Criminal Displacement and Policing

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Abstract

This paper develops a search model of crime, in which criminals sequentially choose a target among many alternatives (neighborhoods). Criminals rank alternatives and decide where to start and when to exit. The crime rates reflect the total successful crimes committed in each target. By applying the optimal sequential search rule from Weitzman (1979), we characterize the optimal behavior of criminals. Criminals find it optimal to voluntarily stop the search as soon as they successfully commit a crime without being caught. We then study the deterrent and displacement effects of policing and vigilance on crime rates. We find that increasing policing in a given neighborhood not only reduces crimes in that neighborhood, but also it *reduces* the crime rates in neighborhoods that are searched afterward. By contrast, an increase in vigilance, or private protection, in a neighborhood reduces crimes in that neighborhood, but it *raises* the crime rates in neighborhoods that are subsequently searched. Using data from the city of Chicago, we explore the effect of district's own level and its adjacent districts' level of policing and vigilance on daily crime rates. Using these spatial data, we find suggestive evidence that corroborate the predictions of the model.

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1 Introduction

In the model of optimal police enforcement (Becker, 1968), where criminals are rational agents making decisions based on their expected utility, an increase in police enforcement is thought to decrease crime rates through deterrence. Following this, empirical studies have examined the effect of increasing policing force on reducing crime rates in various types of crime. On the other hand, increased policing in one area could potentially displace criminals to nearby areas with less policing. Recent studies have been measuring the size of deterrent effect and displacement effect associated with increasing policing. Therefore, understanding displacements effect is crucial in designing more effective policing policies.

In this paper, we examine the displacement effects of crime from a search theoretic perspective. Our model accounts for the search behavior of criminals as they move from neighborhoods to neighborhoods, building on optimal sequential search model from Weitzman (1979).[1] In particular, criminals observe the potential reward, probability of success or "vigilance," and probability of apprehension of each target, and attempt crimes sequentially in an order based on these observed factors. Modeling the search behavior of criminals is crucial because it allows us to realistically capture not only the deterrent effects of policies, but also their potential displacement effects. Unlike consumer search in product markets (e.g., Choi et al., 2018), criminals would not find it optimal to return to previously visited targets, since reattempting a crime is associated with the same risk of being caught. Indeed, we find that the criminals voluntarily terminate their search as soon as they succeed without being caught.

We then study the effect of policing and vigilance on crime in a neighborhood and its adjacent neighborhoods. The model predicts negative deterrent and displacement effects of policing. An increase in policing in a neighborhood reduces crime rate in that neighborhood by increasing the probability of apprehension for criminals. This brings positive spillovers to other neighborhoods that are subsequently searched by criminals, as it increases the probability that criminals are captured and removed from the market before moving onto the next neighborhood. The magnitude of these *own* and *adjacent* effects depends on the current policing levels of each neighborhood. By contrast, we uncover a displacement effect of raising vigilance. Specifically, an increase in vigilance in a given neighborhood decreases the crime rate in that neighborhood, as it reduces the probability of success for criminals. However, an increase in vigilance reduces the probability that criminals succeed in that neighborhood and,

[1] The optimal search behavior has been included in different markets. Armstrong (2017) and Choi et al. (2018) both introduce a consumer search model where consumers could search products based on their prior partial information on the product and make the final purchase decision based on information acquired through the search.

therefore, it raises the probability that they move onto the next neighborhood of observation, giving rise to a *displacement effect*.

We take these predictions to the data. To this end, we combine data from three main sources. We use data from the Chicago Police Department from 2013 to 2018 to calculate daily crime rates in each police district as well as that in its neighboring districts. We combine these data with data on the number of police officers and housing prices in each district as well as all adjacent districts. We proxy with the latter for vigilance and with the former for policing. Employing an OLS regression with year and district fixed effect, we obtain correlations that align with the predictions of the model. We further consider an alternative specification using the spatial Durbin model to account for the potential spatial correlation between variables in nearby districts. In both specifications, we obtain statistically significant negative correlation between a district's policing and crime and a district's adjacent policing and crime, providing suggestive evidence regarding the predictions of negative deterrent and displacement effects in the model.

We review the literature in §2, set up the model in §3, and discuss the effects of policing and vigilance in §4. We then discuss the data and empirical strategy, and test the predictions of the model in §5. Finally, we conclude in §6.

2 Literature Review

We consider two bodies of literature related to our work. The first strand of literature we examine is related to the deterrence and displacement effect.

Becker (1968) establishes a model of optimal police enforcement with criminals making rational decisions based on expected utility, where he explores the criminal's response to probability of conviction, probability of apprehension, and the size of punishment. The criminal commits a crime if and only if the expected utility. We follow this approach but introduce the optimal search of criminals in our model.

There is an empirical literature that analyzes the interaction of displacement and deterrent effect. Levitt (2002), McCrary (2002) and Evans and Owens (2007) use various empirical data to study the effect of police level on crime rates. Evans and Owens (2007) study the relationship between the size of COPS grant and the crime rates. These studies show that an increase in police levels reduces crime. The literature of deterrence effects is reviewed in Nagin et al. (2013) and Chalfin and McCrary (2017). Guerette and Bowers (2009) examine 102 studies in situationally focused policing and finds that only 26% of the observations demonstrate displacement effect. Later, Bowers et al. (2011) review and find that in the case of geographically focused policing, the deterrence effect to nearby targets are more likely than the displacement effect. They also point out that a variety of factors including types of crime, types of policing intervention, the perceptions of criminals might have an impact on the degree of deterrence and displacement and should be considered. In our model, we analyze the degree of displacement effect that varies depending on the difference in potential reward between two neighborhoods and the difference in observed level policing between two neighborhoods. Di Tella and Schargrodsky (2004) examine the effect of increased police presence on auto theft. They find that there is significant decrease in auto theft in the block where there is increased police presence, but the blocks close to the protected block do not exhibit significant decrease in car theft. Ayres and Levitt (1998) find that unobserved GPS-based tracking devices reduce auto theft. Gonzalez-Navarro (2013) studies the effect of observed stolen vehicle recovery device on auto theft in Mexico, and finds that despite the reduction in auto theft in the automobiles equipped with such device due to deterrence effect, 18% of the reduction is displaced to other unequipped automobiles of the same mode.

Recently, Maheshri and Mastrobuoni (2020) develop a model that separates the deterrence effect and displacement effect. They perform empirical analysis on the data of Italian bank robberies and their level of visible guard and find that despite the deterrent effect associated with increased police level, half of the crimes are displaced to nearby banks without guards. Consequently, increasing the level of policing in one option without coordination among nearby options is not efficient in reducing total crime rates.

Eeckhout et al. (2010) introduce a model in which under certain circumstances, it is optimal for the policymakers, subject to a resource constraint, to divide the population into two groups randomly and place different levels of policing in each group, while announcing such random crackdowns in advance. They estimate the deterrence effect of increasing policing by applying the model to the speeding interdiction in Belgium. They find that the marginal benefit associated with an increase in the policing resource is close to the marginal cost, suggesting that the current level policing is close to optimal.

On the theoretical side of the literature, Helsley and Strange (2005) solve a two-stage game theoretical model where the public and private sector chooses level of policing in the first stage and the criminal chooses target of crime and severity with no search in the second stage. They find that as private policing increases in one target decreases both the crime rate and severity of crime in that target, but increases both in other targets. In our model with unobserved policing, accounting for the optimal search behavior of criminals, we have the criminal chooses the search order without observing the level of policing in each target.

Burdett et al. (2004) introduce an on-the-job search model where they consider three groups of agents, the employed, the unemployed, and the agents in jail. They connect the crime market with the labor market. The employed choose to commit crime only if the reservation wage is lower than the crime wage. They introduce policing variables, including the flow payment in jail, the rate at which prisoners are released into the unemployed pool, and the rate which jobs are destroyed. By changing these policing variables, the policy makers are not only able to change crime rates, but also have an impact on the amount of unemployment. İmrohoroğlu et al. (2004) introduces a dynamic model over a time horizon where the heterogeneous agents are faced with stochastic employment opportunity throughout their life. The agents are heterogeneous in their income-earning abilities. They find that the probability of apprehension, which is observed by the agents, has a notable effect on the crime rates, specifically reflected in the decline in crime rates in the period from 1980 to 1986. Amodio (2019) presents a fictional market on crime, where the cost of crime increases with friction. He finds there always exists an equilibrium fraction of unprotected potential victims and the equilibrium fraction of active criminals. The dominance between deterrence and displacement effect is determined by the equilibrium of the two. Vásquez (2019) introduces a model of crime and vigilance with no search, in which the potential victims choose the level of vigilance to place on their property. He finds that if the vigilance expense exceeds the expected property loss, then increasing policing leads to an increase in crime rate. Blattman et al. (2021) perform an experiment that random assigns 1,919 streets in Bogotá with intensive policing, and find a spillover effect of crimes to streets with 250 meters from the treated hot spots. They find that the spillover effect is larger for property crimes.

The second strand of literature we examine is the optimal search. The literature of crime focuses on the optimal policing for one crime at the time. In our work, we account for the fact that criminals can reoptimize and reattempt crimes with other options.

The idea of optimal search is initially presented in Weitzman (1979) in which he develops a model that characterizes the optimal search behavior using reservation prices, known as the Pandora's rule, which is to search in the descending order of the reservation prices among all available boxes. Recently, Choi et al. (2018) develop a related idea in the context of consumer search. There, they have a consumer's prior value and a residual value that is only revealed to consumers after the search. In light of this characteristic, in the context of criminal search, the criminals have an intrinsic value that the criminal receives for attempting the crime alone, which varies across all criminals. On the other hand, there exists another residual value that is revealed to the criminals in the form of potential reward and potential penalty only after the search and attempt.

3 The Model

Consider a continuum of criminals. There are *neighborhoods* $n \in \mathcal{N} = \{1, \ldots, N\}$, with $N > 1$, to potentially attempt a crime. Each neighborhood is indexed by both the *failure chance* of an attempted crime $\phi_n \in [0, 1]$ and the *probability of being caught* by the police $p_n \in [0, 1]$. The failure chance ϕ_n reflects the level of private protection, or *vigilance*, in each neighborhood. Conditional on attempting a crime in neighborhood n, the criminal (he) succeeds with chance $1 - \phi_n$ and obtains a *reward* $r_n > 0$; if he is captured by the police, he pays a *fine* $f \in (0, r_n)$. If the criminal fails and is not captured, he gets 0. Henceforth, we assume that the criminal faces an *outside option* u_0, which we normalize to zero.

The problem of the criminal is to choose a sequential search strategy that indicates *where to start* the search and *when to stop* it. Criminal search could end for voluntarily reasons (e.g., criminal was successful in stealing property and not caught) or for involuntarily ones (e.g., criminal was caught while attempting a crime). To solve this problem, we exploit Weitzman's optimal search rule (Weitzman, 1979). This requires finding *reservation indexes* z_n for each neighborhood $n \in \mathcal{N}$. These reservation indexes z_n reflect the payoff that makes the criminal indifferent between searching and not. Specifically, if the criminal is captured, then the criminal's expected payoff is $r_n(1 - \phi_n) - f$. However, if the criminal avoids the police then his expected payoff is $(1 - \phi_n)r_n + \phi_n z_n$, where $\phi_n z_n$ captures the option value of searching: the criminal can keep searching and obtain z_n whenever he is not captured and fails to steal property. Thus, index z_n must solve the following recursive equation:

$$z_n = p_n(r_n(1 - \phi_n) - f) + (1 - p_n)((1 - \phi_n)r_n + \phi_n z_n)$$

Solving for z_n yields:

$$z_n = \frac{r_n(1 - \phi_n) - p_n f}{1 - \phi_n(1 - p_n)} \tag{1}$$

We are now ready to characterize the optimal criminal search behavior. Applying Weitzman's rule (Weitzman, 1979) yields a natural optimal sequential search rule:

(a) *Search order:* the criminal visits the neighborhoods in the descending order of z_n.

(b) *Stopping rule:* the criminal stops if he is caught. Otherwise, the criminal stops as soon as he succeeds and is not caught; if the criminal never succeeds after visiting all neighborhoods, he stops and takes the outside option.

Because the criminal faces a chance of being caught, recalling or re-visiting a neighborhood is suboptimal, since it would yield a payoff that is strictly below the outside option value ($u_0 = 0$). Specifically, given the optimal search rule, criminals keep searching only when they fail to steal property, so there is no reason to return to a previously explored neighborhood, where property is impenetrable, given the risk of being caught. Altogether, the criminal never revisits previous neighborhoods and stops searching if he fails in all neighborhoods (of course, the chance of this event falls as the number of neighborhoods rises). In addition, given (1), the reservation index z_n is strictly less than reward r_n. Thus, the search voluntarily terminates when the criminal succeeds without being caught, for then the criminal gets r_n which is higher than the reservation index z_n and, by the search rule, higher than the reservation indexes of all remaining neighborhoods not searched.

Notice from expression (1) that $\phi_n(1 - p_n)$ is the chance that a criminal fails and is not caught by the police. Thus, $1 - \phi_n(1 - p_n)$ is the chance that the criminal stops the search: either the criminal is caught, or he is successful in stealing property and not caught. So the reservation index z_n can be seen as the expected payoff of attempting a crime in neighborhood n, conditional on stopping the search in n. Moreover, *the reservation index z_n is decreasing in failure chance ϕ_n, increasing in rewards r_n, and decreasing in probability of capture p_n.* This indicates that criminals rank neighborhoods higher if they have lower failure rates ϕ_n, higher rewards r_n, and lower capture probability p_n, which is natural.

4 The Effects of Policing and Vigilance on Crime

Crime rates. Having explained how criminals optimally search for targets, we turn to the determination of crime rates. The *crime rate* κ_n in neighborhood n is given by the probability that the criminal succeeds in stealing property and is not caught. To find these crime rates, suppose criminals search in the following order from most to least attractive *targets*: $\tau_1, \tau_2, \ldots, \tau_n$, where $\tau_1 = \arg\max\{z_n : n \in \mathcal{N}\}$ denotes the neighborhood with the highest reservation index, $\tau_2 = \arg\max\{z_n : n \in \mathcal{N} \setminus \{\tau_1\}\}$ denotes the one with the second highest index, etc.[2] Given the optimal search rule, the criminal continues searching in neighborhood τ_{n+1} if and only if the criminal fails and is not caught in neighborhood τ_n. Therefore, the crime rate in neighborhood τ_n, $n > 1$, is given by

$$\kappa_{\tau_n}(\mathbf{p}) = (1 - \phi_{\tau_n})(1 - p_{\tau_n}) \prod_{i=1}^{n-1} \phi_{\tau_i}(1 - p_{\tau_i}), \tag{2}$$

where $\prod_{i=1}^{\tau_{n-1}} \phi_{\tau_i}(1 - p_{\tau_i})$ is the probability that the criminal fails without getting caught in the first $\tau_1, \ldots, \tau_{n-1}$, neighborhoods searched, whereas $(1 - \phi_{\tau_n})(1 - p_{\tau_n})$ is the probability

[2]For $j > 1$, the j^{th} target is given by $\tau_j = \arg\max\{z_n : n \in \mathcal{N} \setminus \{\tau_1, \ldots, \tau_{j-1}\}\}$.

that the criminal succeeds without getting caught in neighborhood τ_n. As a result, the crime rate in neighborhood τ_n not only depends on its own vigilance ϕ_{τ_n} and policing p_{τ_n}, but also depends on the vigilance and policing of all the neighborhoods that are more preferred to it.

The effect of policing. The crime rate κ_{τ_n} decreases in its own policing p_{τ_n} and the policing level in all previously searched neighborhoods :

$$\frac{\partial \kappa_{\tau_n}(\mathbf{p})}{\partial p_{\tau_n}} = -(1-\phi_{\tau_n}) \prod_{i=1}^{n-1} \phi_{\tau_i}(1-p_{\tau_i}) < 0 \tag{3}$$

$$\frac{\partial \kappa_{\tau_n}(\mathbf{p})}{\partial p_{\tau_j}} = -(1-\phi_{\tau_n})(1-p_{\tau_n})\phi_{\tau_j} \prod_{i\neq j}^{n-1} \phi_{\tau_i}(1-p_{\tau_i}) < 0 \tag{4}$$

for $j = 1, \ldots, n-1$. Intuitively, increasing policing in neighborhood τ_n would decrease crime rate in this neighborhood, because it decreases the probability that a criminal successfully commits a crime without getting captured in neighborhood τ_n. On the other hand, increasing policing in any of the neighborhoods searched before τ_n would also decrease crime rate in neighborhood τ_n, because it lowers the probability that the criminal moves to neighborhood τ_n without getting captured in any of the previously attempted neighborhoods. This implies that *increasing policing in any neighborhood does not displace crime to other neighborhoods.*

Indeed, the deterrent effect of own policing p_{τ_n} is absolutely higher than that of adjacent policing p_{τ_j} if and only if the level of policing is higher in neighborhood τ_n, namely, $p_{\tau_n} > p_{\tau_j}$ for $j = 1, \ldots, n-1$. To see this, write expression (3) as:

$$\frac{\partial \kappa_{\tau_n}(\mathbf{p})}{\partial p_{\tau_n}} = -(1-\phi_{\tau_n})(1-p_{\tau_j})\phi_{\tau_j} \prod_{i\neq j}^{n-1} \phi_{\tau_i}(1-p_{\tau_i})$$

Then, comparing the above expression with (4) implies the aforementioned claim.

Finally, we examine the cross interaction between own policing p_{τ_n} and adjacent policing p_{τ_i}:

$$\frac{\partial^2 \kappa_{\tau_n}(\mathbf{p})}{\partial p_{\tau_n} \partial p_{\tau_j}} = (1-\phi_{\tau_n})\phi_{\tau_j} \prod_{i\neq j}^{n-1} \phi_{\tau_i}(1-p_{\tau_i}) > 0$$

Observe that there is a positive interaction between a neighborhood's own policing and the policing in its previously searched neighborhoods, meaning that the marginal effect of increasing policing in neighborhood τ_n is (absolutely) lower when policing in previously searched neighborhood τ_j is higher. In other words, *low policing levels in previously searched neighborhoods τ_j raises the marginal efficacy of policing in neighborhood τ_n.*

The effects of vigilance. We now turn to examine the effects of vigilance, or failure rates. We find that the crime rate in neighborhood τ_n falls in it own failure chance ϕ_{τ_n}, but it *rises* in the failure chances of the neighborhoods searched before it. Formally,

$$\frac{\partial \kappa_{\tau_n}(\mathbf{p})}{\partial \phi_{\tau_n}} = -(1 - p_{\tau_n}) \prod_{i=1}^{n-1} \phi_{\tau_i}(1 - p_{\tau_i}) < 0 \tag{5}$$

$$\frac{\partial \kappa_{\tau_n}(\mathbf{p})}{\partial \phi_{\tau_j}} = (1 - \phi_{\tau_n})(1 - p_{\tau_n})(1 - p_{\tau_j}) \prod_{i \neq j}^{n-1} \phi_{\tau_i}(1 - p_{\tau_i}) > 0 \tag{6}$$

for $j = 1, \ldots, n-1$. Intuitively, as failure chance in neighborhood ϕ_{τ_n} increases, the crime rate κ_{τ_n} decreases, because the probability that the criminal successfully commits a crime in such neighborhood decreases. This reflects the *deterrent effect* of own vigilance. On the other hand, increasing the failure chance in adjacent neighborhoods, i.e. neighborhoods searched before τ_n, lowers the probability that the criminal succeeds and exits the market before reaching neighborhood τ_n, implying that the probability that the criminal moves to neighborhood τ_n rises. We conclude that *increasing vigilance in any neighborhoods does displace crime to other neighborhoods.*

We also compare the magnitude of the effect of increasing vigilance in a neighborhood and its previously searched neighborhood. Observe that

$$\left|\frac{\partial \kappa_{\tau_n}(\mathbf{p})}{\partial \phi_{\tau_n}}\right| = (1 - p_{\tau_n})\phi_{\tau_j}(1 - p_{\tau_j}) \prod_{i \neq j}^{n-1} \phi_{\tau_i}(1 - p_{\tau_i})$$

and

$$\left|\frac{\partial \kappa_{\tau_n}(\mathbf{p})}{\partial \phi_{\tau_j}}\right| = (1 - p_{\tau_n})(1 - \phi_{\tau_n})(1 - p_{\tau_j}) \prod_{i \neq j}^{n-1} \phi_{\tau_i}(1 - p_{\tau_i}).$$

Then, $\left|\frac{\partial \kappa_{\tau_n}(\mathbf{p})}{\partial \phi_{\tau_n}}\right| > \left|\frac{\partial \kappa_{\tau_n}(\mathbf{p})}{\partial \phi_{\tau_j}}\right|$ if and only if $\phi_{\tau_j} > 1 - \phi_{\tau_n}$. Intuitively, the negative effect of increasing failure rate in neighborhood τ_n on crime rate in τ_n is higher than the positive effect of increasing failure rate in a neighborhood searched before τ_n, when the success rate in neighborhood τ_n is lower than the failure rate in the neighborhood j searched before.

Finally, we examine the cross-partial derivative of own and adjacent vigilance:

$$\frac{\partial^2 \kappa_{\tau_n}(\mathbf{p})}{\partial \phi_{\tau_n} \partial \phi_{\tau_j}} = -(1 - p_{\tau_n})(1 - p_{\tau_j}) \prod_{i \neq j}^{n-1} \phi_{\tau_i}(1 - p_{\tau_i}) < 0.$$

for $j = 1, \ldots, n-1$. The interaction between neighborhood τ_n's failure chance and the failure chance in its previously searched neighborhood τ_j is negative, which suggests that when failure chance in previously searched neighborhood τ_j is higher, increasing failure chance in neighborhood τ_n is more effective in reducing crime in τ_n at the margin. In other words, when ϕ_{τ_n} is higher, the increase of crime rate in neighborhood τ_n owed to an increase in ϕ_{τ_j} is lower.

5 Empirical Analysis

5.1 Empirical Model

We attempt to test the prediction of the model by estimate the following equation:

$$\begin{aligned}\kappa_{i,t} = \beta_0 + \beta_1 police_{i,t} + \beta_2 houseprice_{i,t} + \beta_3 adjacentpolice_{i,t} + \beta_4 adjacenthouseprice_{i,t} \\ + \beta_5 police_{i,t} * adjacentpolice_{i,t} + \delta_i + \lambda_t + \epsilon_{i,t}. \quad (7)\end{aligned}$$

where $\kappa_{i,t}$ is the daily number of crime incidents in district i and day t. In addition, to having daily crime rates as dependent variable, we also consider examine crimes where no arrest was made. A key component of the model is attempted crime rate κ_t. Unfortunately, we observe only crime incidents reported in the data. In our model the crime rate κ_n in (2) reflects the number of attempted crimes in which the criminal succeeds in stealing property and is not caught by the police. We proxy for crime rate κ_{τ_n} with the number of report crime incidents that did not result in an arrest classifying these incidents as not caught by police. $police_{i,t}$ is the number of police officers employed in each district on each day; $houseprice_{i,t}$ is the median house sale price per square foot. As usual, δ_i captures the year-fixed effect, and λ_t captures time-specific characteristics that do not vary across police districts.

To proxy for p_j, namely, the policing in previously searched neighborhoods $j \neq i$ in the model, for each district i, we take the mean of the numbers of police officers in all of its adjacent districts, $adjacentpolice_{i,t}$.[3] Likewise, $adjacenthouseprice_{i,t}$, the mean of the median sale price per square foot in all the adjacent districts, proxies for ϕ_j, for $j \neq i$. There are severe limitations with these proxies. First, our data doesn't allow us to identify which adjacent districts are searched first. Second, we need to make the strong assumption that that criminals search the whole radius of a district rather than a particular one. Lastly, data on vigilance in the US does not exists so we recognize that housing prices might not

[3] We define two police districts to be *adjacent* when they share a border in the map displayed in Figure 1. Since each district shares borders with 2-8 different districts, this measure allows us to proxy for the policing in neighboring districts.

be an ideal proxy. Yet, we conjecture that houses with higher values are usually associated with better protection towards the property, therefore higher vigilance. However, higher housing values also imply higher rewards, which requires us to assume that the vigilance is proportional to the reward in each district.

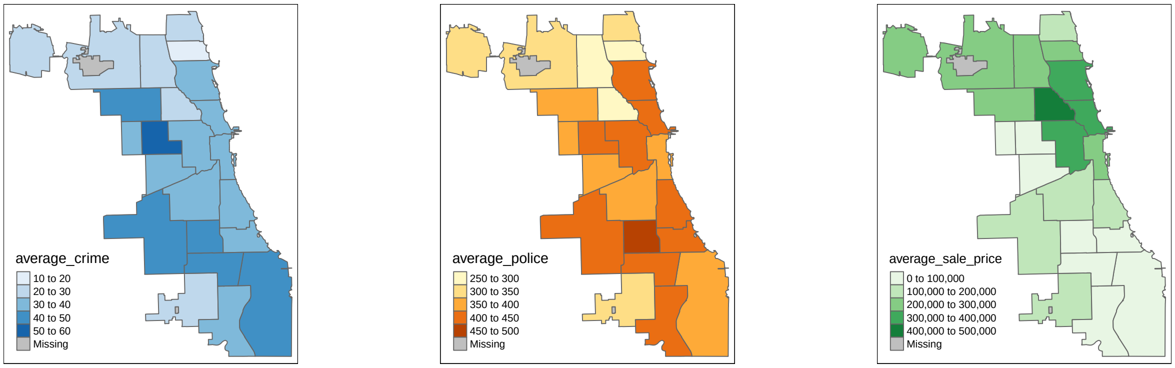
We anticipate that β_1 and β_2 to be negative ad they capture the deterrent effect and displacement effect of policing respectively, as seen from equations 3 and 4. β_3 and positive β_4 measure the deterrent and displacement effect of vigilance, and based on our theoretical model should have opposite signs. β_5 captures the positive interaction between a district's own policing and the policing in its neighboring districts. Although we estimate a district fixed effect model, there might be unobservant time-variant factors that can affect both crime rates and policing or housing prices. Thus our empirical results should not be interpreted as causal.

5.2 Data

We use data from three main sources. First, reported crime incidents come from Chicago Police Department (CPD) from 2001 to 2021. These data includes information on exact location and timing of each reported crime and provides a description of the incident and whether an arrest was made. Second, we use the police profile data provided to the public by Citizens Police Data Project of the Invisible Institute. We observe the district to which each police officer is assigned, their appointment date, and their resignation date. We compute the number of police officers employed in each police district each month.[4] Finally, we use data on residential property values from Cook County Assessor's Office. These data contain information on sale date, sale price, square footage of the land of the property, and coordinate location for all property sales from 2013 to 2019.

Figure 1 displays the spatial distribution of the average daily crime, the average number of police officers, and the average residential sales prices in each district. Table 1 presents summary statistics of the sample. The mean for daily number of all crime incidents reported excluding murders is 35, 1/4 of which are cleared with an arrest. The mean for crimes where no arrest was made is 26; the mean for daily property crimes is 16; and the mean for daily burglary incidences is 1.8.

[4] We restrict our sample to officers whose units are police districts under the Bureau of Patrol Chief.



(a) Average daily crimes in each district

(b) Average number of police officers in each district

(c) Average housing price in each district

Figure 1

Table 1: Descriptive Statistics

	Count	Mean	SD	Min	Max
Overall Crime	38148	34.61	12.81	1.00	144.00
Arrest Rate	38148	0.24	0.11	0.00	0.83
Property Crime	38148	15.67	6.74	0.00	120.00
Burglary	38148	1.83	1.69	0.00	13.00
Number of Police Officers	38148	382.76	62.91	255.00	506.00
Number of Adjacent Police Officers	38148	383.38	44.79	258.00	441.50
Median Sale Price per Square Foot	38148	36.64	32.07	5.69	134.92
Adjacent Median Sale Price per Square Foot	38148	40.98	19.57	9.81	83.48
N	38148				

Notes: The sample consists of 38148 observations for each police district in Chicago and each day from January 2013 to August 2018. This table shows the number of crime incidents for different types of crime, number of police officers, and median sale price per square foot. The number of adjacent police officers is computed as the mean of number of police officers in a district's adjacent districts. The adjacent median sale price is computed as the mean of median sale price in a district's adjacent districts. Data are from Chicago Police Department and Cook County Assessor's Office.

5.3 Results

Table 2 presents the estimated effects of policing and housing prices on the daily number of all crimes, property crimes, burglary, and theft. We find a negative correlation between the number of police officers in a district and the daily crime rate in the district and a negative correlation between the daily amount of crime reported and the number of police officers in adjacent districts. We observe the daily amount of crime in a district to be negatively correlated with the median residential sale price of the district, but positively correlated to the median housing price in its adjacent districts. The estimated displacement effect relative to the means is greatest for burglary.

These results align with the predictions in the model. Specifically, the negative estimated coefficients on a district's own policing and adjacent policing corroborates the prediction of positive deterrent and displacement effects associated with increased policing in both observed neighborhood and its nearby neighborhoods. On the other hand, the estimated coefficients on residential sales price supports the prediction that there is a deterrent effect of increasing vigilance that decreases crime rate in the observed neighborhood and a displacement effect of increasing vigilance in nearby neighborhoods that increases crime rate in the observed neighborhood. Additionally, the positive estimated coefficient on the interaction term between own policing and adjacent policing corroborates the prediction that the marginal effect of increasing policing in a neighborhood is higher when policing it its nearby neighborhoods are lower.

Table 2

	(1) Daily Crime b/se	(2) Daily Property Crime b/se	(3) Daily Burglary b/se	(4) Daily Theft b/se
Police	-0.11838	-0.03854**	-0.02343***	-0.05247***
	(0.066)	(0.014)	(0.004)	(0.009)
Adjacent Police	-0.12201	-0.03331**	-0.01978***	-0.04826***
	(0.060)	(0.012)	(0.004)	(0.008)
Police * Adjacent Police	0.00015	0.00003	0.00005***	0.00008***
	(0.000)	(0.000)	(0.000)	(0.000)
Median Sale Price Per Square Foot	-0.07737	-0.03952***	-0.00694**	-0.02994***
	(0.069)	(0.009)	(0.002)	(0.007)
Adjacent Median Sale Price Per Square Foot	0.07189	0.12585***	0.02869***	0.06183***
	(0.097)	(0.014)	(0.004)	(0.010)
constant	106.86538***	40.88484***	8.95645***	42.84667***
	(24.654)	(4.882)	(1.540)	(3.294)
r2	0.60900	0.45405	0.22925	0.51919
N	38148.00000	38148.00000	38148.00000	38148.00000
ymean	34.60915	15.67401	1.82890	7.86183

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Column 1 reports the OLS estimated effect of policing and residential sale price on daily all crime incidents, controlling for district and year-fixed effects. Column 2, 3, and 4 report the same specification on property crime, burglary, and theft respectively. Robust standard errors are included in parentheses.

The estimated coefficients on own policing are greater in magnitude than those on adjacent policing for property crimes, burglary, and theft, suggesting that the deterrent effect is greater than displacement effect. Recall from comparison of expressions 3 and 4 that the deterrent effect is greater only if the initial policing in the district is greater than its adjacent districts. On the other hand, the estimated coefficients on adjacent house price are greater than those for own district's house price in absolute magnitude for three specifications of property crimes. Similarly, recall from 5 and 6 that this is the case only if the success rate of attempting a crime in the district is greater than the failure rate in its adjacent districts.

Table 3 presents the same specification on all crimes and crimes that were not cleared with an arrest. Since crime rate is defined as successfully committed crimes without a capture, the crimes on which no arrest is made could reflect the nature of crime rate defined in the theoretical model. The direction of the estimated effect of policing and vigilance stay stable to what is found on all crimes and other property crimes.

Table 3

	(1) Daily Crime b/se	(2) Daily Crime with No Arrest b/se
Police	-0.05832**	-0.03015***
	(0.018)	(0.003)
Adjacent Police	-0.06787*	-0.04142***
	(0.024)	(0.005)
Median Sale Price Per Square Foot	-0.07805	-0.06616***
	(0.069)	(0.012)
Adjacent Median Sale Price Per Square Foot	0.05928	0.16773***
	(0.096)	(0.020)
constant	85.57152***	49.83190***
	(10.191)	(2.012)
r^2	0.60893	0.48314
N	38148.00000	38148.00000
ymean	34.60915	25.96831

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Column 1 reports the OLS estimated effect of policing and residential sale price on daily all crime incidents, controlling for district and year-fixed effects. Column 2 reports the same specification on all crimes that were not cleared with an arrest. Robust standard errors are included in parentheses.

Since the policing and vigilance in one district could be correlated with those in its neighboring district, a potential issue for our estimation might be the existence of spatial correlation of crime, policing, and vigilance between districts. (Elhorst, 2014). Using Spatial Durbin Model (SDM), we then present an alternative specification examining the displacement effect of policing and vigilance, accounting for potential spatial correlation between districts. We first construct a spatial weighting matrix W using first-order contiguity from the spatial polygon data of 22 police districts in Chicago.

We estimate the following specification:

$$\kappa_t = \alpha l_N + \rho W \kappa_t + \beta_1 X_t + \beta_2 W X_t + u_t \tag{8}$$

$$u_t = \lambda W u_t + \epsilon \tag{9}$$

where α, β_1, and β_2 are the parameters to be estimated. κ_t is a $N \times 1$ vector of daily crime in each police district; W is the $N \times N$ spatial weighting matrix; X_t represents a N vector of explanatory variables, $policing_t$ and $houseprice_t$. $W\kappa_t$ represents the endogenous interaction effect of daily crime in districts, and WX_t represents the exogenous interaction effects of policing and house sale price in each district.

Column 1 of table 4 estimates equation 8 that controls for both exogenous and endogenous interaction effects, and controls for district fixed effect. Column 2 estimates the same specification using spatial autoregressive model (SAR) that does not control for exogenous interaction effect WX_t.

The direct effect on policing reflects the estimated effect of policing in district i on daily crime in district i, namely the deterrent effect of policing. The indirect effect measures the estimated displacement effect, namely the estimated effect of policing in district i on daily crime in district j, and the estimated effect of policing in district j on daily crime in district i. Our results show that the deterrent effect of number of police officers and median house sale price on daily crime is negative and statistically significant in both model specifications, suggesting the increase in policing and vigilance in a district both reduce crime in the district The displacement effect of median house sale price on daily crime is negative and statistically significant, suggesting that increase in vigilance in a district reduces crime in its neighboring district.

6 Conclusion

This paper develops a model of crime where criminals sequentially choose where to attempt a crime among many alternatives. Criminals choose where to start attempting crimes and when to exit the market. The crime rate in each neighborhood depends not only on the policing and vigilance in its own neighborhood, but also on those in its nearby neighborhoods. The model predicts that increases in policing and vigilance in a neighborhood both decrease the crime rate in that neighborhood. Moreover, an increase in policing in a neighborhood also decreases the crime rate in subsequently searched neighborhoods. However, an increase in vigilance in a given neighborhoods increases the crime rate in neighborhoods searched afterward, giving rise to a displacement effect.

Table 4

	(1) daily_crime b/se	(2) daily_crime b/se
Main		
police_number_	-0.09812***	-0.09070***
	(0.003)	(0.002)
med_sqft_saleprice	-0.15425***	-0.19893***
	(0.009)	(0.007)
Wx		
police_number_	0.03850***	
	(0.007)	
med_sqft_saleprice	-0.09576***	
	(0.016)	
Spatial		
rho	0.48325***	0.48315***
	(0.008)	(0.008)
Variance		
sigma2_e	57.93366***	58.03099***
	(0.424)	(0.425)
LR_Direct		
police_number_	-0.09860***	-0.09365***
	(0.003)	(0.003)
med_sqft_saleprice	-0.16643***	-0.20588***
	(0.009)	(0.007)
LR_Indirect		
police_number_	-0.00867	-0.04559***
	(0.007)	(0.002)
med_sqft_saleprice	-0.17658***	-0.10023***
	(0.013)	(0.004)
LR_Total		
police_number_	-0.10727***	-0.13924***
	(0.007)	(0.004)
med_sqft_saleprice	-0.34300***	-0.30611***
	(0.013)	(0.010)
N	38148	38148

Notes: Column 1 presents maximum likelihood estimation on all daily crimes, controlling for district-fixed effects, spatial interaction in both the outcome variable - crime - and the explanatory variables - policing and residential price. Column 2 controls for district-fixed effects and spatial interaction in outcome variable - crime - only. The direct effect reflects the effect of a district's own policing and house price on crime in its own district, whereas the indirect effects reflects the spillover effect of a district's own policing and house price on crime in its neighboring districts. Robust stnad

We provide empirical corroborations to the testable predictions of the model using data from Chicago. We use the number of patrol officers in each police district to proxy for policing level, and the median residential sale price to proxy for vigilance. Using OLS, we find the signs of deterrence and displacement effects of policing and vigilance to align with the predictions with the model. These results are robust to different types of crimes, including property crimes, crimes that are not cleared with an arrest, burglary, and theft. To account for the potential spatial correlation among crime, policing, and house price across districts, we also test the effects using the spatial Durbin model. The signs of the deterrent and displacement effects of policing maintain the same directions as in the OLS regression.

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