadratic but negative, which follows the formula of combined effects and also suggests the outstanding of indirect effect. For property crime rates, both results show that the effect is positive and rather stable over distance.

These results correspond to our daily observations. Since violent crimes are more purposeful, if anyone is in the danger of becoming the victim of a certain violent crime, it's too late for him to move away to another city; for those who are not, however, it's less likely to come up with a random violent crime, so residents hardly feel the urgency to leave the city; therefore, the indirect effect becomes the dominating effect. On the contrary, property crimes are usually committed at random, and thus more likely to scare away residents; in this case, the direct effect is so significant that it completely oversets the indirect effect.

For the next step, we'll examine the direct and indirect effect respectively. To examine direct effect, the regressions will be:

$$H_{i(t+1)} = \beta_0 + \mu_i^H + \nu_t^H + \beta_1(V_{0t} - V_{it}) + \beta_2(P_{0t} - P_{it})$$

$$H_{i(t+1)} = \beta_0 + \mu_i^H + \nu_t^H + \beta_1(V_{0t} - V_{it}) + \beta_2(P_{0t} - P_{it}) + \beta_4(V_{0t} - V_{it})D_i + \beta_5(P_{0t} - P_{it})D_i$$

We include the regressions without the intersection items to better capture the characteristic of the effect, just as we have done in capturing the combined effect. Since we have assumed that only residents in the higher crime rates city will move out and push up the housing prices of low crime rates cities, we expect both β_1 and β_2 to be positive. However, this effect shall vanish over distance, for that people may not move too far away only for fear of high crime rates, or in other words, we expect negative β_4 and β_5.

Measure	(5) Area	(6) Area	(7) Population	(8) Population
$V_{0t} - V_{it}$	-94.11152 (232.1208)	549.4613 (463.3876)	-64.38657 (175.3401)	447.6022 (346.2315)
$P_{0t} - P_{it}$	540.7183*** (82.28554)	73.21914 (136.7536)	293.288*** (59.76608)	120.8477 (109.1938)
$(V_{0t} - V_{it})D_i$		-22.43423* (12.48578)		-15.88871* (9.002205)
$(P_{0t} - P_{it})D_i$		18.294*** (4.286964)		5.713044* (3.073876)
N	912	912	912	912
Overall R^2	0.0393	0.0188	0.1098	0.1655

$^{***}p < 0.01;^{**} p < 0.05;^{*} p < 0.1$

Table 4: Direct Effect

For violent crime rates, the ambiguous results fit well with our interpretation in the combined effect part. For property crime rates, results from both measures show that the direct effect is positive without the intersection, but ambiguous if we include the intersection, which may suggests that the overall effect follows our expectation, but when residents take distance into consideration, they think differently from our expectations. When residents are moving away, they tend to move further, and some residents in the cities closest to the center city may even move away as well, resulting in the positive sign of the intersection and the ambiguous sign of the property crime rates.

Finally we will examine the indirect effect:

$$V_{it} = \phi_0 + \mu_i^V + \nu_t^V + \phi_1 V_{0t} + \phi_3 V_{0t} D_i$$

$$P_{it} = \psi_0 + \mu_i^P + \nu_t^P + \psi_1 P_{0t} + \psi_3 P_{0t} D_i$$

Intuitively, criminals will not commit crimes too far away, so we shall expect positive ϕ_1 and ψ_1, but negative ϕ_3 and ψ_3, suggesting that the indirect effect shall vanish over distance as well.

	(9)	(10)	(11)	(12)
Measure	Area	Area	Population	Population
Dep. Var.	V_{it}	P_{it}	V_{it}	P_{it}
V_{0t}	0.0542596**		0.0507526**	
	(0.0232642)		(0.0228658)	
P_{0t}		0.3915703***		0.3043924***
		(0.0668131)		(0.0749344)
$V_{0t}D_i$	-0.0014528**		-0.0019988***	
	(0.0006287)		(0.000618)	
$P_{0t}D_i$		-0.007965***		-0.0059455***
		(0.0018056)		(0.0020251)
N	912	912	912	912
Overall R^2	0.0922	0.1832	0.0492	0.1337

$^{***}p < 0.01; ^{**}p < 0.05; ^{*}p < 0.1$

Table 5: Indirect Effect

All the results follow our expectation. Some simple mathematics tell us that the indirect effect will decay in approximately 25∼60 miles, and cities further than this distance will even have negative influence. The center city seems to have become a nest of criminals, with criminals gathering from other cities and committing crimes in a certain range.

There's still some questions cannot be solved in our analysis: The results in the combined effect part show that the effect of property crime rates is not quadratic, which is inconsistent with the findings in the other two parts that both $(\beta_2 + \beta_5 D_i)$ and $1 - (\psi_1 + \psi_3 D_i)$ are increasing in distance. The abnormal behaviour of residents tending to move away further for fear of property crimes is also confusing. Another problem is the impractical assumptions of unilateral moving and spreading, which may require more considerations.

5 Conclusion

Comparing to the stream of literature on the effect of crime rates on local housing prices, little attention has been paid to the spill-over effect of high crime rates on nearby cities' housing prices. This paper tries to illustrate the whole picture of this problem, by showing not only the combined effect but also the decomposition into a direct part of how people scared away push up the housing prices(”SCARE”), and an indirect part of how crime rates in nearby cities raised by spreading criminals reduce the housing prices(”SPREAD”). We use mainly the fixed-effect regression model with city- and time-invariant derived from some equilibrium identities introduced by economic intuition, and data from some Bay Area cities centered at Oakland.

Results from the regressions support the existence of the indirect effect, but the direct effect is ambiguous for violent crime rates, and ambiguous but increasing in distance for property crime rates, which we interpret as that citizens hardly move away for fear of violent crimes but they tend to move far away for fear of property crimes. As for the combined effect, higher violent crime rates will decrease the nearby cities' housing prices mainly due to the indirect effect, but higher property crime rates will increase the nearby cities' housing prices mainly due to the direct effect.

For further research, we could focus on three groups of people,i.e. residents, violent criminals and property criminals, and solve for the utility maximizing problems for each of them to achieve more precise equilibrium identities. We can also borrow the idea of ”Vote by feet” from the Tiebout model, where we treat crime rates and housing prices as the public good supplied in each city. Both ways can provide us with a more reliable theoretical support on the relations between the examined variables.

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