# To catch a thief: Endogenous policing and choice of location by criminals*

Siddhartha Bandyopadhyay[†], Antonio Cabrales[‡] and Kaustav Das[§]

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**Abstract**

This paper develops a tractable model of offender location choice and police resource allocation across multiple areas. Individuals differ in the cost of apprehension and choose whether to commit crime and, if so, where. Each area contains a fixed value of criminal opportunities, so offenders impose congestion on one another, while policing affects expected apprehension. For arbitrary policing levels, equilibrium sorts offenders by apprehension cost across areas ordered by policing per unit of criminal opportunity value. With a fixed police budget, welfare maximization equalizes policing-to-value ratios across all active areas. The model shows when place-based policing should target the value of criminal opportunities rather than observed crime counts alone, since observed crime may already reflect prior police allocation and offender displacement.

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**Keywords:** crime, policing, hot spot policing, displacement, spatial sorting, resource allocation, law enforcement, congestion.

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[†]University of Birmingham; e-mail: s.bandyopadhyay@bham.ac.uk
[‡]Universidad Carlos III de Madrid; e-mail: antonio.cabrales@uc3m.es
[§]University of Leicester; email: kd224@leicester.ac.uk

# 1 Introduction

Police departments around the world have to decide how to allocate their scarce resources over different activities or areas. They do this using different strategies. For example, hot spot policing is celebrated as a success story of policing. The idea behind it is to police high crime places (or hot spots as they are often called in the literature[1]) more intensively.[2] The rationale for its application seems to be a straightforward corollary of optimal policing. Given limited resources, police effort should be focused on minimizing crime. Some of the literature develops this further, focusing on minimizing the gains from crime. They refer to this as harm spot policing (see Weinborn et al. (2017)).

While there is undoubtedly reasonable evidence on the effectiveness of some of these strategies, there is very little formal modeling of it. In particular, they tend to pay little attention to the incentives they give for criminals to relocate. If criminals are rational (as in Becker (1968)), they will respond to incentives. One would expect to see them move in response to increases or decreases in policing activity that affects their probability of apprehension. That is, they would consider not just whether to commit crime, but where to commit that crime, if they do. There are few models that consider together the dual problems of criminals optimally choosing locations and police optimally choosing allocation (we will reference them in the literature review).

Given this limited understanding of the problem, we ask two questions. First, how should police allocate resources across regions when individuals can choose where to commit crime? Second, given rational policing and

[1]See Brantingham and Brantingham (2016), Pierce et al. (1988), Sherman and Weisburd (1995), Sherman et al. (1989)

[2]In a more expanded version of this called problem-oriented policing, the focus is not just on more policing or enforcement but also on solving some of the underlying socio-economic conditions that lead to high crime.

endogenous offender location choice, what does the equilibrium distribution of policing and criminal activity look like? We provide a tractable model in which both offender location choices and police allocation are endogenous. The key insight is that optimal policing should be proportional to the value of criminal opportunities, rather than to observed crime counts, because observed crime is itself shaped by policing and offender relocation.

We propose a model of multiple locations that differ in the value of criminal opportunities, and use it to study the impact of police and criminals behaving optimally. In our model there are a given number of regions and a fixed mass of individuals. Those individuals have different costs of being apprehended if they are caught upon committing a crime. They have to decide whether to become criminals, and if so, where to undertake their activity. The total value of crime opportunities is given in each region. There is congestion in the sense that the total number of people who commit crime in a region compete for this fixed value of crime opportunities, so the value of crime decreases as more people potentially compete for it.

Police have resources that are deployed across the different regions. For a fixed level of policing, the chance of being caught decreases with the number of criminals operating in a region. In order to understand the problem better, we first characterize the equilibrium conditions for criminals' location choice with police resources fixed across regions. We then analyze the equilibrium with a fixed police budget which can be optimally spread across regions. Finally, we undertake an analysis where police budgets are set optimally.

We first show the equilibrium location choices of criminals with a fixed arbitrary level of policing per region. To understand the structure, note that areas with high policing per unit of criminal opportunity are attractive only to offenders with relatively low apprehension costs, while offenders with higher apprehension costs either move to less-policed areas or abstain from crime. To make this more precise, let us order the regions by the ratio of total level of policing to total value of resources in the region. The citizens are ordered by intervals of the apprehension cost. Those with the highest apprehension costs decide not to commit crimes. Then the second highest interval in terms of apprehension cost goes to the region with the lowest ratio of policing to value of resources, and so on in decreasing level of cost and increasing ratio of policing to value of resources. Moreover, in the characterization of this equilibrium, the individuals in the borders between intervals are indifferent between the two adjacent regions characterized by the ratios. Everyone else strictly prefers to be in their region than in any other region (including those who end up deciding not to commit crimes), whenever the ratio differences are strict.

Then, the optimal level of policing must be such that the ratio of level of policing to total value of resources is equalized across all areas. If this were not true, we show a rearrangement of policing that decreases the number of criminals in all regions (except the first one that depends only on the total level of policing). This can be done by increasing policing marginally in the regions with low ratios of policing to value, and decreasing it in the regions with high ratios. In this equilibrium with optimal policing the equalization of ratios has the implication that all criminals are indifferent between locating in their current region or any of the others. These results go through with endogenously chosen police budgets. In fact, because the distribution of policing is linear in the values, we can then write the decision of total level of policing independently of the distribution between regions.

While our objective is to develop a theoretical model of crime location choice and police resource allocation choice, we think that our model is useful to interpret the available evidence and to provide hypotheses to be tested in future empirical work.

The model provides a formal foundation for place-based policing, but with an important qualification. We show that the relevant target is not necessarily the current number of crimes in an area, but the underlying value of criminal opportunities after accounting for offender relocation.

Many empirical studies consider displacement, that is, the possibility that police activity in one area may move crime to another area. However, studies of hot spot policing usually examine relatively short periods, so medium- and long-term displacement effects remain understudied.[3] While many of these short-term studies find little or no displacement, there are exceptions. For example, Operation Menas in London, which involved a double patrol team of uniformed officers patrolling bus stops three times a day, for 15 minutes did show some displacement effects. While there was a 37% reduction in incident reports by bus drivers, the evaluation showed a 25% increase in victims reporting incidents in nearby areas.[4]

Overall, the short run evidence on displacement is limited. However, criminal relocation may take time, so some displacement effects may appear only over longer horizons. We will return to the empirical evidence in the conclusion when we talk about the implications of our model.

In terms of interpretation, the "regions" in our model need not be physical spaces. They could also represent different criminal activities, victim groups, transport networks, times of day or online/offline opportunities. The important point is that police resources and offender choices can be meaningfully allocated across them.

# 2 Related literature

Our paper contributes to the economic and game-theoretic literature on the spatial allocation of law-enforcement resources. A central theme in this literature is that policing one location changes not only deterrence at that

[3] See Gaffney et al. (2022).
[4] See Gaffney et al. (2022).

location, but also the relative attractiveness of other locations. This is the main issue in the analysis of hot spot policing by Lazzati and Menichini (2016), who study place-based policies in a two-stage game and emphasize when targeted enforcement generates displacement or spillovers. It is also central in the empirical reassessment of the Buenos Aires natural experiment by Donohue et al. (2013), where the evidence is consistent with crime being displaced from protected to nearby blocks, and in the local-displacement model of da Matta and Andrade (2011), where the strength of displacement depends on distance and relative area size. More recently, Gao and Vásquez (2025) develop a model in which criminals may search sequentially across heterogeneous neighborhoods before committing crime, and show that optimal policing depends on whether criminals actively search for targets. Newball-Ramírez et al. (2024) estimate a location discrete-choice model using experimental variation in police presence in Bogotá and use the resulting own- and cross-elasticities to evaluate counterfactual police deployments.

Relative to this strand, our contribution is to provide a tractable analytical model in which the spatial distribution of criminals and the allocation of police are jointly determined for an arbitrary number of locations. Rather than starting from a discrete target-choice problem or from sequential search across neighborhoods, we consider a continuum of heterogeneous individuals who differ in their cost of being apprehended. Individuals choose whether to commit crime and, conditional on committing crime, where to locate. Since the value of criminal opportunities in each area is fixed, criminals impose congestion on one another. This generates a simple sorting result: when areas are ordered by the ratio of policing to the value of criminal opportunities, $P_k/v_k$, individuals sort by apprehension cost across areas, with marginal types indifferent between adjacent locations. The model therefore gives a precise equilibrium account of displacement. If police resources are not allocated in the equilibrium proportions, criminals have incentives to relocate until the sorting conditions are restored. For a fixed aggregate police budget, the welfare-maximizing allocation equalizes $P_k/v_k$ across areas. Thus, the paper provides a foundation for a form of hot spot policing, but one that depends on the value of criminal opportunities rather than on observed crime counts alone, which is connected to harm spot policing, as discussed in the Introduction.

Our paper also relates to spatial-equilibrium models of crime, segregation, and mobility. Galiani et al. (2018) study public protection regimes in a general-equilibrium urban model and show how concentrated versus dispersed protection affects crime, residential sorting, housing prices, and welfare. Khanna et al. (2023) use a spatial general-equilibrium framework and administrative data from Medellín to study whether improved transport links reduce crime by expanding legitimate opportunities or instead export crime to new destinations. Helsley and Strange (1999) show that private gating can divert crime to other communities and may lead to excessive security investment in equilibrium, while Verdier and Zenou (2004) show how location and beliefs can generate self-fulfilling differences in crime and labor-market outcomes. These papers emphasize that space affects crime through housing markets, commuting costs, private protection, or access to legal opportunities. Our model shares the focus on endogenous spatial outcomes, but isolates a different mechanism. We stress the interaction between police resources, the value of criminal opportunities, offender heterogeneity, and congestion among offenders. This allows us to characterize explicitly both the equilibrium distribution of criminal activity and the optimal allocation of public policing across space without modeling housing markets, transport costs, or labor-market feedbacks.

Our work is also related to game-theoretic, computational, and simulation-based models of policing and security resource allocation. Espejo et al. (2016) model police deployment against both organized and independently acting offenders and use the framework as a decision-support tool. The Stackelberg-security-games literature studies related resource-allocation problems in settings where a defender commits to a strategy and an adversary responds after observing it; examples include urban network security and patrol allocation in Tsai et al. (2010), the survey of deployed security-game applications in Kar et al. (2017), adaptive opportunistic-crime patrolling in Zhang et al. (2016), and dynamic transportation-network interdiction in Samanta et al. (2024). Bosse and Gerritsen (2010) use agent-based simulation to study the dynamics of criminal hot spots, reputation, and displacement, while DeAngelo (2012) studies spatial competition among criminal organizations and shows how enforcement can change market shares by affecting entry, exit, and spatial differentiation. These papers are primarily concerned with randomized deployment, learning criminal responses, criminal competition, what-if simulations, or computational scalability in networked environments. By contrast, our objective is not to compute patrol schedules, learn a behavioral model from data, or model competition among organized criminal suppliers. We abstract from routing, learning, and market pricing in order to obtain a closed-form equilibrium mechanism linking police intensity, opportunity values, and individual sorting.

Finally, the paper is connected to work on information, reporting, profiling, and police discretion. Bandyopadhyay and Chatterjee (2000) model crime reporting and neighborhood observation, showing that citizen reports and profiling can have unintended effects when reports are biased or when low reporting costs make reports uninformative. Coviello and Persico (2015) study racial disparities in stop-and-frisk and distinguish bias at the level of the officer's stop decision from bias in the allocation of police across precincts. These papers highlight that the information used to direct policing is itself endogenous and potentially distorted. Our model abstracts from the reporting and classification stage. In our model, the values $v_k$ and policing levels

$P_k$ are treated as the relevant primitives. This makes the mechanism a more salient part of the model. Even when police correctly know the spatial value of criminal opportunities, optimal allocation must account for the fact that offenders relocate in response to the full vector of policing intensities.

# 3 Environment

Consider a region $R$ with a continuum population of measure $M > 0$. The region is geographically divided into $N \geq 2$ distinct areas. Individuals are free to locate in any of these areas, and relocation between areas is costless. In each area, individuals may engage in criminal activities. If a positive measure of individuals (denoted by $n_k > 0$) engage in crime in area $k$, then this group of *criminals* jointly obtains a payoff of $v_k > 0$. For any individual $i$ (of measure zero) belonging to the region $k$ with population size $n_k$, the expected gain from engaging in criminal activity in area $k$ is given by $\frac{v_k}{n_k}$.

Let $P_k$ denote the level of policing in area $k$, and let $P = \sum_{k=1}^{N} P_k$ denote the aggregate level of policing in region $R$. For an individual $i$ in the set $n_k$, the apprehension intensity is $P_k/n_k$. This reflects the fact that with more criminals in the area ($n_k$) the police will be stretched and the intensity with which individuals are pursued diminishes. This implies that the expected cost to individual $i$ from being caught is $c_i \frac{P_k}{n_k}$.

The parameter $c_i$ represents the type of individual $i$, reflecting how strongly the individual is affected by being caught by the police. The parameter $c_i$ is uniformly distributed over the population $M$ on the interval $[0, C]$, where $C > 0$. This implies the net expected payoff to individual $i$ from getting involved in criminal activity in area $k$ is given by

$$U_{ik} = \frac{v_k - c_i P_k}{n_k} \tag{1}$$

Without loss of generality, we assume that the net expected payoff to an individual who does not engage in criminal activity is zero. We further assume that for any $k = 1, \ldots, N$, $(v_k - CP_k) < 0$. This ensures that not everyone in the population engages in criminal activity. It should be noted that, since mobility across areas is costless, a non-criminal does not find it beneficial to engage in criminal activity in any area.

We will now define and characterize equilibria in this game. For a fixed level of policing $P$, individuals simultaneously decide whether to engage in crime, and where to locate their activity. A (pure strategy) equilibrium is a set of location and activity choices where no individual has an incentive to modify those choices.

## 3.1 An example

We first illustrate an example in which the region consists of only two areas. This will help us demonstrate the nature of the equilibrium we seek, after which we will extend the analysis to the generalized case of $N \geq 2$ areas.

We label the areas so that

$$\frac{P_1}{v_1} \geq \frac{P_2}{v_2}.$$

In this way the areas are arranged in order of policing per unit of criminal opportunity value. Intuitively, the individuals with the lowest cost of crime should sort themselves in the region where this ratio is highest, since they are less deterred by a higher relative policing intensity. We will now show formally that this is indeed the case in equilibrium.

We conjecture a Nash equilibrium characterized by two thresholds, $c_1$ and $c_2$, where $0 < c_1 < c_2 < C$. All individuals of type $c_i \in (0, c_1]$ engage in criminal activities in area 1, while those of type $c_i \in (c_1, c_2]$ engage in criminal activities in area 2. Individuals of type $c_i \in (c_2, C]$ do not engage in any criminal activities and are indifferent between the two areas. In the following proposition, we show that the conjectured equilibrium always exists.

**Proposition 1** *There exists an equilibrium as conjectured above.*

**Proof.** We first establish necessity. Suppose the conjectured equilibrium exists with thresholds $c_1$ and $c_2$ satisfying

$$0 < c_1 < c_2 < C.$$

In the conjectured equilibrium, the number of criminals in areas 1 and 2 are given respectively by $n_1 = \frac{c_1}{C}M$ and $n_2 = \frac{c_2 - c_1}{C}M$. Since an individual of type $c_2$ is indifferent between engaging in criminal activities in area 2 and not engaging in criminal activity at all, we obtain the following indifference condition:

$$\frac{v_2 - c_2 P_2}{c_2 - c_1} = 0.$$

This implies

$$c_2 = \frac{v_2}{P_2}.$$

Similarly, since an individual of type $c_1$ is indifferent between engaging in criminal activities in areas 1 and 2, we have the indifference condition

$$\frac{v_1 - c_1 P_1}{c_1} = \frac{v_2 - c_1 P_2}{c_2 - c_1}.$$

Solving this expression yields

$$c_1 = \frac{v_1}{P_1 + P_2}.$$

The conjectured equilibrium is indeed an equilibrium if the following two conditions hold. First, for any

$$c < c_1 (\text{respectively } c \in (c_1, c_2)),$$

we have

$$\frac{v_1 - cP_1}{c_1} \geq \text{(respectively } \leq) \frac{v_2 - cP_2}{c_2 - c_1}.$$

Second, for any $c > c_2$, we require $v_1 - cP_1 < 0$ and $v_2 - cP_2 < 0$. For any $c \in (0, C]$, define the function $\Gamma(c)$ by

$$\Gamma(c) = \frac{v_1 - cP_1}{c_1} - \frac{v_2 - cP_2}{c_2 - c_1}.$$

By construction,

$$\Gamma(c_1) = 0.$$

Hence, the conjectured equilibrium is indeed an equilibrium iff

$$\Gamma'(c) \leq 0.$$

Using the expressions for $c_1$ and $c_2$ derived above, we obtain that this condition holds if and only if

$$\frac{P_1}{v_1} \geq \frac{P_2}{v_2}.$$

This is true given how the areas were labeled. Note that the above condition also ensures that individuals of type $c > c_2$ find it optimal not to engage in criminal activity in either area. This concludes the proof of the proposition. ■

### 3.1.1 Optimal Allocation of Policing for a Fixed Aggregate Level of $P$

Consider a social planner who is adversely affected by crime. In particular, if there are $n_1$ and $n_2$ criminals in areas 1 and 2, respectively, then the social planner's payoff is given by

$$U_P(n_1, n_2) = -F(n_1, n_2) - \frac{1}{\beta}(P_1 + P_2)^{\beta} \tag{2}$$

where $\beta > 1$, so that the policing-cost term is strictly concave in total policing, and $F(n_1, n_2)$ is strictly increasing in $n_1$ and $n_2$. To avoid excessive notation, we normalize $M/C = 1$, and maintain the normalization for the remainder of the paper.

**Proposition 2** *For a fixed aggregate level of policing, $P$, the social planner's payoff is maximized at the allocation satisfying*

$$\frac{P_1}{v_1} = \frac{P_2}{v_2}.$$

**Proof.** From the equilibrium values of $c_1 = v_1/\left(P_1 + P_2\right)$ and $c_2 = v_2/P_2$ for a given aggregate level of policing $P$, we obtain

$$U_P(n_1, n_2) = -F\left(\frac{v_1}{P}, \left(\frac{v_2}{P_2} - \frac{v_1}{P}\right)\right) - \frac{1}{\beta}P^{\beta}.$$

From the above expression, we can infer that for a given level of $P$, the social planner's payoff is maximized at the maximum value of $P_2$ subject to the condition that, under the resulting allocation, individuals sort themselves according to the equilibrium characterized above. Thus, the social planner's payoff is maximized when

$$\frac{P_1}{v_1} = \frac{P_2}{v_2}.$$

This concludes the proof of the proposition. ■

The above proposition admits the following intuitive explanation. When the aggregate level of policing is fixed, the total number of criminals in area 1 is unaffected by any reallocation of policing across areas. Consequently, the social planner's payoff can only be improved through a reduction in the

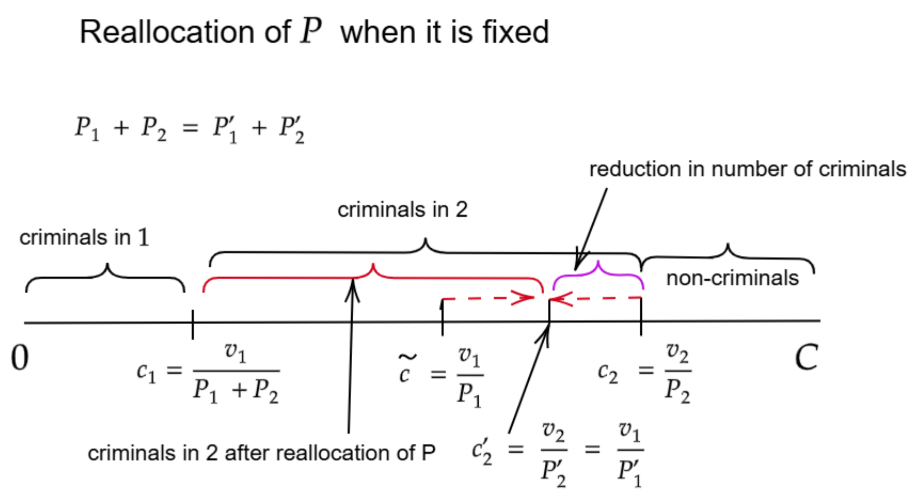


Figure 1: Optimal (re-)allocation of policing

number of criminals in area 2.

From the expression for $c_2$, we know that, for fixed $P$, this can be achieved by increasing $P_2$ and correspondingly decreasing $P_1$. This reallocation can continue up to the point where

$$\frac{P_1}{v_1} = \frac{P_2}{v_2}.$$

This is illustrated in Figure 1.

### 3.1.2 Optimal level of policing

Choosing the optimal level of policing can be viewed as a two-stage process. First, for a given level of total policing $P$, welfare maximization implies

$$\frac{P_1}{v_1} = \frac{P_2}{v_2}.$$

This condition yields

$$P_2 = \frac{Pv_2}{v_1 + v_2}.$$

Substituting this into the planner's payoff in 2, we obtain

$$U_P = -F\left(\frac{v_1}{P}, \frac{v_2}{P}\right) - \frac{1}{\beta}P^{\beta}.$$

Define $G(P) \equiv F\left(\frac{v_1}{P}, \frac{v_2}{P}\right)$. If $G(\cdot)$ is strictly convex in $P$, then the first-order condition $U_P'(P) = 0$ yields the optimal level of policing as

$$-G'(P) - P^{\beta-1} = 0.$$

# 4 Equilibrium of the general model

In this section, we demonstrate that the equilibrium described in the two-area model above extends to the main model with $N \geq 2$ areas. We start by describing the equilibrium for an exogenous vector of policing $(P_1, P_2, \ldots, P_N)$. We now label the areas so that

$$\frac{P_1}{v_1} \geq \frac{P_2}{v_2} \geq \ldots \geq \frac{P_N}{v_N}.$$

As in the two-area example, we conjecture an equilibrium characterized by thresholds $c_k$ $(k = 0, \ldots, N)$ such that a criminal cost $c \in (c_{k-1}, c_k]$ locates in area $k$, where $c_0 = 0$. The following proposition characterizes these thresholds.

**Proposition 3** *Suppose* $0 = c_0 < c_1 < \ldots < c_N < C$. *Now consider an area* $k$. *Then*

$$c_k = \frac{v_k + c_{k-1}(P - \sum_{i=1}^{k} P_i)}{P - \sum_{i=1}^{k-1} P_i}$$

*with* $c_0 = 0$.

**Proof.** We will prove this proposition using the logic of backward induction. First, we will show that it is true for $k = N$. For $k = N$, we have

$$\frac{v_N - c_N P_N}{c_N - c_{N-1}} = 0 \Rightarrow c_N = \frac{v_N}{P_N} = \frac{v_N + c_{N-1}(P - \sum_{i=1}^{N} P_i)}{P - \sum_{i=1}^{N-1} P_i}$$

Next, we will show that whenever this is true for $k = K$, it will be true for $k = K - 1$. Suppose it is true for $k = K$. This means we have

$$c_K = \frac{v_K + c_{K-1}(P - \sum_{i=1}^{K} P_i)}{P - \sum_{i=1}^{K-1} P_i}$$

Since the criminal with cost $c = c_{K-1}$ is indifferent between locating in $K - 1$ and $K$, we have

$$\frac{v_{K-1} - c_{K-1} P_{K-1}}{c_{K-1} - c_{K-2}} = \frac{v_K - c_{K-1} P_K}{c_K - c_{K-1}}$$

The denominator of the right-hand side is equal to

$$\begin{aligned} c_K - c_{K-1} &= \frac{v_K + c_{K-1}(P - \sum_{i=1}^{K} P_i)}{P - \sum_{i=1}^{K-1} P_i} - c_{K-1} \\ &= \frac{v_K + c_{K-1}P - c_{K-1}\sum_{i=1}^{K} P_i - c_{K-1}P + c_{K-1}\sum_{i=1}^{K-1} P_i}{P - \sum_{i=1}^{K-1} P_i} \end{aligned}$$

$$= \frac{v_K - c_{K-1} P_K}{P - \sum_{i=1}^{K-1} P_i}$$

Thus the indifference relation between area $K - 1$ and $K$ becomes

$$\frac{v_{K-1} - c_{K-1} P_{K-1}}{c_{K-1} - c_{K-2}} = P - \sum_{i=1}^{K-1} P_i$$

$$\Rightarrow c_{K-1}(P - \sum_{i=1}^{K-1} P_i + P_{K-1}) = v_{K-1} + c_{K-2}(P - \sum_{i=1}^{K-1} P_i)$$

$$\Rightarrow c_{K-1} = \frac{v_{K-1} + c_{K-2}(P - \sum_{i=1}^{K-1} P_i)}{P - \sum_{i=1}^{K-2} P_i}$$

Hence, it is true for $k = K - 1$. Since it is true for $k = N$ and whenever it is true for $k = K$ it is true for $k = K - 1$, we can infer that it is true for all $k = 1, 2, \ldots, N$. ■

Note that since $c_0 = 0$, we have $c_1 = \frac{v_1}{P}$. Moreover, as described above, we have $c_N = \frac{v_N}{P_N}$. Therefore, irrespective of the number of areas, the expressions for the first and the last thresholds remain the same.

In the proposition below, we will show that the equilibrium conjectured above is indeed an equilibrium.

**Proposition 4** *The thresholds conjectured in Proposition 3 give rise to an equilibrium.*

**Proof.** For any $k = 1, 2, \ldots, N - 1$, define the function $\Gamma_k$ as

$$\Gamma_k(c) = \left\{ \frac{v_k - cP_k}{c_k - c_{k-1}} - \frac{v_{k+1} - cP_{k+1}}{c_{k+1} - c_k} \right\}$$

Since the mass of criminals in area $k$ is given by $c_k - c_{k-1}$, $\Gamma_k(c)$ measures the difference in payoff for an individual with cost $c$ between locating and engaging in criminal activities in area $k$ and area $k + 1$. By construction, $\Gamma_k(c_k) = 0$. The conjectured equilibrium is indeed an equilibrium if and only if

$$\Gamma_k'(c) = -\left[ \frac{P_k}{c_k - c_{k-1}} - \frac{P_{k+1}}{c_{k+1} - c_k} \right] \leq 0$$

Using the expression for $c_k$ from the previous proposition, we have

$$c_k - c_{k-1} = \frac{v_k + c_{k-1}\left(P - \sum_{i=1}^{k} P_i\right)}{P - \sum_{i=1}^{k-1} P_i} - c_{k-1} = \frac{v_k - c_{k-1}P_k}{P - \sum_{i=1}^{k-1} P_i}.$$

This gives

$$c_{k+1} - c_k = \frac{v_{k+1} - c_k P_{k+1}}{P - \sum_{i=1}^{k} P_i}.$$

Hence,

$$\frac{P_k}{c_k - c_{k-1}} = \frac{P_k \left(P - \sum_{i=1}^{k-1} P_i\right)}{v_k - c_{k-1} P_k},$$

and

$$\frac{P_{k+1}}{c_{k+1} - c_k} = \frac{P_{k+1} \left(P - \sum_{i=1}^{k} P_i\right)}{v_{k+1} - c_k P_{k+1}}.$$

Therefore,

$$\frac{P_k}{c_k - c_{k-1}} - \frac{P_{k+1}}{c_{k+1} - c_k} = \frac{P_k \left(P - \sum_{i=1}^{k-1} P_i\right)}{v_k - c_{k-1} P_k} - \frac{P_{k+1} \left(P - \sum_{i=1}^{k} P_i\right)}{v_{k+1} - c_k P_{k+1}}.$$

The sign of the above expression is the same as the sign of its numerator, which is

$$\begin{aligned} & P_k v_{k+1} \left(P - \sum_{i=1}^{k-1} P_i\right) - P_k P_{k+1} c_k \left(P - \sum_{i=1}^{k-1} P_i\right) \\ & - v_k P_{k+1} \left(P - \sum_{i=1}^{k} P_i\right) + P_k P_{k+1} c_{k-1} \left(P - \sum_{i=1}^{k} P_i\right). \end{aligned} \tag{3}$$

Combining the second and fourth terms yields

$$-P_k P_{k+1} c_k \left(P - \sum_{i=1}^{k-1} P_i\right) + P_k P_{k+1} c_{k-1} \left(P - \sum_{i=1}^{k} P_i\right) \tag{4}$$

$$= -P_k P_{k+1} \left\{ c_k \left(P - \sum_{i=1}^{k-1} P_i\right) - c_{k-1} \left(P - \sum_{i=1}^{k} P_i\right) \right\}. \tag{5}$$

Since

$$c_k \left(P - \sum_{i=1}^{k-1} P_i\right) = v_k + c_{k-1} \left(P - \sum_{i=1}^{k} P_i\right),$$

expression (5) becomes

$$-P_k P_{k+1} \left\{ v_k + c_{k-1} \left( P - \textstyle\sum_{i=1}^{k} P_i \right) - c_{k-1} \left( P - \textstyle\sum_{i=1}^{k} P_i \right) \right\}$$
$$= -P_k P_{k+1} v_k.$$

Thus, (3) reduces to

$$P_k v_{k+1} \left( P - \sum_{i=1}^{k-1} P_i \right) - P_k P_{k+1} v_k - v_k P_{k+1} \left( P - \sum_{i=1}^{k} P_i \right),$$

which can be rewritten as

$$P_k v_{k+1} \left( P - \sum_{i=1}^{k-1} P_i \right) - P_{k+1} v_k \left\{ P_k + P - \sum_{i=1}^{k} P_i \right\},$$

and hence

$$P_k v_{k+1} \left( P - \sum_{i=1}^{k-1} P_i \right) - P_{k+1} v_k \left( P - \sum_{i=1}^{k-1} P_i \right).$$

Therefore,

$$\left( P - \sum_{i=1}^{k-1} P_i \right) \left( P_k v_{k+1} - P_{k+1} v_k \right).$$

It follows that $\Gamma_k'(c)$ is non-positive if the above expression is positive, which is equivalent to

$$P_k v_{k+1} - P_{k+1} v_k \geq 0 \quad \Longleftrightarrow \quad \frac{P_k}{v_k} \geq \frac{P_{k+1}}{v_{k+1}}.$$

This condition is true by the assumed ordering of the regions.

If $c \in (c_{k-1}, c_k]$, then for every $j < k$ we have $c > c_j$, so area $j+1$ is weakly preferred to area $j$. Iterating, area $k$ is weakly preferred to all lower-index areas. Similarly, for every $j \geq k$, $c \leq c_j$, so area $j$ is weakly preferred to area $j+1$. Iterating, area $k$ is weakly preferred to all higher-index areas.

For $c > c_N$, area $N$ yields negative payoff, and by the preceding ordering argument no other area yields a higher payoff. Hence, these individuals optimally abstain from crime.

$\blacksquare$

We have established that the qualitative feature of the equilibrium reflected in the two-area example discussed earlier is preserved in the model with $N \geq 2$ areas as well. In the proposition below, for a given level of policing in each area, we characterize a measure of the total number of criminals in each area.

**Proposition 5** *In any area $k$ ($k = 1, 2, 3, \ldots, N$), the number of criminals is given by*

$$c_k - c_{k-1} = \sum_{j=1}^{k-1} \frac{[v_k P_j - P_k v_j]}{\sum_{i=j}^{N} P_i \sum_{i=j+1}^{N} P_i} + \frac{v_k}{P}$$

**Proof.** We will first prove the following lemma.

**Lemma 6** *Suppose for any $l \in \{1, 2, \ldots, k-2\}$ the following is true*

$$c_k - c_{k-1} = \sum_{j=k-l}^{k-1} \frac{[v_k P_j - P_k v_j]}{\sum_{i=j}^{N} P_i \sum_{i=j+1}^{N} P_i} + \frac{v_k - P_k c_{k-(l+1)}}{\sum_{i=k-l}^{N} P_i}$$

*then it is true for $l+1$ as well.*

**Proof.** Suppose the hypothesis is true for $l$, so that

$$c_k - c_{k-1} = \sum_{j=k-l}^{k-1} \frac{v_k P_j - P_k v_j}{\left(\sum_{i=j}^{N} P_i\right)\left(\sum_{i=j+1}^{N} P_i\right)} + \frac{v_k - P_k c_{k-(l+1)}}{\sum_{i=k-l}^{N} P_i}.$$

We first expand $c_{k-l-1}$ in the numerator of the last term above. We know that

$$c_{k-l-1} = \frac{v_{k-l-1} + c_{k-l-2} \sum_{i=k-l}^{N} P_i}{\sum_{i=k-l-1}^{N} P_i}.$$

Therefore, the last term becomes

$$\frac{v_k - P_k\left[\frac{v_{k-l-1}+c_{k-l-2}\sum_{i=k-l}^{N} P_i}{\sum_{i=k-l-1}^{N} P_i}\right]}{\sum_{i=k-l}^{N} P_i},$$

which simplifies to

$$\frac{v_k \sum_{i=k-l-1}^{N} P_i - P_k v_{k-l-1} - P_k c_{k-l-2} \sum_{i=k-l}^{N} P_i}{\left(\sum_{i=k-l-1}^{N} P_i\right)\left(\sum_{i=k-l}^{N} P_i\right)}.$$

Rearranging terms,

$$\begin{aligned}
&= \tfrac{v_k P_{k-(l+1)} - P_k v_{k-(l+1)} + v_k \sum_{i=k-l}^{N} P_i - P_k c_{k-l-2} \sum_{i=k-l}^{N} P_i}{\left(\sum_{i=k-l-1}^{N} P_i\right)\left(\sum_{i=k-l}^{N} P_i\right)} \\
&= \tfrac{v_k P_{k-(l+1)} - P_k v_{k-(l+1)}}{\left(\sum_{i=k-l-1}^{N} P_i\right)\left(\sum_{i=k-l}^{N} P_i\right)} + \sum_{i=k-l}^{N} P_i \left[\tfrac{v_k - P_k c_{k-l-2}}{\left(\sum_{i=k-l-1}^{N} P_i\right)\left(\sum_{i=k-l}^{N} P_i\right)}\right].
\end{aligned}$$

Hence,

$$= \frac{v_k P_{k-(l+1)} - P_k v_{k-(l+1)}}{\left(\sum_{i=k-l-1}^{N} P_i\right)\left(\sum_{i=k-l}^{N} P_i\right)} + \frac{v_k - P_k c_{k-l-2}}{\sum_{i=k-l-1}^{N} P_i}.$$

This implies that

$$\begin{aligned}
c_k - c_{k-1} \;&=\; \sum_{j=k-l}^{k-1} \frac{v_k P_j - P_k v_j}{\left(\sum_{i=j}^{N} P_i\right)\left(\sum_{i=j+1}^{N} P_i\right)} \\
&\quad + \frac{v_k P_{k-(l+1)} - P_k v_{k-(l+1)}}{\left(\sum_{i=k-l-1}^{N} P_i\right)\left(\sum_{i=k-l}^{N} P_i\right)} + \frac{v_k - P_k c_{k-l-2}}{\sum_{i=k-l-1}^{N} P_i}.
\end{aligned}$$

Therefore,

$$c_k - c_{k-1} = \sum_{j=k-(l+1)}^{k-1} \frac{v_k P_j - P_k v_j}{\left(\sum_{i=j}^{N} P_i\right)\left(\sum_{i=j+1}^{N} P_i\right)} + \frac{v_k - P_k c_{k-(l+2)}}{\sum_{i=k-(l+1)}^{N} P_i}.$$

Hence, the statement holds for $l+1$. This concludes the proof of the lemma. ■

Next, by expanding $c_{k-1}$ using Proposition 3, we have

$$c_k - c_{k-1} = \frac{v_k - P_k \frac{v_{k-1} + c_{k-2}\sum_{i=k}^{N} P_i}{\sum_{i=k-1}^{N} P_i}}{\sum_{i=k}^{N} P_i}$$

$$\Rightarrow c_k - c_{k-1} = \frac{v_k P_{k-1} - P_k v_{k-1} + v_k \sum_{i=k}^{N} P_i - P_k c_{k-2} \sum_{i=k}^{N} P_i}{\sum_{i=k-1}^{N} P_i \sum_{i=k}^{N} P_i}$$

$$\Rightarrow c_k - c_{k-1} = \frac{v_k P_{k-1} - P_k v_{k-1} + \sum_{i=k}^{N} P_i [v_k - P_k c_{k-2}]}{\sum_{i=k-1}^{N} P_i \sum_{i=k}^{N} P_i}$$

$$\Rightarrow c_k - c_{k-1} = \frac{v_k P_{k-1} - P_k v_{k-1}}{\sum_{i=k-1}^{N} P_i \sum_{i=k}^{N} P_i} + \frac{v_k - P_k c_{k-2}}{\sum_{i=k-1}^{N} P_i}$$

Hence, for $l = 1$, we have

$$c_k - c_{k-1} = \sum_{j=k-l}^{k-1} \frac{[v_k P_j - P_k v_j]}{\sum_{i=j}^{N} P_i \sum_{i=j+1}^{N} P_i} + \frac{v_k - P_k c_{k-(l+1)}}{\sum_{i=k-l}^{N} P_i}$$

Using lemma 6 and the logic of mathematical induction we know that it is true for $l = k-1$. This gives us

$$c_k - c_{k-1} = \sum_{j=k-(k-1)}^{k-1} \frac{[v_k P_j - P_k v_j]}{\sum_{i=j}^{N} P_i \sum_{i=j+1}^{N} P_i} + \frac{v_k - P_k c_{k-(k)}}{\sum_{i=k-(k-1)}^{N} P_i}$$

$$\Rightarrow c_k - c_{k-1} = \sum_{j=1}^{k-1} \frac{[v_k P_j - P_k v_j]}{\sum_{i=j}^{N} P_i \sum_{i=j+1}^{N} P_i} + \frac{v_k - P_k c_0}{\sum_{i=1}^{N} P_i}$$

Since $c_0 = 0$, we have

$$c_k - c_{k-1} = \sum_{j=1}^{k-1} \frac{[v_k P_j - P_k v_j]}{\sum_{i=j}^{N} P_i \sum_{i=j+1}^{N} P_i} + \frac{v_k}{P}$$

This concludes the proof of the proposition. ■

# 5 Welfare maximization for a fixed level of policing

Let $n_i$ denote the number of criminals in area $i$ ($i = 1, 2, 3, \dots, N$). We define our welfare function as

$$U(n_1, n_2, \dots, n_N) = -F(n_1, \dots, n_N) - \frac{1}{\beta} P^{\beta} \tag{6}$$

where $F(n_1, \dots, n_N)$ is strictly increasing in all the $n_i$.

**Proposition 7** *Fix an allocation with $P_i > 0$ for all $i$ and all areas active. Suppose there exists $k \in \{1, \dots, N-1\}$ such that*

$$\frac{P_k}{v_k} > \frac{P_{k+1}}{v_{k+1}}.$$

*Then, for sufficiently small $\Delta > 0$, there is a reallocation of a fixed total policing budget that preserves the ordering, keeps all areas active, and increases welfare. Hence any welfare-maximizing allocation with all areas active must satisfy*

$$\frac{P_1}{v_1} = \dots = \frac{P_N}{v_N}.$$

**Proof.** Suppose that

$$\frac{P_k}{v_k} > \frac{P_{k+1}}{v_{k+1}}.$$

Consider the following reallocation. We increase $\sum_{i=k+1}^{N} P_i$ by a sufficiently small positive amount $\Delta$ to preserve the ordering, and decrease $\sum_{i=1}^{k} P_i$ by the same amount. Since $\frac{P_k}{v_k} > \frac{P_{k+1}}{v_{k+1}}$, such an adjustment is feasible while maintaining our ordering of regions assumption,

$$\frac{P_k}{v_k} \geq \frac{P_{k+1}}{v_{k+1}}.$$

For $l = k+1, \ldots, N$, we increase each $P_l$ according to the rule that, for all $j = k+1, \ldots, N-1$,

$$\frac{\Delta P_j}{\Delta P_{j+1}} = \frac{v_j}{v_{j+1}}.$$

Iterating this recursion yields

$$\Delta P_j = \frac{v_j}{v_N} \Delta P_N, \qquad j = k+1, \ldots, N.$$

Imposing the aggregate constraint

$$\sum_{j=k+1}^{N} \Delta P_j = \Delta,$$

we obtain

$$\sum_{j=k+1}^{N} \frac{v_j}{v_N} \Delta P_N = \Delta,$$

which implies

$$\Delta P_N = \frac{\Delta v_N}{\sum_{i=k+1}^{N} v_i}.$$

Hence,

$$\Delta P_j = \frac{v_j \Delta}{\sum_{h=k+1}^{N} v_h}, \qquad j = k+1, \ldots, N.$$

Note that if all $P_j$ for $j \geq k+1$ are adjusted according to the above rule, then for all $j = k+1, \ldots, N-1$,

$$d(P_j v_{j+1} - v_j P_{j+1}) = 0,$$

which implies that the ordering conditions for the regions $j \geq k+1$ are preserved.

Similarly, for $l = 1, \ldots, k$, each $P_l$ is decreased in a manner such that for all $j = 1, \ldots, k-1$

$$\frac{\Delta P_j}{\Delta P_{j+1}} = \frac{v_j}{v_{j+1}}$$

with $\sum_{j=1}^{k} \Delta P_j = \Delta$, and again

$$\Delta P_j = \frac{v_j \Delta}{\sum_{h=1}^{k} v_h}$$

where $\Delta P_j$ denotes the magnitude of the decrease in $P_j$. As before, this preserves the equilibrium conditions for all $l < k$.

We now show that the reallocation leaves $n_1$ unchanged and decreases $n_l$ for every $l > 1$. Since $n_1 = v_1/P$ and total policing $P$ is fixed, $n_1$ is unchanged.

Now consider $2 \leq l \leq k$. Because the decrease in policing within the first block preserves the ratios $P_j/v_j$, the numerator $v_l P_j - P_l v_j$ in each term remains unchanged. At the same time, the relevant suffix sums in the denominator increase. Hence each term in the summation weakly decreases, and at least one decreases strictly, so $n_l$ decreases.

Next, consider $l > k$.

$$n_l = c_l - c_{l-1} = \sum_{j=1}^{l-1} \left[ \frac{v_l P_j - P_l v_j}{\sum_{i=j+1}^{N} P_i \sum_{i=j}^{N} P_i} \right] + \frac{v_l}{P}$$

$$\Rightarrow n_l = c_l - c_{l-1} = \sum_{j=1}^{k} \left[ \frac{v_l P_j - P_l v_j}{\sum_{i=j+1}^{N} P_i \sum_{i=j}^{N} P_i} \right] + \sum_{j=k+1}^{l-1} \left[ \frac{v_l P_j - P_l v_j}{\sum_{i=j+1}^{N} P_i \sum_{i=j}^{N} P_i} \right] + \frac{v_l}{P}$$

The numerator of each term under the first summation sign decreases and the numerator of each term under the second summation sign remains the same. Further, the denominators of all the terms under the summation sign increase. Hence, $n_l$ decreases. This is true because the terms $v_l P_j - P_l v_j$ are nonnegative under the ordering. The changes within each block preserve the proportions in numerators and the denominator increases for suffix sums.

This proves that we can find a reallocation that increases $U$. Hence, for a fixed level of total policing, welfare maximization is not consistent with

$$\frac{P_k}{v_k} > \frac{P_{k+1}}{v_{k+1}}$$

for any $k = 1, \ldots, N-1$. ■

**Corollary 8** *For a fixed aggregate police budget $P$, the unique ratio vector consistent with welfare maximization and active areas is*

$$\frac{P_k}{v_k} = \frac{P}{\sum_{j=1}^{N} v_j} \quad \textit{for all } k,$$

*or equivalently*

$$P_k = \frac{v_k}{\sum_{j=1}^{N} v_j} P.$$

# 6 Optimal global level of policing

We have established that for a given level of total policing $P$, welfare maximization implies

$$\frac{P_i}{v_i} = \frac{P_j}{v_j} \text{ for all } i, j$$

This implies that for any $l = 1, \ldots, N$

$$n_l = c_l - c_{l-1} = \sum_{j=1}^{l-1} \left[ \frac{v_l P_j - P_l v_j}{\sum_{i=j+1}^{N} P_i \sum_{i=j}^{N} P_i} \right] + \frac{v_l}{P} = \frac{v_l}{P}$$

Substituting this into the planner's payoff in 6, we obtain

$$U_P = -F\left(\frac{v_1}{P}, \frac{v_2}{P}, \ldots, \frac{v_N}{P}\right) - \frac{1}{\beta} P^{\beta}.$$

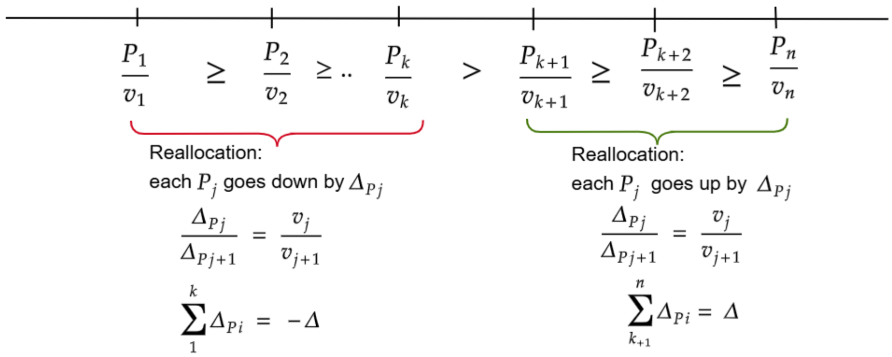


Figure 2: Optimal (re-)allocation of policing

Define

$$G(P) \equiv F\left(\frac{v_1}{P}, \frac{v_2}{P}, \dots, \frac{v_N}{P}\right).$$

Then

$$U_P(P) = -G(P) - \frac{1}{\beta}P^{\beta}.$$

If $G$ is differentiable and strictly convex in $P$, and the optimum is interior, the optimal total policing level satisfies

$$-G'(P) - P^{\beta-1} = 0.$$

# 7 Conclusion

This paper studies how rational offenders choose where to commit crime and how a planner should allocate policing resources across areas. The model combines heterogeneous apprehension costs, fixed criminal opportunities, congestion among offenders, and spatially differentiated policing. For an arbitrary allocation of police, equilibrium has a simple sorting structure: areas can be ordered by the ratio of policing to criminal opportunity value, and individuals sort across these areas according to their cost of apprehension. High-apprehension-cost individuals either abstain from crime or locate in relatively less-policed areas, while lower-cost individuals locate in areas with higher policing intensity relative to criminal opportunity value.

The main contribution of the paper is to show that optimal policing depends on the value of criminal opportunities, not only on observed crime levels. For a fixed aggregate police budget, welfare maximization equalizes the ratio of policing to criminal opportunity value across all active areas. This result provides a formal foundation for place-based policing, but also qualifies simple hot spot rules. We find that concentrating police where crime is currently high may be misleading if observed crime already reflects previous police allocation and offender displacement. The model therefore gives a tractable way to think about displacement as an equilibrium response to the full vector of policing intensities.

Several extensions are natural. First, the model could allow the value of criminal opportunities to be endogenous, for example through victim avoidance, private security, or changes in commercial activity. Second, relocation costs could be introduced to distinguish short-run from long-run displacement. Third, the planner could face imperfect information about criminal opportunities or offender types, linking the model to predictive policing and reporting systems. Finally, the framework could be taken to data by estimating area-level opportunity values and testing whether changes in police allocation move crime in the way predicted by the sorting conditions.

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