Beyond Hot Spots: Enhancing Police Effectiveness by Incorporating a Spatial Network Approach*

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Abstract

How can crime be disrupted most effectively without increasing resources? To answer this question, we develop a spatial network model to analyze crime diffusion, using London as a case study. Moving beyond traditional hot spot policing, we identify key player neighborhoods—highly connected areas in the network. Our analysis reveals that while hot spots mainly attract crime locally, key player neighborhoods predominantly propagate it. Simulations show that targeting the top 10% of key players reduces crime by 10.7% (5.8 percentage points) more than hot spot strategies. This approach offers a cost-effective solution, with potential annual savings exceeding £130 million.

Keywords: Crime, hot spot policing, social interactions, key players.
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1 Introduction

The persistence of crime poses a significant challenge to societies worldwide. While the UK, like many developed nations, experienced a decline in crime rates through the early 2000s, this trend has reversed in recent years, with crime rates once again on the rise. The renewed surge in crime is not only a matter of public concern but also a significant economic burden, estimated to impose social costs of approximately £59 billion in 2016.[1] At the same time, fiscal pressures have forced a reduction in police resources, with officer numbers falling from 172,000 in 2011 to 150,000 by 2019. Although recruitment efforts have partially offset these reductions since 2020, the current ratio of officers to population remains below its 2010 level.[2] The challenge of rising crime amidst resource constraints has spurred policymakers and researchers to seek more effective and efficient crime prevention strategies.

One approach that has gained considerable attention is hot spot policing. Its premise is that crime tends to concentrate in relatively small geographic zones, or "hot spots", and that concentrating additional patrols, targeted enforcement, or community outreach to these zones can yield more efficient crime reductions (Sherman et al., 1989, Weisburd, 2015, Braga, 2017). Indeed, meta-analyses – mostly focused on the USA – such as Braga et al. (2019) find that hot-spot policing produces small but meaningful reductions in crime. In contrast to the documented benefits, researchers have raised concerns that hot spot policing may, however, displace crime to nearby neighborhoods and strain police-community relations, particularly in socially vulnerable districts (Rosenbaum, 2006, Briggs and Keimig, 2017). These displacement concerns highlight a critical insight: criminal activity is not confined to isolated localities but is influenced by interactions and dependencies among neighboring areas. Neglecting these broader spatial dynamics can limit the effectiveness of crime prevention strategies.

In this paper, we develop and empirically assess an enhanced hot spot appraoch that explicitly incorporates a network perspective to account for spatial spillovers. Building on the framework of Ballester et al. (2006), our approach shifts the focus from merely targeting areas with the highest crime counts (i.e., traditional hot spots) to identifying and prioritizing key player areas. These are areas that, due to their central role in the spatial diffusion of crime, have an outsized impact on overall criminal activity—even if their local crime might not be necessarily the highest. By recognizing that criminal activity in one area can propagate into surrounding localities—via channels such as offender mobility and co-offending

[1]For trends over time in police recorded crime, see `https://data.justice.gov.uk/cjs-statistics/cjs-crime#chart-tab-ons-crime-survey`. The figure of social costs refers to 2015–2016 and is taken from Heeks et al. (2018).

[2]See `https://researchbriefings.files.parliament.uk/documents/SN00634/SN00634.pdf`.

ties—our approach addresses a critical shortcoming of conventional hot spot strategies. Ignoring the interconnections and spillovers across areas underestimates the broader impact that interventions in strategically important locations can have on overall crime reduction. The central aim of our approach is to demonstrate that integrating a network dimension into crime prevention can uncover intervention strategies capable of achieving more substantial reductions in overall crime (and its associated financial burden) compared to a standard focus on high-crime areas.

To achieve this aim, we develop an empirical framework using neighborhood-level crime data in London as a case study. Our framework unfolds in four main steps. First, we establish the extent of spatial correlation in crime. We do so by estimating a spatial autoregressive panel model with fixed effects using panel data of neighborhood-level crime from 2013 to 2019, considering separately property and violent crime. This step quantifies how crime in each neighborhood is influenced by that in nearby areas, while controlling for unobserved heterogeneity and local trends. The estimates of the spatial econometric model serve as the foundation for our second step, wherein we compute an intercentrality (i.e., key player) measure for each neighborhood following the methodology of Ballester et al. (2006). This measure captures not only a neighborhood's direct crime levels but also its role in sustaining and propagating crime through connections with other influential areas. A neighborhood with high intercentrality occupies a strategic position that amplifies crime diffusion across other neighborhoods. Consequently, removing key player neighborhoods yields the largest reduction in overall crime in the network, making these areas crucial targets for public intervention. Third, we compare two alternative crime prevention policies: the conventional hot spot policy, which prioritizes enforcement in the neighborhoods with the highest observed crime levels, and the key player policy, which targets the most influential neighborhoods based on their intercentrality. To assess the effectiveness of these policies, we conduct a simulation exercise. Specifically, we simulate the crime reduction that would occur if law enforcement were able to completely eliminate crime in the top 500 neighborhoods (10% of the total) identified under each policy. This exercise allows us to quantify the additional crime reduction achieved by targeting key players rather than conventional hot spots. By comparing these scenarios, we provide direct evidence of the potential gains from incorporating network effects into policing strategies. In the fourth step, we use cost-of-crime estimates to quantify the financial benefits of crime reduction under the key player policy.

Our findings from the spatial econometric model reveal that property crime exhibits substantial spatial spillovers: crime in an averagely connected neighborhood is roughly 70 percent higher than in an otherwise comparable but isolated neighborhood. This suggests that conventional hot spot strategies, which focus solely on crime volume, may systematically overlook neighborhoods that, despite not having the highest crime rates, play a crucial role in diffusing criminal activity. Our simulation exercise confirms this: targeting the top 500 key player neighborhoods could yield an additional 5.8 percentage point reduction in crime compared to targeting the top 500 hot spots. We show that this difference arises because only two-thirds of the top hot spots are also key players. Therefore, a traditional hot spot policy would allocate about one-third of its resources to high-crime areas that have limited influence on broader crime diffusion, whereas a key player strategy would redirect those resources to neighborhoods that, despite lower crime levels, play a central role in sustaining and spreading criminal activity across the network. The resulting crime reduction translates into estimated annual savings exceeding £130 million, underscoring the broader efficiency gains from targeting the most influential nodes in the crime network. By contrast, our results indicate no meaningful spatial spillovers for violent crime. This suggests that, unlike property crime, interventions targeting either high-crime areas or key players in London yield similar outcomes in reducing violent crime.

After establishing that the key player approach produces significantly greater crime reductions than conventional hot spot policies, we turn to a crucial question: why are key player neighborhoods more effective than hot spots? In other words, what makes key players so critical in diffusing crime across the network? We delve into this question by empirically examining the sociodemographic and built environment characteristics that differentiate key player neighborhoods from hot spot neighborhoods. The comparison uncovers systematic distinctions between the two types of areas. Key player neighborhoods tend to be more deprived, have higher population density, and are situated closer to central London. Yet, unlike hot spot neighborhoods—which are endowed with features such as extensive public transport hubs, parks, and other amenities that concentrate local crime – key player neighborhoods lack these features. A key indicator of these differences is that offenders from key player neighborhoods are more likely to commit crimes outside their residential areas, as reflected in the lower ratio of crimes within their neighborhoods to those committed by residents.

Building on this, we analyze offender-level data and uncover distinct spatial search patterns. Offenders residing in key player neighborhoods tend to commit crimes at shorter distances from home and are more likely to co-offend with local partners, reinforcing their role in spreading criminal activity beyond their immediate area. The combination of these findings suggests that while hot spot neighborhoods serve as "crime attractors" that concentrate criminal activity locally, key player neighborhoods act as "crime dissipators", enabling the spread of crime across the network. To complement this evidence, and as final step, we develop a simple theoretical model to explain why offenders in key player neighborhoods are more likely to commit crimes outside their area of residence compared to those in hot spot areas. The model formalizes the trade-offs faced by offenders and demonstrates how the strategic network position of key player neighborhoods lowers the external costs of committing crimes elsewhere, reinforcing their role in crime diffusion.

Our paper contributes to the literature on social networks and the economics of crime in several ways. First, it enhances the understanding of spatial patterns in property crime by documenting significant spatial spillovers and demonstrating that accounting for these spillovers can improve the effectiveness of crime reduction policies (Zenou, 2003, Durlauf and Nagin, 2011). While prior research has highlighted the concentration of crime (Glaeser et al., 1996), our findings reveal that these concentrations are influenced by underlying network structures,[3] which has direct implications for the design of targeted interventions.[4] Second, our work provides a novel application of key player theory to crime prevention, extending its use from contexts such as R&D (König et al., 2019), economic development (Amarasinghe et al., 2020), and financial networks (Denbee et al., 2021). By identifying key player neighborhoods that influence crime diffusion, we underscore the importance of network centrality in formulating efficient law enforcement strategies. Finally, we contribute to the hot spot policing literature by illustrating that a solely crime-based ranking of neighborhoods may overlook those with significant network impacts, thereby underestimating the potential for citywide crime reduction. Our study also engages with a policy environment characterized by sustained resource pressures, providing evidence on cost-effective policing strategies in London—one of Europe's largest urban areas—thereby addressing a gap in the predominantly US-based literature (Braga et al., 2019, Chalfin, 2025).

The remainder of the paper is structured as follows. Section 2 details the data sources, the construction of neighborhood-level variables, and key summary statistics. Section 3 presents the empirical framework, outlining the spatial panel model and identification strategy. Section 4 reports the main estimates and assesses their robustness. Section 5 derives the key player based on the estimates of the spatial econometric model and quantifies, through simulations, the impact on crime and its financial implications of both the key player and the hot spot policy. Section 6 investigates the underlying mechanisms. Section 7 concludes.

[3]For overviews of the crime and network literature, see Carrington (2011), Faust and Tita (2019), and Lindquist and Zenou (2019).

[4]While Bhuller et al. (2018), Lee et al. (2021), and Lindquist et al. (2024) also examine the role of network structure in crime, their approaches differ significantly. Bhuller et al. (2018) focus on incarceration spillovers within criminal and brother networks, Lee et al. (2021) explore the methodological aspects of the key player policy, and Lindquist et al. (2024) investigate how the exogenous deaths of criminals influence the criminal activities of their co-offenders.

2 Data

We use data on crime and other characteristics at the neighborhood level for London for the period 2013 to 2019.[5] London accounts for about one quarter of all crimes in England and Wales, with average neighborhood crime rates (87 per 1,000 residents) being substantially higher than outside the city (65 per 1,000 residents). Moreover, some areas in London have the highest crime incidence in the country (with peaks of 689 per 1,000 residents). This considerable variance in crime incidence highlights the need for nuanced approaches to crime prevention, particularly for high-crime areas that drive much of the overall rates. Studying London also offers a unique advantage for policy simulation, as the Metropolitan Police Service oversees crime prevention and resource allocation for the entire Greater London Area, enabling a unified approach to social planning and resource distribution. Furthermore, London's diverse socioeconomic landscape and high population density make it an ideal setting to study the spatial dynamics of crime.

Crime data are obtained from the Single Online Home National Digital Team and the British Transport Police, which gather information from police forces and publish them at the street-by-month level for each crime type. We aggregate the raw data to obtain yearly counts of crime at the Lower Layer Super Output Areas (LSOA) level. LSOAs are geographic areas widely used to report neighborhood-level statistics.[6] There are 4,835 LSOAs in London, with an average population of about 1,800 during the period of our analysis. We focus separately on property and violent crimes, which together account for more than 95% of all crimes observed during the period of interest. However, we also show separately key results for drug crimes (the third largest category) and total crime (the aggregate of property, violent, drug, and other crime). We use crime levels as the preferred outcome because, when targeting particular areas for crime prevention purposes, police authorities are interested in absolute measures. At the same time, crime rates are an important statistic widely used to describe crime incidence, and for this reason, we present robustness analyses also using these. It is important to note that our crime data reflects reported crimes. Therefore, our analysis is subject to the limitations of official crime statistics, such as potential underreporting of certain types of offenses.

In our analysis, we also use data on additional neighborhood characteristics. Firstly, we include the yearly LSOA population using data from the ONS population estimates. This allows to account for variations in neighborhood size, ensuring that observed crime

[5]Our analysis spans 2013-2019, the period for which we have the earliest consistent data series for all variables. We limit the analysis to the pre-COVID-19 period to avoid the confounding influence of pandemic-related disruptions on crime patterns.

[6]LSOAs are built up of output areas (OA), which are the smallest statistical unit for Census data in England and Wales. For a map of neighborhoods, see Figure **??** in the Appendix.

patterns are not driven solely by population differences. We then construct a proxy for LSOA unemployment using the number of people claiming unemployment-related benefits, obtained from the DWP Alternative Claimant Count statistics. Unemployment is included as a key control variable because it can influence crime through mechanisms such as financial hardship and weakened social cohesion. Finally, we include a variable capturing the "local bite" of the National Living Wage (NLW) for young adults. This is constructed using the average of three age-specific NLW rates (16-17 years old, 18-20 years old, 21-24 years old), weighted by the share of the corresponding population age groups over the total population and by the share of individuals aged 16-24 among the population of low-qualified individuals in each LSOA.[7] This variable is included to capture the local economic conditions relevant to young adults, who may be particularly vulnerable to economic factors influencing criminal activity.

Our balanced panel dataset consists of 33,845 neighborhood-year observations. Table 1 presents key summary statistics; for each characteristic, we report the mean value and the overall, between (i.e., across neighborhoods), and within (i.e., the variation over time within each neighborhood) standard deviations. The table reveals substantial variation in crime levels across neighborhoods, as well as significant within-neighborhood variation over time. Property crimes account for about 60% of all crimes, with violent crimes representing just less than one-third of the total. Less than 5% of the total pertains to crimes related to drugs.

Figure 1 provides a first impression of the spatial pattern of crime in London. The maps represent the 500 neighborhoods with the highest levels of property and violent crime in the year 2016. These 500 hot spots make up just 10% of all neighborhoods but alone account for 40% of the property crime and 30% of the violent crime in London. The co-occurrence of two features is striking. First, the bulk of crime crime concentrates in a small fraction of areas, a pattern that naturally lends itself to targeted interventions such as hot spot policing. Second, these high-crime areas exhibit marked spatial clustering, particularly in central London, a pattern that both underscores the potential for spatial spillovers and provides a

[7] Formally, this variable is calculated as $NLW_t = \sum_j nlw_{j,t} \times \frac{pop_{j,t}}{pop} \times pop^l_{16\text{-}24} \quad j \in \{16\text{-}17, 18\text{-}19, 21\text{-}24\}$, where *pop* is the share of individuals aged 16-24 among the population of low-qualified individuals. This "local bite" of the NLW for young adults is constructed as a weighted average of three age-specific NLW rates. The weights are determined by: (i) the share of the corresponding population age groups over the total population, and (ii) the share of individuals aged 16-24 among the population of low-qualified individuals in each LSOA. This weighting scheme aims to reflect local aspects of economic well-being of younger residents, whose financial stability may be linked to their likelihood of engaging in criminal activities. The age-specific population shares in each year are derived using the ONS population estimates. The share of low-qualified youth population is constructed as the fraction of individuals aged 16-24 reporting either "No qualifications" or "Level 1 qualifications" as highest qualification over all individuals aged above 16 reporting "No qualifications" or "Level 1 qualifications". Qualification data at the neighborhood level are only available from the 2011 Census and thus we use this source to construct them. This assumes that these shares are relatively stable over the period of our analysis.

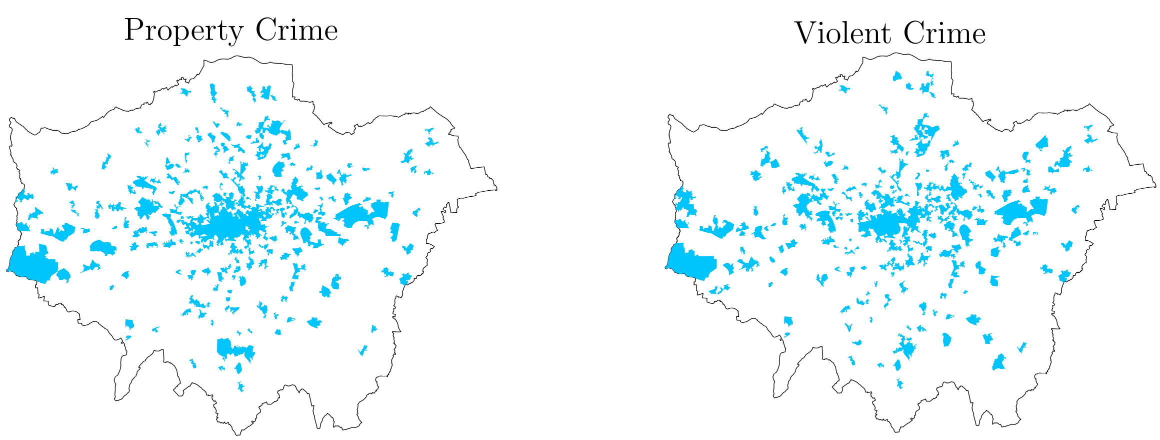
Table 1: Summary Statistics

	Mean	Standard Deviation		
		Total	Between	Within
N. Crimes – All	160.33	252.98	245.13	62.65
N. Crimes – Property	100.92	188.42	181.58	50.35
N. Crimes – Violent	51.42	61.61	58.62	18.98
N. Crimes – Drugs	7.99	15.68	14.01	7.05
Population Size	1804.95	396.29	377.98	119.17
N. Unemployed	47.66	30.68	28.28	11.90
National Living Wage	581.80	44.67	22.66	38.49

Notes. N=33,845; n=4,835; t=7. All observations are at the LSOA level. Means are calculated over the period 2013-2019. N. Crimes is the number of crimes related to each category occurring in a neighborhood. Definitions of the other variables and the data sources, including those for crime, are provided in section 2.

compelling rationale for considering spatially-informed policing strategies. Furthermore, a visual comparison of the property and violent crime maps suggests that property crime hot spots exhibit a more pronounced spatial concentration than violent crime hot spots, hinting at potentially different underlying spatial dynamics. We will use these 500 areas in our simulations, where we will compare the hot spot policy with the key players approach.

Figure 1: Crime Hot Spots



Notes. The map highlights in blue the top 500 neighborhoods classified as hot spots for property crime (left panel) and violent crime (right panel). Hot spots are identified based on the average annual crime level for each neighborhood over 2013-2019. LSOA boundaries are from the 2011 Census shapefiles (`https://geoportal.statistics.gov.uk`). Crime data sources are detailed in section 2.

3 Empirical Framework

The empirical strategy is structured in three steps. First, we estimate an econometric model that captures the spatial dependencies of crime, highlighting how crime in one neighborhood is influenced by crime in neighboring areas within the same network. To effectively embed the network approach, we utilize a spatial econometric model, which is essential for accurately estimating the interdependencies inherent in crime dynamics. This approach allows us to explore the geographic links between neighborhoods and understand how local interactions can shape crime patterns. The network is defined geographically; a "link" exists between two areas if they are within a certain radius (see subsection 3.3 for details). Second, we identify the "key players" in crime–neighborhoods whose removal would lead to the greatest overall crime reduction in the network. This step uses the insights gained from the spatial model to determine which neighborhoods are most critical in influencing crime dynamics across the network. Third, we simulate policy interventions, comparing scenarios where police focus resources on these key neighborhoods versus the conventional "hot spot policing" strategy. In this phase, we quantify the financial implications of adopting the key player approach, providing practical insights into resource allocation strategies for law enforcement. In this section, we illustrate the spatial econometric model, while the key player analysis is presented in Section 5.

3.1 Spatial Econometric Model

Our empirical model is a spatial autoregressive Durbin model (SDM), defined as follows:

$$y_{it} = \rho \mathbf{G} y_{it} + X'_{it}\beta + \mathbf{G} X_{it}\gamma + \eta_i \tau + \varepsilon_{it}, \tag{1}$$

where y_{it} represents the vector of crime outcomes in neighborhood i at time t, and $\mathbf{G}$ is the spatial weights matrix capturing the connections between neighborhoods. Specifically, $\mathbf{G}y_{it}$ captures the spatial lag of the dependent variable, reflecting how crime in one neighborhood is influenced by crime in neighboring areas. In our baseline analysis, $\mathbf{G}$ is constructed such that its entries are 1 for neighborhoods whose centroids lie within an 800-meter radius of the centroid of neighborhood i, and 0 otherwise. This radius is selected to reflect immediate spatial interactions. The matrix is not normalized, resulting in a local aggregate model (see Liu et al., 2014), allowing us to interpret the total influence of neighboring neighborhoods' crime dynamics on the focal neighborhood's crime levels. In contrast, a normalized spatial weights matrix would adjust for the number of connections each area has, measuring the average effect of neighboring crime dynamics—i.e., a local average model. [8]

The matrix X includes key neighborhood characteristics, such as total population, unemployment, and the National Living Wage for young adults, with β capturing the direct effects of these characteristics on local crime. The spatial lags of the independent variables, $\mathbf{G}X$, capture spillover effects, allowing changes in the economic and demographic conditions of neighboring areas to influence local crime patterns. This inclusion accounts for the impact of socio-economic factors in surrounding neighborhoods on local crime rates through social interactions across areas. By incorporating these spatial lags, the SDM offers a comprehensive understanding of how broader neighborhood dynamics shape crime. The model also includes neighborhood fixed effects (η) and time trends (τ) to control for time-invariant unobserved heterogeneity and neighborhood-specific linear changes over time, respectively. Neighborhood fixed effects control for time-invariant factors that may differ across neighborhoods but remain constant over the study period. These fixed effects capture the unique characteristics of each neighborhood, such as long-standing cultural factors, historical crime rates, or geographic features, which might influence crime but are not explicitly measured in the model. By accounting for these unobserved characteristics, the model reduces the risk of omitted variable bias, ensuring that the estimated effects of the observed characteristics are more accurate and reliable. Time trends account for linear changes in crime rates or neighborhood characteristics over time. These trends are essential for capturing any temporal patterns or shifts in crime that may occur due to broader economic changes, policy interventions, or social dynamics. By including these, the model can differentiate between changes in crime rates attributable to the observed characteristics and those arising from general time-related factors. This allows for a clearer interpretation of how specific neighborhood characteristics and spatial dynamics impact crime over time. In our estimation, we cluster the standard errors at the neighborhood level to address potential issues of spatial autocorrelation in the error terms Drukker (2003).

While the Spatial Durbin Model captures both direct effects of neighborhood characteristics and spillover effects on local crime, we also estimate an alternative Spatial Autoregressive model (SAR) specification. The SAR focuses on spatially lagged crime outcomes, providing a more straightforward interpretation of spatial dependence. By comparing results from both models, we evaluate the robustness of our findings and ensure the reliability of the relationships between neighborhood characteristics and crime across different econometric specifications.

[8]For the uniqueness of equilibrium in the model underpinning the key player analysis, the condition $|\phi\rho| < 1$ must hold, where ϕ is the largest eigenvalue of $\mathbf{G}$. This ensures that spatial crime dynamics do not become "explosive" and that neighboring influences remain bounded. In our case, $\phi = 18.267$, so the condition $\rho \leq 1/18.267 = 0.055$ is satisfied in our key estimates.

3.2 Identification

The model is estimated using the panel data maximum likelihood (ML) approach, primarily developed by Lee and Yu (2010). Identifying the causal effects of crime dynamics within a network model needs careful consideration of potential biases, particularly those arising from the endogeneity of spatial lags and the influence of unobserved local factors that can induce spurious correlations among neighboring areas. The latter pertain to the influence of unobserved local factors that may lead to spurious correlations among the crime rates of neighborhoods within the same network. This potential source of bias adds to the well-known omitted variables problem that affects OLS estimation. In our settings, where we exploit the use of panel data, the role played by unobservable factors is mitigated in several ways. First, the neighborhood fixed effects η allow us to purge the effect of unobservable, time-invariant local characteristics – such as cultural or geographic factors – that could confound our estimates. Second, the terms X and $\mathbf{G}X$ control for exogenous time-varying characteristics, with X capturing characteristics specific to the neighborhood itself, and $\mathbf{G}X$ accounting for the characteristics of the neighboring areas within the same network. Finally, neighborhood-specific time trends τ help to capture time-varying unobservable factors that are specific to each neighborhood and evolve linearly over time.

The endogeneity of the spatial lag arises because y (crime in a neighborhood) and $\mathbf{G}y$ (crime in neighboring areas) are determined simultaneously via spatial feedback loops. Addressing this structural simultaneity is critical for credible causal inference. The maximum likelihood (ML) approach is particularly well-suited for spatial panel data models because it directly models the joint determination of y and $\mathbf{G}y$ within the likelihood function, thereby fully capturing the mutual dependence inherent in spatial networks. This structural modeling yields consistent and efficient parameter estimates by explicitly incorporating spatial correlation. Lee and Yu (2010) develop a transformation-based quasi-maximum likelihood estimator that eliminates the fixed effects via a within-group transformation. Their Monte Carlo experiments demonstrate that this transformation approach achieves substantially lower bias and variance compared to direct ML estimation.

While we rely on ML as our baseline approach, it is important to acknowledge its potential limitations. ML estimation depends on strong distributional assumptions regarding the error term and may be sensitive to model misspecification. To address these concerns and reinforce the credibility of our findings, we also implement an IV approach using the generalized spatial two-stage least squares (GS2SLS) estimator of Kelejian and Prucha (1998). Although GS2SLS is more robust to heteroskedasticity and less sensitive to distributional assumptions, it faces challenges in spatial models. Specifically, because GS2SLS typically employs spatially lagged exogenous variables as instruments, the variation in these lags may be limited –

particularly in highly connected networks – resulting in weak instruments. Moreover, unlike ML, which models the interdependence between all neighborhoods in the network, IV methods typically rely on variation in the spatial lag induced by a specific instrument. Therefore, IV estimates can diverge depending on the instruments employed, particularly in presence of significant spatial heterogeneity. In such cases, each instrument may capture a unique aspect of the network's dependence structure, resulting in distinct local effects..

The strong consistency of our ML and GS2SLS estimates for both property and violent crime, as we will show in Section 4, reassures us that our key results are robust to the choice of estimation technique. Additional robustness analyses – such as tests for functional form, alternative specifications of the spatial weights matrix, and normality diagnostics – lend further support to our choice of adopting the ML approach as a baseline.

3.3 Choosing the Weights Matrix

The weights matrix $\mathbf{G}$ encapsulates the connections among neighborhoods by capturing the spatial correlation in crime dynamics – specifically, how crime in one area influences crime in nearby areas. In our setting, we assume that these connections are primarily driven by geographic proximity, consistent with empirical evidence where distance serves as a proxy for spatial interdependence in crime patterns.[9] Our approach also aligns with findings by Kirchmaier et al. (2024), who show that crime is highly localized, with the likelihood of criminal activity diminishing sharply with distance.

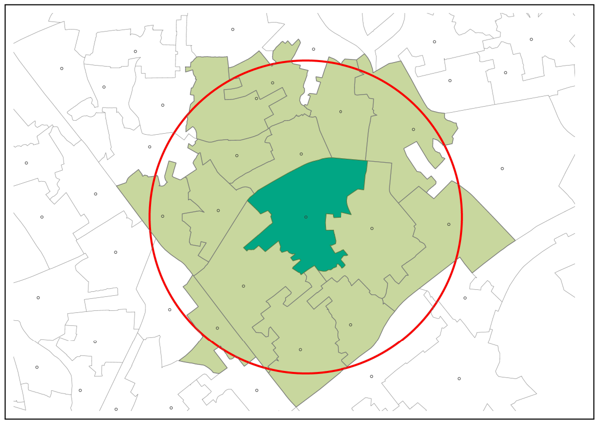
For each neighborhood, we define its network as consisting of all other neighborhoods whose centroids lie within an 800-meter radius (measured using Euclidean distance). In other words, for a given neighborhood i, its network comprises every neighborhood j such that the distance between their centroids does not exceed 800 meters. Figure 2 illustrates this network structure for a selected neighborhood, highlighting its connections within the 800-meter boundary.

To substantiate our choice of an 800-meter cutoff, we employ an empirical "elbow" approach. Figure 3 displays the estimated spatial lag parameter, $\hat{\rho}$ (based on Equation 1), across a range of distance thresholds. This approach identifies the point at which further increases in the cutoff yield only marginal changes in $\hat{\rho}$.[10] In the left panel of Figure 3, which

[9] There are several methods for estimating $\mathbf{G}$ when weights are unknown (e.g., Bhattacharjee and Jensen-Butler, 2013, Sun, 2016, Lam and Souza, 2020, De Paula et al., 2025), as well as methods that endogenize the weights (e.g., Kelejian and Piras, 2014, Qu and Lee, 2015, Qu et al., 2016, 2017). Endogenizing $\mathbf{G}$ is beyond the scope of our paper. Instead, we focus on sensitivity analyses using alternative definitions of $\mathbf{G}$ to ensure that our results are not driven by a particular specification.

[10] Note that when the cutoff exceeds approximately 1,000 meters for property crime, $|\phi\rho| > 1$, indicating an explosive spatial process.

Figure 2: The Spatial Network: An Example

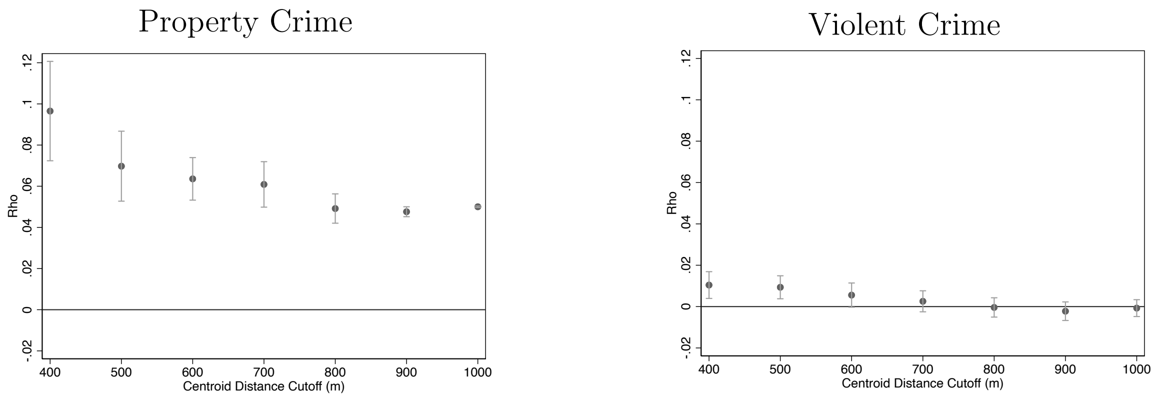


Notes. The figure represents a selected neighborhood (shown in darker green), chosen to provide a graphical illustration of the network. The lighter green areas represent the network, consisting of neighboring neighborhoods whose centroids fall within an 800-meter Euclidean distance from the centroid of the selected neighborhood. The red circle indicates the 800-meter radius, marking the boundary within which these neighboring neighborhoods are included in the network. LSOA boundaries are from the 2011 Census shapefiles (`https://geoportal.statistics.gov.uk`).

displays the spatial autocorrelation parameter ($\hat{\rho}$) for property crime, we observe a distinct "elbow" pattern. $\hat{\rho}$ shows a rapid decline from 400 meters to 800 meters, beyond which the rate of decline significantly slows. This indicates that the marginal impact of including more distant neighbors on the spatial autocorrelation becomes substantially smaller, supporting our choice of the 800-meter cutoff. The right panel displays the estimates for violent crime, revealing a similar but less pronounced pattern. First, we observe a relatively smaller estimated spatial autocorrelation compared to property crime. Second, although the pattern also flattens out at 800 meters, $\hat{\rho}$ becomes statistically insignificant already after 700 meters, suggesting a lack of reliable spatial correlation beyond this point. We will return to the important difference in the estimated spatial autocorrelation parameters between property and violent crime later in our analysis.

The specification of the spatial weights matrix is crucial, as it directly influences the estimated spatial dependencies and the resulting policy implications. To rigorously assess the robustness of our findings to different spatial assumptions, Section 4 examines an alternative, contiguity-based specification of $\mathbf{G}$.

Figure 3: Choosing $\mathbf{G}$



Notes. The figure shows estimates of $\hat{\rho}$ and 95% confidence intervals from Equation 1 for different distance cutoffs of the spatial weights matrix $\mathbf{G}$ for property crime (left panel) and violent crime (right panel). The X-axis represents the distance cutoff (in meters). The matrix $\mathbf{G}$ is defined as 1 for neighborhoods within m meters of the selected neighborhood centroid, and 0 otherwise, where m represents various distance cutoffs.

4 Results

4.1 Main Results

Baseline estimates for Equation (1) are presented in Table 2. Our preferred panel estimates from the Spatial Durbin model (SDM) are reported in columns 1 and 3 for property and violent crime, respectively. For comparative purposes, columns 2 and 4 present the panel estimates based on the Spatial Autoregressive model (SAR). The SAR only includes spatial lags of the dependent variable, meaning it captures the extent to which crime in one area is influenced by crime in neighboring areas, providing a useful contrast to the SDM's fuller specification.

The spatial lag estimate $\hat{\rho}$ in the SDM for property crime is 0.049, statistically significant at the 1% level. This indicates significant spatial autocorrelation, suggesting that property crime rates in one area are positively influenced by those in neighboring areas. To quantify the magnitude of the spillover effect, we calculate the spatial multiplier as $\frac{1}{1-\hat{\rho}\bar{g}}$, where $\bar{g}$ represents the average network size. This calculation is based on $y = (I - \rho\mathbf{G})^{-1}\varepsilon$, which is a transformation derived from the simplified (for exposition purposes) version of Equation 1, $y = \rho\mathbf{G}y + \varepsilon$. Using the average network size of 8.48 neighborhoods, the spatial multiplier is approximately 1.71. This implies that property crime rates within an average-sized network are 71% higher than they would be in isolated neighborhoods, highlighting the substantial amplifying effect of spatial interactions. This spillover effect highlights the critical role of geographic and spatial dynamics in shaping crime rates. It suggests that interventions targeting crime in one area may have significant impacts on surrounding areas, underscoring the need for coordinated strategies in crime prevention policies, as our simulation exercise in the next section will reveal.

Table 2: Spatial Estimates of Crime – Baseline

	Property		Violent	
G × N. Crimes ($\hat{\rho}$)	.049***	.049***	−.000	.000
	(.004)	(.004)	(.002)	(.002)
Population Size	.031**	.031**	.010***	.011***
	(.012)	(.012)	(.002)	(.002)
N. Unemployed	.067	.055	−.076***	−.098***
	(.098)	(.093)	(.023)	(.022)
National Living Wage	−.039	−.039	−.026**	−.027**
	(.056)	(.056)	(.012)	(.012)
G × Population Size	.002		.001	
	(.003)		(.001)	
G × N. Unemployed	−.008		−.019***	
	(.015)		(.005)	
G × National Living Wage	−.008		.002	
	(.019)		(.005)	
Model specification	SDM	SAR	SDM	SAR
Neighborhood Fixed Effects	Yes	Yes	Yes	Yes
Neighborhood Time Trends	Yes	Yes	Yes	Yes
Pseudo-R^2	0.007	0.004	0.004	0.003
N	33,845	33,845	33,845	33,845

Notes. Standard errors in parentheses clustered at the LSOA level. Estimates are obtained using maximum likelihood. SDM = Spatial Durbin Model; SAR = Spatial Autoregressive Model. The dependent variable is the number of crimes occurring in a LSOA in each year. **G** × N. Crimes is the spatial lag of the dependent variable. For the definition of **G** see subsection 3.1. Definitions of the remaining variables and the data sources are provided in section 2. The Pseudo-R^2 refers to the within R^2. $^{*}\ p < .10$; $^{**}\ p < .05$; $^{***}\ p < .01$.

When interpreting the estimates, it is useful to consider both the potential drivers of the spatial lag and how it is identified within our model. The positive spatial correlation may arise through various channels, including supply- and demand-side spillovers, as well as the transmission of localized shocks across neighborhood boundaries in the short to medium run. In our model, the spatial lag coefficient $\hat{\rho}$ is identified conditional on neighborhood fixed effects, which absorb all time-invariant characteristics, and on neighborhood-specific linear time trends, which account for systematic local trends over time. These controls are crucial in isolating the estimated spatial effect from stable or slowly evolving factors – such as demographic composition, housing stock, or policing infrastructure – that may influence crime but are unlikely to fluctuate significantly in the short run.

The model also controls for additional time-varying economic factors, such as unemployment and the national living wage, which may influence the demand for crime. While both variables exhibit the expected sign, they are statistically insignificant. Population size is positively and significantly associated with property crime, as expected. Additionally, some coefficients, particularly the spatial lag of population size, suggest a degree of spatial spillover in socio-economic factors influencing crime, further motivating the use of the SDM. The estimated $\hat{\rho}$ could be further influenced by supply-side mechanisms that exhibit spatial and temporal variation and are not directly accounted for in the estimation. These may include the spatial mobility of offenders, the operation of co-offending networks spanning multiple neighborhoods, or the diffusion of criminal opportunities and information. In Section 6, we further investigate these mechanisms to better understand the sources of spatial spillovers in crime. None of the spatial lags of the dependent variables in the SDM for property crime are significant. This is also mirrored in the SAR results for the spatial lag of property crime being remarkably consistent with those from the SDM.

For violent crime, the panel estimates show no significant spatial spillover effects, as indicated by the statistically insignificant spatial lag estimates for both the SDM and the SAR. This suggests that, unlike property crime, violent crime in a given area is not strongly influenced by crime levels in neighboring areas. This result is also consistent with the visual patterns observed in Figure 1, which showed relatively less clustering of violent crime in the top 500 crime areas. One of the potential explanations for this may be the more spontaneous and spatiotemporally random nature of violent crimes, which tends to be reactive and impulsive—often arising from personal conflicts, domestic violence, or substance abuse. These crimes are less likely to spread across spatial boundaries, as they are driven by individual-level factors rather than broader environmental ones. In contrast, property crime often involves more planning and is more opportunistic, making it more likely to exhibit spillover effects. Additionally, violent crime may be contained by localized social norms or enforcement strategies, especially when it occurs in private settings.

Turning to the other control variables, columns 3 and 4 show that both population and the NLW show statistically significant coefficients, with the expected sign. A puzzling result is the negative relationship between unemployment and violent crime, which seems counterintuitive given the expectation that worsening economic conditions should lead to higher crime. However, it is important to recognize that violent crime, encompassing offenses like assault, domestic violence, and robbery, has different patterns and determinants than property crime. While robbery may be more sensitive to economic fluctuations, the effect of unemployment on other violent crimes, such as domestic violence, is less straightforward.[11]

To further understand the null results for violent crime and the importance of controlling for unobserved heterogeneity, in Table **??** in the Appendix we compare cross-sectional estimates for each year (using both ML and 2SGLS) with panel estimates. The results reveal that neglecting unobserved fixed neighborhood characteristics and local-specific linear trends leads to upwardly biased estimates, especially for the spatial lag coefficient. While the bias is moderate for property crime, it is substantial for violent crime. For the latter, cross-sectional estimates of spatial spillovers are entirely spurious, a mere artifact of unobserved heterogeneity. This starkly underscores the necessity of our panel approach, as cross-sectional methods would yield fundamentally misleading conclusions.

4.2 Robustness checks

To thoroughly assess the consistency of our findings, we conducted several robustness tests, exploring variations in network definitions, outcome variables, and estimation techniques. These checks are designed to probe the sensitivity of our spatial spillover estimates and to ensure the validity of our conclusions under alternative assumptions. The results of these tests are presented in Table 3.

First, we examined the impact of network definition by constructing a spatial weights matrix, $\mathbf{G}$, based on contiguity rather than distance. This specification defines a neighborhood's network as those areas sharing a border or corner, thus testing whether adjacency-based spatial dependence yields different spillover effects compared to distance-based proximity. This exercise is particularly interesting given that the geographical size of neighborhoods is heterogeneous due to the relatively fixed population size of each LSOA, with less populated neighborhoods in peripheral areas physically larger than densely populated neighborhoods in inner London. Remarkably, the overarching pattern of our results remains consistent: significant spatial correlations persist for property crime, while violent crime continues to exhibit no significant spatial spillovers.[12]

Next, we examined the robustness of our results to the choice of dependent variable

[11] One possible interpretation for this negative relationship is that unemployment may reduce violent crime in public spaces. Unemployed individuals often spend more time at home, which can limit their opportunities for engaging in public violence. Furthermore, it is conceivable that some criminals may "substitute" between property and violent crime, focusing more on property crime when unemployment increases.

[12] While the estimates from this specification are not directly comparable with those in Table 2 due to the change in weighting matrix, they provide valuable insights into the sensitivity of spatial spillover effects to the definition of neighboring areas. Notably, for property crime, the spatial lag estimate of 0.112 implies a substantial spatial multiplier of 3.02, significantly exceeding the 1.71 obtained with the distance-based matrix. This discrepancy likely arises from the nature of contiguity matrices, which define connections solely based on adjacency, potentially overestimating spatial spillovers in contexts where distance plays a significant role.

by replacing crime counts with crime rates (columns 2 and 6). This specification directly addresses potential scaling effects by accounting for population size through the denominator, allowing us to assess whether our findings are sensitive to the use of raw crime counts versus rates.[13] Notably, the spatial lag estimates for both property and violent crimes remain remarkably consistent with those in Table 2, further reinforcing the robustness of our main findings.

In the final set of results, we present estimates from two alternative instrumental variable approaches. First, we utilize the approach introduced by Baltagi and Liu (2011), which extends the GS2SLS technique of Kelejian and Prucha (1998) to panel data. This method addresses the endogeneity of the spatial lag by employing higher-order spatial interactions of the dependent variable as instruments. Specifically, we instrument $\mathbf{G}y$ with $\mathbf{G}^2X$, where $\mathbf{G}^2$ maps the neighbors of neighbors, or 'distance-two' neighborhoods. The rationale behind this instrument is that the characteristics of second-order neighbors are correlated with the endogenous spatial lag but are likely to be uncorrelated with the error term in the main equation. By leveraging second-order neighbors' exogenous characteristics as instruments, we mitigate simultaneity bias in spatial interactions. For our analysis, $\mathbf{G}^2$ assigns a value of 1 to neighborhoods whose centroids are within 800 meters of the centroid of the first-order neighborhoods (i.e., $\mathbf{G}$). Figure **??** in the Appendix provides an illustrative example of first-order and second-order neighbors for a selected neighborhood. Results in columns 3 and 7 are consistent with our baseline findings, though the estimated spatial lag for property crime is somewhat larger than in Table 2. While first-stage diagnostics indicate that the instruments for property crime are relevant, concerns emerge about potential instrument weakness in the case of violent crime.

In the second instrumental variable approach, we employ an "external" instrument using a shift-share strategy. Instead of using $\mathbf{G}^2X$ as an instrument, we utilize $\mathbf{G}^2z$, where z represents the shift-share instrument for crime. This shift-share instrument is constructed as:

$$z_{it} = \frac{y_{i2012}}{\sum_{j=1}^{4835} y_{j2012}} \times \sum_{j=1, j\neq i}^{4835} y_{jt} \tag{2}$$

Here, the share component, $\frac{y_{i2012}}{\sum_{j=1}^{4835} y_{j2012}}$, captures the proportion of total crime in 2012 accounted for by neighborhood i. The shift component, $\sum_{j=1, j\neq i}^{4835} y_{jt}$, represents the annual,

[13] In this specification, population size is inherently controlled through the denominator in the crime rate, eliminating the need for a separate population control. Similarly, unemployment is measured as the unemployment rate, rather than the absolute number of unemployed individuals.

leave-one-out sum of crime across all neighborhoods, excluding neighborhood i. By using $\mathbf{G}^2 z$, we make use of second-order neighborhood crime dynamics while ensuring that the instrument primarily reflects variation in crime driven by broader spatial trends rather than local simultaneity. Columns 4 and 8 of Table 3 show that the estimates of the spatial lag remain broadly consistent with the results so far, reinforcing the robustness of our findings. However, the spatial lag coefficient for property crime is again somewhat larger than in the baseline specification. Notably, the first-stage F-statistic indicates that the shift-share instrument is strongly relevant. The estimates for violent crime are also in line with the null effect observed thus far. Importantly, the shift-share instrument performs well, reassuring us that the observed null result is not attributable to potential instrument weakness. Overall, the consistency of the GS2SLS results with our baseline findings provides further evidence of the robustness of our spatial spillover estimates

5 Key Player Analysis

Building on the spatial model estimates, this section presents the key player analysis. We begin by deriving the intercentrality measure and ranking key player neighborhoods. We then evaluate the policy implications of targeting these key players, comparing this strategy to traditional hot spot policing through a simulation exercise. This allows us to evaluate the crime impact of shifting from hot spot to key player targeting, and to identify the areas where police resources should be reallocated. Finally, we quantify the potential financial savings achievable through the key player policy.

5.1 Deriving the Key Player

We follow the seminal approach of Ballester et al. (2006) in defining key players. In their paper, they formalized the concept of key players as the most influential nodes in a network, whose removal maximally reduces the system's equilibrium outcome. In our context, the key player is the neighborhood that has the largest influence in propagating crime spillovers to other neighborhoods.

The first step to identify the key player neighborhoods involves calculating the Katz-Bonacich centrality measure (Ballester et al., 2006). This quantifies the influence of each neighborhood within the crime network, taking into account both direct and indirect connections. It is defined as:

$$b_{it} = (\mathbf{I} - \hat{\rho}\mathbf{G})^{-1}\widehat{RHS}_{it}, \tag{3}$$

Table 3: Spatial Estimates of Crime – Robustness

	Property				Violent			
	Contiguity Matrix	Crime Rates	Instrumental Variable		Contiguity Matrix	Crime Rates	Instrumental Variable	
			$\mathbf{G}^2 \times X$	$\mathbf{G}^2 \times z$			$\mathbf{G}^2 \times X$	$\mathbf{G}^2 \times z$
$\mathbf{G}$ × N. Crimes ($\hat{\rho}$)	.112***	.048***	.076***	.107***	.003	−.004	−.023	.020
	(.015)	(.004)	(.021)	(.027)	(.004)	(.004)	(.058)	(.083)
Population Size	.025***		.029**	.027**	.010***		.011***	.010***
	(.009)		(.012)	(.011)	(.002)		(.003)	(.003)
N. Unemployed	.050	.019	.064	.060	−.064***	.004	−.081***	−.071**
	(.085)	(.043)	(.095)	(.094)	(.024)	(.013)	(.028)	(.030)
National Living Wage	−.022	−.000	−.039	−.039	−.027**	−.000**	−.026**	−.027**
	(.041)	(.000)	(.052)	(.049)	(.012)	(.000)	(.013)	(.013)
$\mathbf{G}$ × Population Size	.002		−.003	−.008*	.001		.001	.000
	(.003)		(.004)	(.005)	(.001)		(.001)	(.001)
$\mathbf{G}$ × N. Unemployed	−.001	−.011	.003	.016	−.035***	−.011***	−.023**	−.016
	(.022)	(.008)	(.015)	(.017)	(.007)	(.003)	(.011)	(.014)
$\mathbf{G}$ × National Living Wage	−.007	−.000	−.016	−.025	−.000	−.000	.002	.003
	(.028)	(.000)	(.020)	(.023)	(.006)	(.000)	(.005)	(.005)
Neighborhood Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.004				0.005			
N	33,845	33,845	33,845	33,845	33,845	33,845	33,845	33,845
	First Stage							
$\mathbf{G}^2$ × Population Size			.048***				.003*	
			(.015)				(.002)	
$\mathbf{G}^2$ × N. Unemployed			−.222***				−.054***	
			(.084)				(.013)	
$\mathbf{G}^2$ × National Living Wage			.364***				.008	
			(.072)				(.012)	
$\mathbf{G}^2$ × Shift Share				1.158***				.081***
				(.092)				(.021)
First-Stage F-Statistics			15.246	157.674			7.321	14.715

Notes. Standard errors in parentheses clustered at the LSOA level. Estimates for the models Contiguity Matrix and Crime Rates are obtained using the maximum likelihood. Estimates for the models Instrumental Variable are obtained using instrumental variable estimation. The dependent variable is the number of crimes occurring in a LSOA in each year, except for the models Crime Rates, where the dependent variable is the number of crimes divided by the total population. $\mathbf{G}$ × N. Crimes is the spatial lag of the dependent variable. For the definition of $\mathbf{G}$ see subsection 3.1. In the models Instrumental Variable, the term $\mathbf{G}$ × N. Crimes is instrumented using: higher order spatial lags of the exogenous regressors (column $\mathbf{G}^2 \times X$) or the distance-two spatial lag of the shift-share (column $\mathbf{G}^2 \times z$). See subsection 4.2 for details. Definitions of the remaining variables and the data sources are provided in section 2. The Pseudo-R^2 refers to the within R^2. * $p < .10$; ** $p < .05$; *** $p < .01$.

where $\mathbf{I}$ is the identity matrix, and $\widehat{RHS_{it}} = X'_{it}\hat{\beta} + \hat{\gamma}\mathbf{G}X'_{it} + \hat{\delta}_t + \widehat{\eta_i}\tau + \hat{\varepsilon}_{it}$. b_{it} reflects the "total crime" in a neighborhood, capturing both the direct effect of local crime and the externalities generated by spatial spillovers from neighboring areas. The "key player" is then identified as the neighborhood with the highest k_{it} value, calculated as (see Ballester et al., 2006, 2010):

$$k_{it} = \frac{b_{it} \sum_j \mathbf{M}_{ij}}{\mathbf{M}_{ii}} = \mathbf{b}_t - \mathbf{b}_t^{[-i]}, \tag{4}$$

where $\mathbf{M}_{ij}$ is the (i, j) cell of $\mathbf{M} = (\mathbf{I} - \hat{\rho}\mathbf{G})^{-1}$, and $\mathbf{b}_t = \sum_{i=1}^{4835} b_{it}$. Importantly, Equation (4) highlights that the sum of all key player contributions, $\sum_{i=1}^{4835} k_{it}$, corresponds to the aggregate crime in the network, $\mathbf{b}_t$. Conceptually, the key player is the area whose removal leads to the largest reduction in total crime, represented by $\mathbf{b}_t - \mathbf{b}_t^{[-i]}$.

Once we have identified the k_{it} for each neighborhood, we can rank them from the largest to smallest value. This ranking is the first step that allows us to prioritize neighborhoods for targeted intervention to achieve the greatest reduction in overall crime. While k_{it} varies over time due to the longitudinal nature of the data, the rankings exhibit notable stability.[14] Therefore, to simplify the exposition, we will use $\widetilde{k}_i$, the time-averaged k_{it}, to visualize our results and presents our simulations.

5.2 Policy Simulation

The key player approach is particularly insightful for policy simulation, especially in the context of crime. It allows for a direct comparison with real-world, existing crime intervention strategies, such as hot spot policing, which are currently implemented by law enforcement agencies. Acknowledging the scarcity of resources, hot spot policies prioritize interventions in a subset of high-crime areas to maximize crime reduction, a strategy that is often practically appealing for law enforcement because it allows for focused and cost-effective allocation of resources within a manageable number of areas. To illustrate why hot spot policies are often considered efficient, let us consider our case study of London. In Figure 1, we showed that 500 hot spots (approximately 10% of all neighborhoods) account for over 1/3 of total crime. Given the concentration of crime in these limited areas and the scarcity of resources, law enforcement agencies would find it intuitive to prioritize these hot spots. Therefore, a compelling question arises: how would crime reduction compare if, instead of targeting the top 500 hot spots, we were to target the 500 highest-ranked key players? Our simulation exercise directly addresses this. We compare the network-wide crime reduction achieved by focusing interventions in the neighborhoods with the highest observed crime levels with the reduction achieved by prioritizing interventions in the neighborhoods with the highest value

[14] Figure **??** in the Appendix demonstrates that although 500 distinct key players are identified each year, nearly 70% of them remain consistent over the 7-year period.

of intercentrality, as calculated in the previous subsection.[15]

We begin our simulation by outlining how we evaluate the crime reduction impact of the key player policy. We start from the definition of a key player as the neighborhood whose removal produces the highest reduction in crime within the network. Let us denote this value as $\widetilde{k}_i^1$, where the superscript indicates the rank in terms of intercentrality. The objective is to compute and sum all crime reductions from the first to the 500$^{\text{th}}$ key player neighborhood, i.e., $\widetilde{k}_i^1, \ldots, \widetilde{k}_i^{500}$, and assess how this sum compares to the total crime in the network, which, as previously noted, equates to $\sum_{i=1}^{4835} \widetilde{k}_i = \widetilde{\mathbf{b}}$. A key challenge arises, however, in that we cannot simply remove the top 500 key players simultaneously. The removal of a collection of key players – or a key group – is, as discussed in Ballester et al. (2010), an NP-hard problem. In other words, as the network grows, the number of possible key groups to eliminate increases exponentially, making it computationally infeasible to determine the optimal solution (i.e., the configuration that yields the highest crime reduction) within a reasonable amount of time. Fortunately, Ballester et al. (2010) derive a method to efficiently approximate the impact of removing a key group. They demonstrate that the optimal key group, which maximizes the reduction in network-wide crime, can be approximated using a greedy algorithm.[16]

To implement the greedy algorithm, we begin by identifying the neighborhood with the highest intercentrality within the network, $\widetilde{k}_i^1$. We then remove this neighborhood, which reduces the network size to $N-1$ and results in a network-wide crime level of $\mathbf{b}^{[-1]}$. Next, we identify the neighborhood with the highest intercentrality in this smaller network, namely $\widetilde{k}_i^2$, and remove it, resulting in a successively smaller network and an updated measure of total network-wide crime. We iterate this process until we have eliminated the top 500 key player neighborhoods from the network. For each iteration, we calculate the proportional reduction in network-wide crime associated with the removal of the key player. This corresponds to the ratio of the neighborhood's intercentrality to the sum of intercentrality measures across all neighborhoods in the original network before any removals. Summing these individual reductions across all 500 iterations gives the cumulative relative crime reduction after removing the key group, denoted as $D^k = \sum_{i=1}^{500} \widetilde{k}_i / \sum i = 1^{4835} \widetilde{k}_i$. The superscript k indicates that the neighborhoods are ranked and summed according to their intercentrality in the greedy algorithm.

For the hot spot policy, we use a similar approach, but with a crucial difference. Instead of removing neighborhoods ranked by intercentrality, we iteratively eliminate the 500 areas with the highest crime levels. The crime reduction is still calculated using the intercentrality

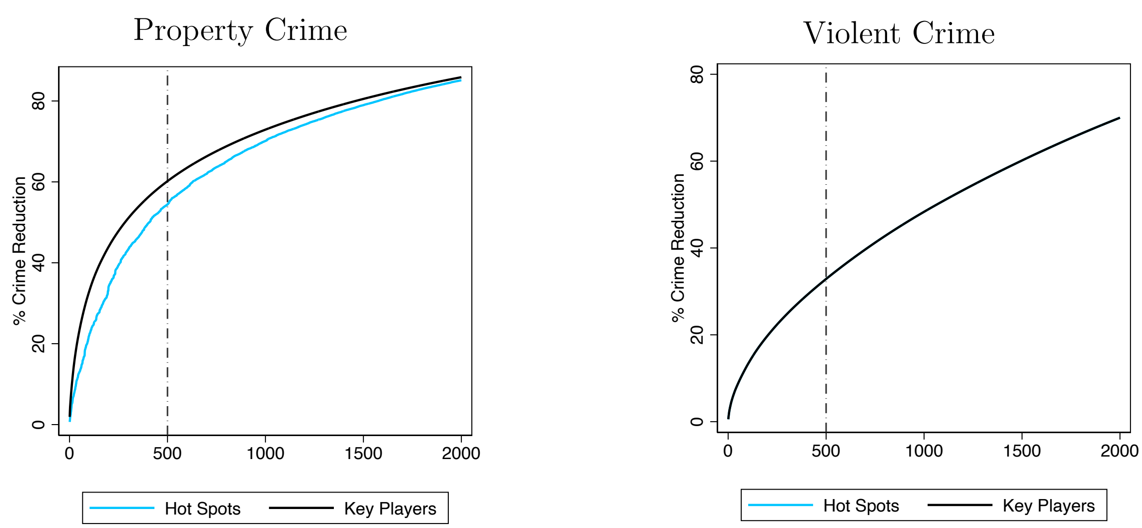
[15] Indeed, selecting the number n of areas for the simulation exercise involves a degree of discretion, and alternative values can be explored. For this reason, while we focus on the example of 10% of areas, our simulation allows for comparing the impact between the two policies across the entire range of neighborhoods.

[16] The authors also show that the approximation error from the greedy algorithm is relatively small.

measure for these areas, following the same formula as above: $D^y = \sum_{i=1}^{500} \widetilde{k}_i / \sum i = 1^{4835} \widetilde{k}_i$. The key distinction lies in the order of elimination: the hot spot policy iteratively eliminates areas ranked by crime levels (as denoted by the superscript y), rather than intercentrality.

To gain a deeper understanding of the comparative performance of the key player and hot spot policies, it is insightful to plot the cumulative crime reductions, D^k and D^y, as a function of the number of areas removed. This visual representation, presented in Figure 4, allows us to directly observe and analyze the relative effectiveness of the two policies across varying intervention scales. While the hot spot policy achieves a notable reduction in crime, the key player approach consistently yields a significantly greater reduction. Specifically, the removal of the top 500 hot spots results in a 54.4% reduction in the total network-wide crime; in contrast, the key player policy achieves a 60.2% reduction, a 5.8 percentage point increase in effectiveness. Figure 4 also reveals that the magnitude of relative gains achieved by the key player policy varies significantly across different intervention scales.[17]

Figure 4: Comparing Key Player and Hot Spot Policies: Impact on Crime Reduction



Notes. The Y-axis represents the cumulative reduction in crime for property crime (left panel) and violent crime (right panel), measured as $D^k = \sum_{i=1}^{500} \widetilde{k}_i / \sum_{i=1}^{4835} \widetilde{k}_i$ for the key player policy and as $D^y = \sum_{i=1}^{500} \widetilde{k}_i / \sum i = 1^{4835} \widetilde{k}_i$ for the hot spot policy, where $\widetilde{k}_i$ represents the intercentrality measure (average over time) calculated according to the formula reported in the text. The X-axis represents areas ranked in terms of intercentrality measure (for the D^k graph) and in terms of observed crime (for the D^y graph). The X-axis only represents the first 2,000 neighborhoods. For full representation, see Figure **??** in the Appendix.

[17]The highest relative reduction in crime is achieved when targeting the first 150 key players (approximately 3% of the total), yielding an 11.5 percentage point greater crime control than the hot spot policy.

In the right panel of Figure 4, we observe a striking contrast for violent crime. Here, the cumulative crime reduction curves for the key player and hot spot policies exhibit a near-perfect overlap, indicating identical performance. This unequivocally demonstrates that for violent crime, there is no discernible incremental benefit derived from adopting the key player approach over the hot spot strategy. This outcome stems from the absence of significant network effects for violent crime, as reflected in our estimates in Table 2.[18]

In Figure **??** in the Appendix, we also compare the key player policy with an alternative policy where police resources are randomly allocated. That is, the greedy algorithm is calculated by iteratively eliminating neighborhood in a random order. The random allocation policy serves as a counterfactual, demonstrating the value of targeted intervention strategies vis-à-vis an arbitrary policy of crime removal.

Having demonstrated the key player policy's superior efficacy in crime reduction, several key questions naturally arise. Which neighborhoods are identified by the key player policy, and where are they located? Furthermore, what factors contribute to the key player neighborhoods' greater effectiveness in reducing crime compared to hot spots? We address the former questions in the remainder of this section, while the analysis of the mechanisms underlying key player effectiveness is deferred to next section.

5.3 Mapping the Key Players

The simulation results presented in Figure 4 reveal a stark divergence in the efficacy of the key player policy between property and violent crime. For violent crime, the near-perfect overlap of the cumulative crime reduction curves indicates that both key player and hot spot strategies identify virtually identical neighborhoods, and that these neighborhoods are ranked in a very similar way in terms of crime level and intercentrality. This suggests that the current resource allocation for violent crime is optimal, as the key player policy would not yield any additional crime reduction compared to the hot spot strategy.

For property crime, a significant discrepancy emerges, with approximately one-third (154) of hot spots and key players exhibiting non-overlap.[19] This non-overlap signifies a critical opportunity for resource reallocation, as shifting resources from high-crime areas to neighborhoods with high intercentrality can enhance crime reduction. To effectively re-target police

[18]Figure **??** in the Appendix provides an alternative representation of the spatial spillover differences between property and violent crime by comparing observed crime levels with the (predicted) intercentrality measure $\widetilde{k}_i$. For property crime, the scatter plot reveals significant deviations from the 45-degree line, particularly in neighborhoods with medium to low crime levels, indicating substantial spatial spillover effects. Conversely, for violent crime, the strong alignment of observations along the 45-degree line indicates a high correlation between observed crime and intercentrality, suggesting a negligible presence of spatial spillovers.

[19]Although our simulations use time-averaged data, it is worth noting that the share of non-overlapping key player and hot spot neighborhoods remains relatively stable over time, as shown in Figure **??**.

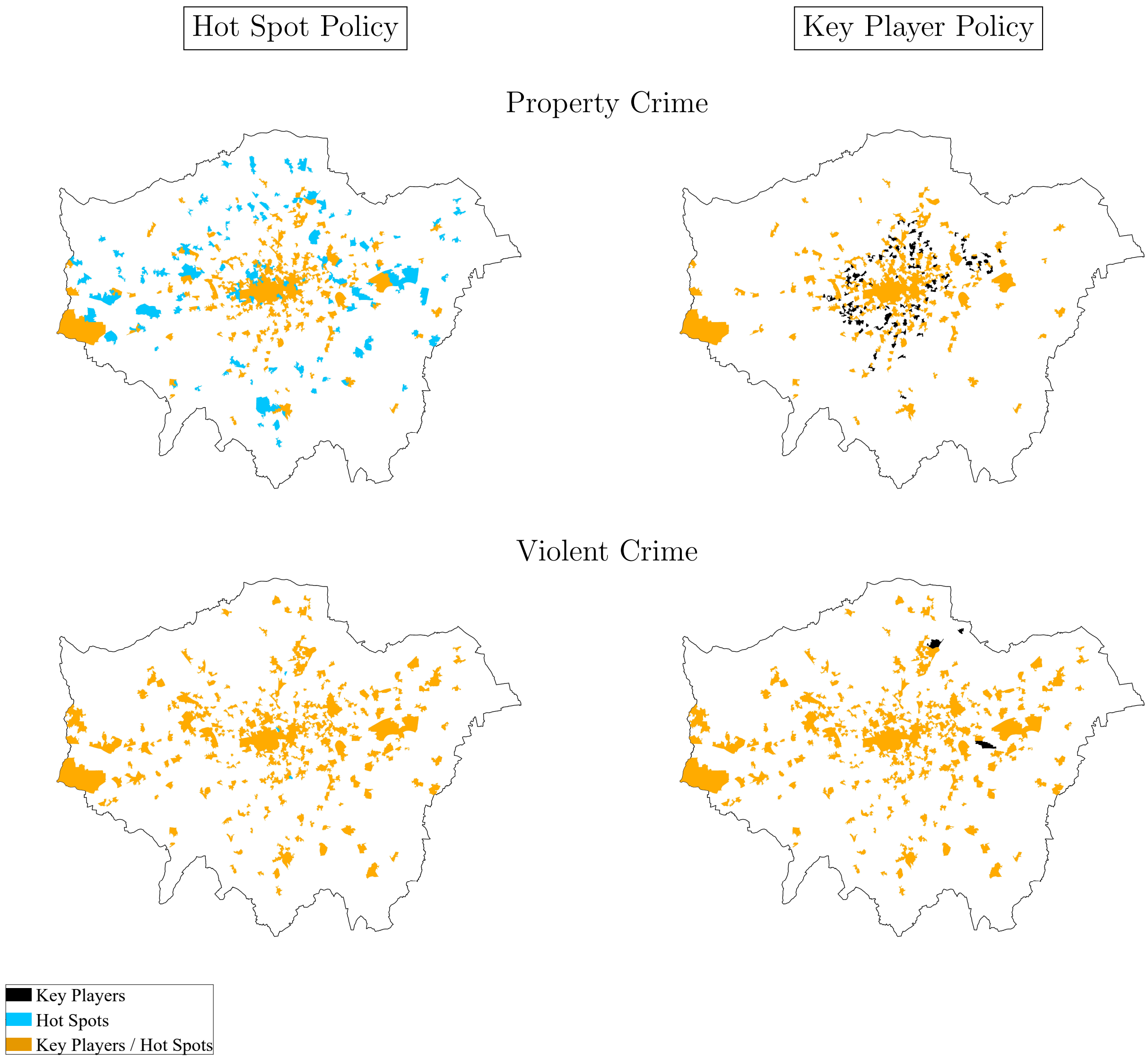
resources, we must determine the location of these non-overlapping areas. Figure 5 visually compares the spatial distribution of neighborhoods under the hot spot and key player policies, for both property and violent crime. Blue-colored neighborhoods represent "hot-spot-only", i.e., areas that exhibit high crime but are not identified among the top 500 key players. Black-colored neighborhoods are "key-player-only", meaning they are influential in crime spread (high intercentrality) but are not among the top 500 crime areas. Gold-colored neighborhoods are those that overlap between the two policies, representing areas where no resource reallocation is necessary.

Focusing on property crime, Figure 5 essentially shows that the key player policy implies a reallocation of police resources from peripheral hot-spot-only areas to more central key-player-only neighborhoods.[20] Interestingly, central London is predominantly populated by neighborhoods identified as both key players and hot spots, while key-player-only neighborhoods are disproportionately located on its immediate outskirts. A critical characteristic of key-player-only neighborhoods is that, by definition, they exhibit crime levels below the top 500 hot spots. Figure **??** in the Appendix illustrates the crime level distribution between these two neighborhood types, revealing that key-player-only areas typically present crime levels that around mean levels. Consequently, these pivotal nodes in crime propagation are effectively "hiding in plain sight" and thus would receive less resource allocation than conventional hot spots. This pattern is further illustrated by the spatial distribution of these neighborhoods in central London. Given that these key-player-only neighborhoods are spatially clustered and proximate to high-crime areas, their potential to generate spatial spillovers, while remaining overlooked, becomes a critical consideration for resource allocation efficiency. To see this point more in detail, Figure **??** in the Appendix illustrates the spatial distribution of key player neighborhoods, zooming in on central London. We rank the 500 neighborhoods by quintiles of intercentrality, and we represent separately key-player-only neighborhoods from those that are both key player and hot spot. We note that several of the neighborhoods with high intercentrality are among those that are both key players and hot spots. However, we also observe areas of high intercentrality among the key-player-only neighborhoods. This means that these very influential neighborhoods, despite their lower crime rates, are located in close proximity to high-crime areas, effectively in a blind spot relative to concentrated police resources.

A final observation is that the policy decision to reallocate police resources from outer-London to central neighborhoods, despite its potential to improve crime reduction, entails potential operational trade-offs and costs. We will discuss these in subsection 5.4.

[20] In our policy simulations, we assume a complete reallocation of police resources from hot spot to key player areas. However, any partial reallocation to key player neighborhoods will enhance crime reduction.

Figure 5: Key Players vs Hot Spots: Location



Notes. The map highlights in blue the hot-spot-only neighborhoods, in black the key-player-only neighborhood and in gold the neighborhoods classified as both key player and hot spot, for property crime (top panel) and violent crime (bottom panel). Hot spots are identified based on the average annual crime level for each neighborhood over 2013-2019. Key players are defined based on the intercentrality measure (average over time) calculated according to the formula in subsection 5.2. The hot spot policy targets the top 500 areas ranked by crime levels. The key player policy targets the top 500 areas ranked by intercentrality measure. LSOA boundaries are from the 2011 Census shapefiles (`https://geoportal.statistics.gov.uk`). Data sources are provided in section 2.

For violent crime, Figure 5 confirms that the key player and hot spot policies are nearly indistinguishable. The maps corrobroates that almost all neighborhoods identified as key players are also hot spots, reflecting the lack of network effects in violent crime, as discussed earlier. This suggests that reallocating resources from hot-spot-only areas to key-player-only areas would produce no additional effect. Since virtually all hot spots overlap with key players, the current hot spot focused approach already captures the most influential areas, making additional reallocation redundant in this context.

To gain deeper insight into network structures and their role in property crime diffusion, Figure 6 zooms in on two specific neighborhoods—one key player and one hot spot. This comparison clarifies how network centrality shapes crime dynamics and highlights the distinct contributions of these two types of neighborhoods. Specifically, the figure depicts their fourth-order networks (N4),[21] with the hot spot shown in the top panel and the key player in the bottom panel, providing a detailed visualization of their structural positioning and influence within the crime network. As before, blue represents hot-spot-only neighborhoods, black indicates key-player-only areas, gold marks neighborhoods classified as both, and grey denotes locations outside the top 500 in crime levels or intercentrality.

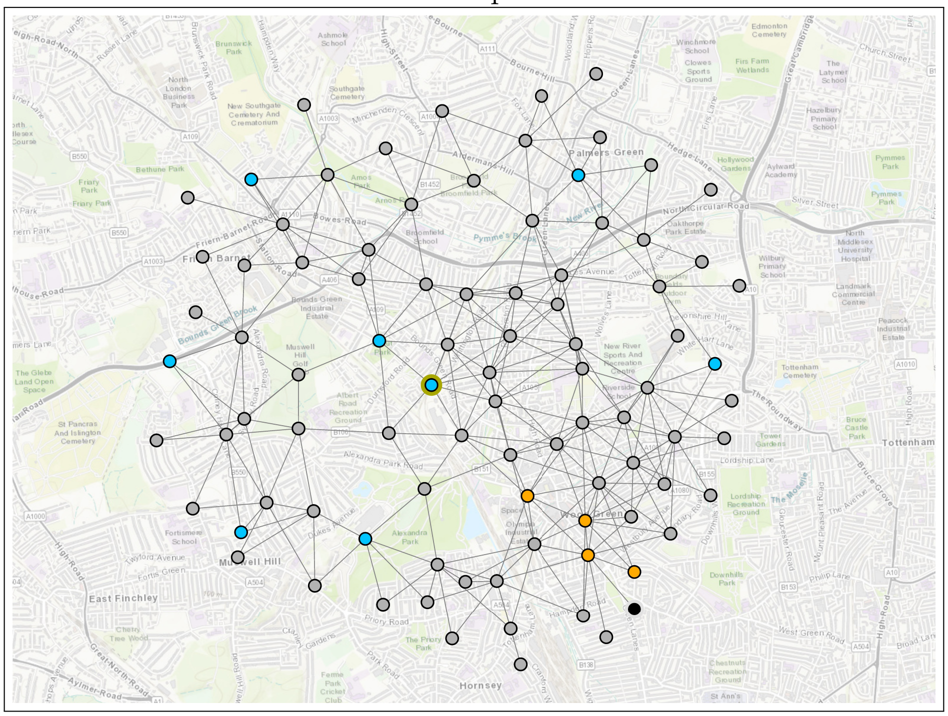
The hot spot neighborhood, located in the London Borough of Haringey, has a relatively high crime level of 174.7, ranking 477$^{\text{th}}$ among all neighborhoods. However, its intercentrality measure is low at 336.5, ranking just 663$^{\text{rd}}$ in network influence. While this confirms its status as a high-crime area, it also suggests that its impact on crime beyond its immediate surroundings is limited. This neighborhood absorbs substantial criminal activity but does not function as a major conduit for crime propagation. In contrast, the key player neighborhood, located in Waltham Forest, has a lower crime level of 132.9 (ranked 765$^{\text{th}}$), yet its intercentrality measure is significantly higher at 714.9 (ranked 301$^{\text{st}}$), more than twice that of the hot spot.

One might wonder what drives this stark difference in intercentrality, given that the key player has lower crime and only a slightly larger network size than the hot spot. The answer lies in the composition of connections. While both neighborhoods contain a similar number of areas that are classified as both key players and hot spots, their non-overlapping connections differ. The hot spot network contains relatively more hot spot-only neighborhoods. This suggests that hot spots tend to be surrounded by other high-crime areas that, while dense in criminal activity, do not play a central role in crime diffusion. As a result, crime in these neighborhoods remains largely localized rather than spreading extensively through the network. The key player network, by contrast, has a larger share of key player-only neighborhoods, which are often connected to or in close proximity to other key player neighborhoods. This clustering reinforces their systemic role in sustaining and diffusing crime across multiple

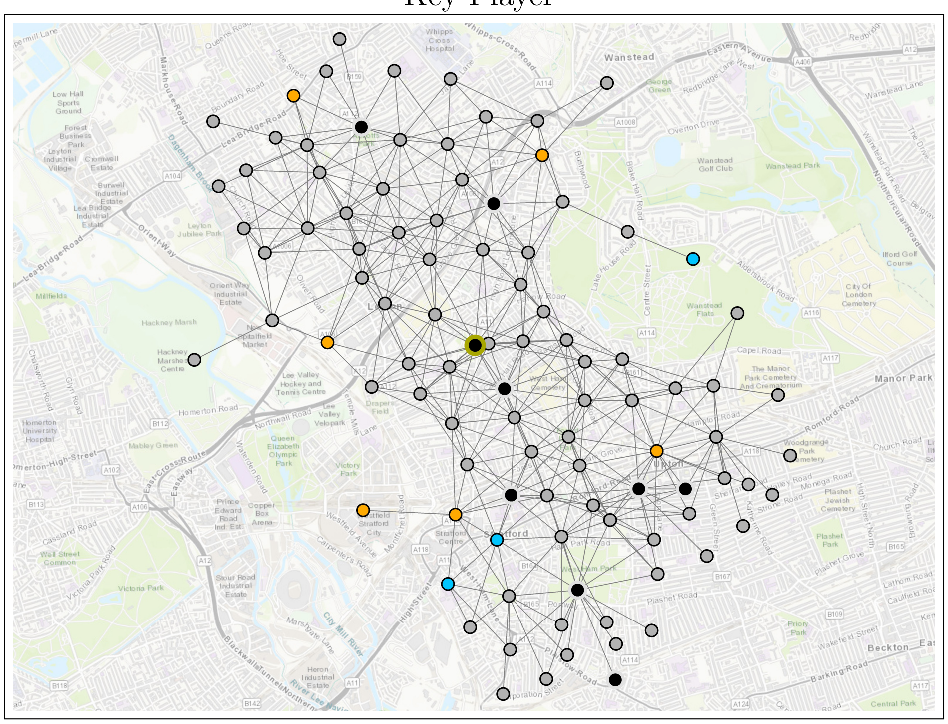
[21] A fourth-order network means that criminal behavior, spillovers, and interventions account for influences traveling through up to four intermediary connections. In other words, a fourth-order network involves considering connections up to four steps away, capturing a broader range of indirect influences.

Figure 6: Key Players vs Hot Spots: Network Structures

Hot Spot



Key Player



Notes. The figure illustrates the 4^{th} order network for two selected neighborhoods, highlighting in blue the hot-spot-only neighborhoods, in black the key-player-only neighborhood, in gold the neighborhoods classified as both key player and hot spot, and in gray the neighborhoods classified as neither key player nor hot spot.

neighborhoods.

This comparison exemplifies the defining characteristic of key players: it is not so much the number of connections or the crime level, but rather network position that shapes their overall impact on crime. Key players are embedded in the crime network in a way that amplifies spillover effects, extending their influence far beyond their own crime levels. While hot spots draw police attention for their high crime levels, key players serve as critical conduits in crime diffusion. Removing them disrupts crime not only locally but across connected neighborhoods, making them a more strategic intervention point.

While these network differences are evident in Figure 6, understanding why key players disperse crime while hot spots attract it requires further analysis of offender behavior, mobility patterns, and neighborhood characteristics. These dimensions will be explored in Section 6.

5.4 Financial Implications of the Key Player Policy

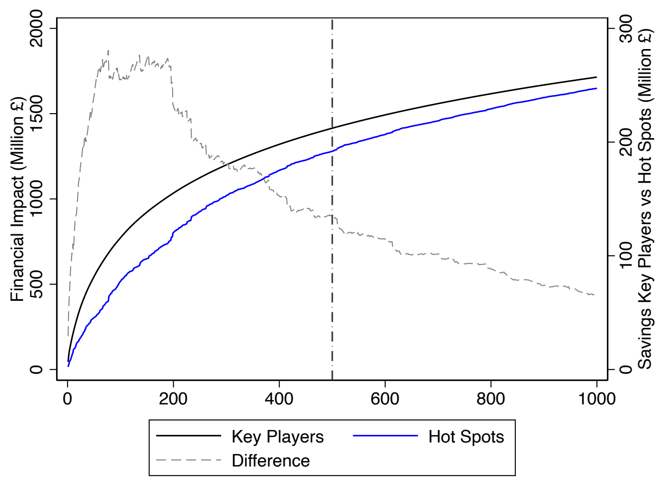
The next phase of our analysis delves into the financial implications of implementing the key player policy. Specifically, we conduct a comparative assessment of the financial impacts of the key player and hot spot approaches. Given the lack of impact on violent crime, our focus will only be on property crime.

To assess the financial implications, we first estimate the total cost of property crime in London, utilizing detailed unit-cost estimates from Heeks et al. (2018) at the sub-offence level. We calculate the unit cost of property crime as a weighted average, based on observed crime rates across sub-offences. This approach yields an estimated average unit cost of approximately £4,818.

Next, we estimate the projected financial impact of the key player and hot spot policies. This involves multiplying the cumulative distributions shown in Figure 4 by the total observed property crime in London and the unit cost of property crime. The resulting financial estimates for each policy are presented in Figure 7, which also highlights the difference between the two scenarios.

Given that the key player policy leads to a larger reduction in total crime, the financial savings from eliminating key player areas would be higher than those from removing hot spot areas. Specifically, under the key player policy—and assuming police interventions successfully eliminate property crime within the 500 targeted neighborhoods—the estimated financial savings would reach approximately £1,415 million. In comparison, the hot spot policy results in savings of around £1,279 million. As a result, the net annual savings from switching from the hot spot approach to the key player policy would be approximately £136 million. The figure also illustrates the savings schedule, which represents the difference in the financial impact between the key player and hot spot policies across various numbers of neighborhoods. In particular it highlights how the savings from choosing the key player policy vary depending on the extent of overlap between the two policies. When the overlap between the hot spots and the key player areas is minimal, the savings from adopting the key player policy are larger. However, as the overlap between hot spots and key players increases, the savings from the key player policy diminish.

Figure 7: Key Players vs Hot Spots – Financial Implications



Notes. The figure illustrates the financial impact of reducing crimes under the key player and hot spot policies. The financial impact is calculated by multiplying the unit cost of property crimes by the number of crimes reduced under each policy. The definition of unit cost of crime is provided in subsection 5.4. The black curve represents the total financial impact for the key player policy, while the blue curve represents the total financial impact for the hot spot policy. The dashed gray line shows the difference in financial impact between the two policies. This difference represents the additional financial benefits of adopting the key player policy over the hot spot policy.

It is important to recognize that these simulations assume a frictionless transition from the hot spot policy to the key player policy, with no associated costs. In practice, however, reallocating police resources—such as shifting officers from outer to inner London, as in our example—may entail some logistical and financial challenges, including retraining costs and adjustments in deployment strategies. Additionally, changes in police presence could influence public perceptions of safety, particularly in areas where patrol coverage is reduced. At the same time, concerns may also arise in neighborhoods receiving increased policing, especially if these areas are already subject to heightened surveillance or have communities that feel disproportionately targeted.

While these factors warrant consideration, the substantial financial savings projected under the key player policy suggest that such a reallocation could be both cost-effective and impactful. Moreover, the long-term benefits of disrupting crime spillovers may extend beyond immediate financial gains, reinforcing the case for a more network-informed approach to policing. Ultimately, understanding both the benefits and the practical considerations of reallocating police resources will be key to effectively implementing this network-based strategy for crime reduction.

6 What Shapes a Key Player Neighborhood?

What differentiates key player neighborhoods from hot spot neighborhoods, and why is it more impactful to target the former than the latter? In this section, we aim to address these questions using a two-pronged approach. First, we take a broad view of the neighborhoods, comparing the characteristics of key player neighborhoods and hot spot neighborhoods across two key dimensions: the sociodemographic nature and the built environment. Next, we focus on offenders, utilizing detailed data on those accused of crimes in London, which includes precise locations of residence and offense, as well as information on co-offending networks. This exercise will enhance our understanding of why key player neighborhoods are so effective at propagating crime, namely whether this is due to the built environment, the criminal tendencies of the residents, or a combination of both.[22]

6.1 Characterizing Hot Spot and Key Player Neighborhoods

Table 4 allows a comparison of the sociodemographic and built environment dimensions of these neighborhoods. From this table, we take three key findings. First, key-player-only neighborhoods are statistically significantly more deprived than hot-spot-only neighborhoods. One can see this directly by noting that the multi-dimensional deprivation index is 11.6 percentile points higher in key-player-only neighborhoods and indirectly by noting higher rates of both social housing accommodation and being out of the labor force. The remaining key findings relate to differences in the built environment of key-player-only vs. hot-spot-only neighborhoods. The second key finding is that hot-spot-only neighborhoods possess more features that can make these areas crime attractors, such as an abundance of parks, green spaces, and transport hubs. These features are likely to increase the inflow of both potential offenders and potential victims. We return to this point in Table 5. The last key finding is that key-player-only areas are located closer to the center of London and therefore have much higher population density. This suggests that criminals living in these neighborhoods can

[22] Our focus remains on property crime, as this is where the overlap between key player and hot spot neighborhoods is minimal, allowing for the greatest potential reduction in crime.

more easily find both criminal partners and potential victims in closer proximity to home, points we will empirically explore in the next subsection.

Table 4: Key Player vs. Hot Spot Neighborhoods: Area-Based Differences

	(1)	(2)	(3)
	Key-Player-Only Neighborhood	**Hot-Spot-Only Neighborhood**	***p*-Value: Test of Equality Across Areas**
Neighborhood-Based Attributes			
Percentile Rank: Deprivation	65.6	54.0	[0.000]
%Social Housing	33.7	22.7	[0.000]
%Private Rented Housing	31.9	30.4	[0.234]
%Homeowner	30.8	43.6	[0.000]
%Routine Occupation	7.0	7.9	[0.025]
%Not in Labor Force	10.1	8.8	[0.012]
%Never Worked	7.8	6.7	[0.012]
%Long-Term Unemployed	2.3	2.1	[0.104]
%Non-White	44.0	42.6	[0.516]
Spatial Aspects of the Neighborhood			
%Area Coverage: Green Space or Parks	7.6	12.8	[0.009]
%Railway or Metro Station Located in Area	13.0	31.8	[0.000]
Number of Bus Stops	3.2	7.9	[0.000]
Population Density	160.7	62.6	[0.000]
Distance to Center of London (km)	6.5	12.8	[0.000]

Notes: N=154. Neighborhood measures are based on the hot-spot/key-player classification for property crime. There are 500 hot spot neighborhoods and 500 key player neighborhoods. The number of non overlapping neighborhoods – hot-spots-only and key-player-only neighborhoods – is 154 (31%). The crime variables are the total number of crimes divided by the total number of neighborhoods, further divided by five—the number of years of data. As such, these crime outcomes are annualized crime rates per neighborhoods. Crime variables are based on property crime only. We additionally compute regression-based p-Values of difference in means. These are based on a neighborhood-level regression of the variable of interest on a constant and an indicator for key-player area, with Eicker-Huber-White standard errors. Neighborhood-Based Attributes are obtained from the 2011 Census.

6.2 Differential Spatial Search Patterns

We next examine various aspects of offender behavior among individuals residing in and committing offenses within key-player-only and hot-spot-only neighborhoods. The results are presented in Table 5. We utilize complementary crime data from restricted-access records of individuals accused of crimes in London, covering nearly the same period as our primary analysis (2015 to 2019).[23] This offender-level data provides a unique perspective for understanding spatial patterns of crime, illuminating both the locations of offenses and the

[23] Although individual-level "accused data" are not directly comparable to reported crime data, they offer valuable insights into criminal activity during the relevant time frame and in the specific neighborhoods we analyze. Figure **??** in the Appendix presents a scatter plot comparing the average number of crimes across neighborhoods in London from the accused and reported crime datasets. While the scales of the two data sources differ (due to differing definitions of crime), the graph indicates a high correlation between the accused and reported crime data, serving as a reliable representation of crime patterns in London.

residences of offenders. This dual perspective allows for the measurement of "crime commuting" distances—reflecting how locally offenders operate—and facilitates an exploration of two mechanisms underlying spatial crime diffusion. First, offenders may extend their activities beyond their home neighborhoods into neighboring areas, thereby contributing to spatial correlation through individual mobility. Second, co-offending networks, where offenders collaborate across proximate neighborhoods, may further amplify the diffusion of crime.

Table 5: Key Player vs. Hot Spot Neighborhoods: Offender-Based Differences

	(1)	(2)	(3)
	Key-Player Area	**Hot-Spot Area**	***p*-Value: Test of Equality Across Areas**
Resident-Based Measures			
%Part of Co-offending Network	17.9	19.9	[0.113]
Number Offenders per Crime	1.25	1.31	[0.260]
Number Offenders per Crime | Multiple Offenders	2.42	2.53	[0.850]
Minimum Distance Residence to Co-Offender Residence	4.19	6.19	[0.000]
Mean Distance Residence to Co-Offender Residence	5.51	7.13	[0.007]
%Commit Crime Outside Home Neighborhood	88.8	84.5	[0.000]
Crime Commute Distance (km)	3.83	4.86	[0.000]
Crimes by Residents	12.08	11.68	[0.322]
Offense-Based Measures			
Crime Commute Distance (km)	3.64	5.01	[0.000]
Crimes Committed in Area	9.28	18.35	[0.002]
Combined Measures			
Deprivation Percentile Rank Gap: Offense-Residence	–9.5	–6.7	[0.239]
Ratio of Crimes Committed in Area to Number of Crimes by Residents	0.769	1.571	[0.000]

Notes: N=154. Area measures are based on the hot-spot/key-player classification for property crime. There are 500 hot-spot areas and 500 key-player areas. The number of non overlapping areas – areas that are hot-spots only and key-players only – is 154 (31%). For Resident-Based Measures, we compute statistics based on offender neighborhood of residence. For Offense-Based Measures, we compute statistics based on neighborhood of offense location. The crime variables are the total number of crimes divided by the total number of neighborhoods, further divided by five – the number of years of data. As such, these crime outcomes are annualized crime rates per area. Crime variables are based on property crime only. Neighborhoods are LSOAs. We additionally compute regression-based p-Values of difference in means. These are based on a neighborhood-level regression of the variable of interest on a constant and an indicator for key-player area, with Eicker-Huber-White standard errors. Neighborhoods are weighted based on the number of resident offenders. Crime data are from the Metropolitan Police data of individuals accused of crimes in London and covers the period 1 January 2015-31 December 2019.

We highlight four broad findings from these results. First, the differences in co-offending network structures do not account for the effectiveness of key-player-only neighborhoods in crime; we find no significant variation in the size or likelihood of being part of a co-offending network. Second, residents of key-player-only neighborhoods are no more criminogenic than their counterparts in hot-spot-only neighborhoods. Third, criminals residing in key-player-only neighborhoods exhibit significantly more localized crime commuting patterns and tend to collaborate with more local co-offending partners, likely due to the denser urban environments found in these neighborhoods. We provide further evidence supporting this third finding in Section **??** in the Appendix.

The final and most significant finding emerging from Table 5 relates to the ratio of crimes committed in a neighborhood to the number of crimes committed by its residents. Our analysis indicates that key-player-only neighborhoods function as "crime dissipators", as evidenced by their ratio being below 1 (0.769), suggesting that offenders residing in these neighborhoods are more inclined to commit crimes elsewhere rather than within their home neighborhoods.[24] In contrast, hot-spot-only neighborhoods display a ratio greater than 1 (1.571).[25] This indicates that even if offenders in hot-spot-only neighborhoods were to commit all their crimes locally, they would account for less than two-thirds of the total crime in those neighborhoods ($1/1.571 < 2/3$). Thus, hot-spot-only neighborhoods can be characterized as "crime attractors", reflecting their capacity to draw offenders from surrounding neighborhoods. Environmental features of these areas, such as parks, green spaces, and transit stations, likely contribute significantly to their attractiveness for criminal activity.

What we learn from the evidence above is that offenders do not appear to differ in underlying criminogenic tendencies across neighborhood types or in criminal network formation patterns. However, they do appear to move through space in statistically significantly different ways, likely interacting with spatial features of the neighborhood. Given these differences, we now consider the spatial search patterns of offenders in hot-spot-only neighborhoods and key-player-only neighborhoods. Can we detect differential search patterns across those living in the two types of areas? The evidence presented in Figure 8 provides clear support for the existence of such differences.

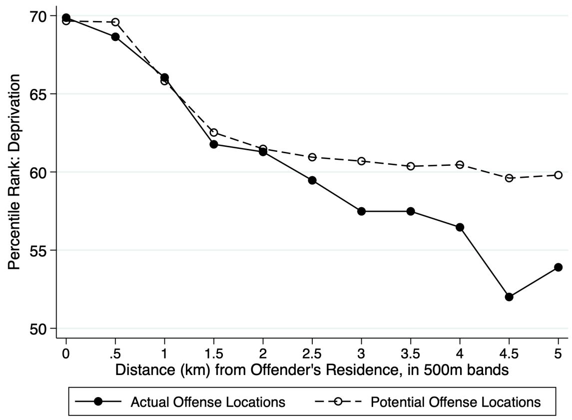
To describe spatial search patterns, we make use of neighborhood-level, geocoded data on (i) the index of local deprivation—a proxy of the likely benefits from crime—and (ii) the proportion of all local crimes for which an offender was arrested and charged for the crime—a proxy for the costs of crime, which we call the sanction rate. Given we have the precise location of offender residence and crime location for all those accused of a crime in London, we can then calculate how costs and benefits of crime evolve as an offender moves away from their home. We do so in two ways. First, we calculate the percentile rank of deprivation and the sanction rate for all areas in 500-meter rings around every offender location—we label these as potential offense locations. Second, we calculate the same statistics for actual offense locations, again in 500-meter rings. We then average these for offenders living in the key-player-only neighborhoods (the left-hand column of Figure 8) and those living in hot-spot-only neighborhoods (the right-hand column of Figure 8). This allows us to visualize the full choice set of property offense locations and those chosen by offenders living in the two areas.

[24] The ratio is statistically significantly different from 1, with a p-value of 0.006.

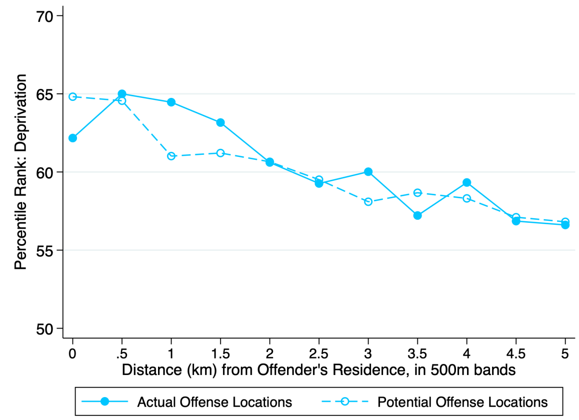
[25] The ratio is statistically significantly different from 1, with a p-value of 0.004.

Figure 8: Differential Spatial Search Patterns of Offenders by Area of Residence

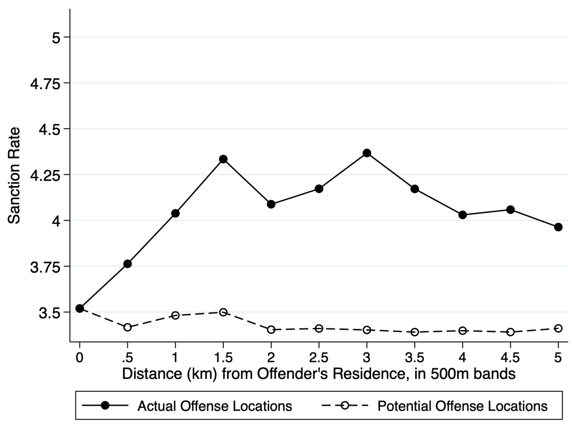
Key Player Neighborhoods **Hot Spot Neighborhoods**



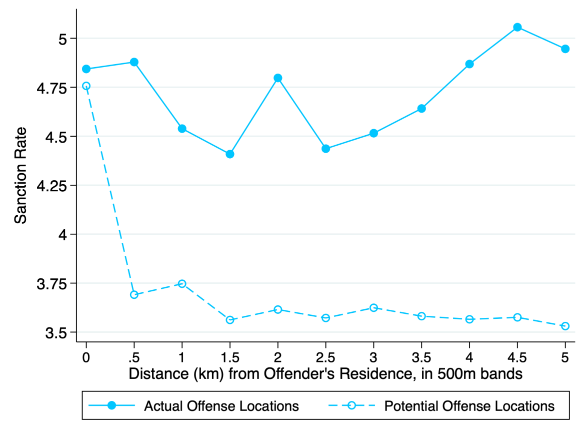
(a) Crime Benefit Proxy



(b) Crime Benefit Proxy



(c) Crime Cost Proxy



(d) Crime Cost Proxy

Notes: Figures (a) and (b) show how average neighborhood deprivation evolves as one moves from offenders' home locations. For each location, we calculate deprivation at 500m intervals for both actual offense location as well as potential offense location, the latter of which uses all deprivation measures in a given radius-based ring. We then average these deprivation statistics across all offenders to calculate the statistics provided in the graphs. Figures (c) and (d) repeat this exercise for the sanction rate in the area – the proportion of recorded offenses that end up in court. We use this as a measure of the perceived cost of crime.

The patterns of spatial search of offenders differ across neighborhoods. Consider the top row of Figure 8, where we present evidence on the evolution of benefits over space, as proxied by the index of local deprivation of the neighborhood. Offenders living in hot-spot-only neighborhoods (Figure 8(b)) do not appear to have sophisticated spatial search patterns—the benefit proxy of the locations they target matches the potential locations. Put differently, offenders in hot-spot-only neighborhoods commit crime conditionally randomly. A different pattern emerges for those living in key-player-only neighborhoods (Figure 8(a)). While close to home, the benefit proxy for actual and potential locations overlaps. Once these offenders move further afield, however, they target considerably less deprived neighborhoods. Five kilometers from home, offenders from key-player-only neighborhoods commit crimes in locations with a percentile rank of 53.9, as opposed to the potential percentile rank of 59.8 for this distance. We conclude that these offenders are engaging in more sophisticated spatial search, trading off the cost of commuting further for higher returns from crime, as proxied by the deprivation index of where they commit their property crime.

A second piece of evidence in support of the lack of sophistication of the spatial search patterns of those living in hot-spot-only neighborhoods can be found in Figure 8(d), where we consider the spatial evolution of the sanction rate as those living in these neighborhoods move further from home. The first thing to note is that the potential sanction rate drops markedly as one moves 500 meters from home—this likely reflects a higher police presence in these hot-spot-only neighborhoods. Offenders living in these neighborhoods do not take advantage of this large drop in the potential cost of crime—the areas where they choose to commit crime remain elevated across the span of distances we consider here. Combining the evidence from Figure 8(b) and Figure 8(d), we conclude that offenders in hot-spot-only neighborhoods do not act strategically when searching for crime locations.

For those living in key-player-only neighborhoods, the sanction rate of potential locations remains extremely constant across space (dashed line, Figure 8(c)). Yet offenders in key-player-only neighborhoods appear to actively choose to commit crime in higher sanction rate areas once they leave their home location. Precisely why this is the case, we cannot tell. From this, we arrive at two conclusions. The first is that the pattern of spatial search differs in pronounced ways for those living in the two neighborhoods. The most likely candidate for this is not different levels of criminality of residents of these two neighborhoods (see Table 5), but rather the way that offenders in the two neighborhoods interact with the notably different urban structures of the two neighborhoods (Table 4). Our second conclusion is that the spatial search patterns of those living in key-player-only neighborhoods are more sophisticated than those living in hot-spot-only neighborhoods. We suspect that these differences in spatial search behaviors likely play a key role in explaining why key-player-only neighborhoods propagate crime so effectively.

6.3 Theoretical Insights

Let us develop a simple model to explain why criminals in key-player areas are more likely to commit crimes outside their area of residence compared to those in hot-spot areas, as illustrated in Tables 4 and 5 and Figure 8.

Consider two areas indexed by $j = 1$ and $j = 2$. Each criminal's residence is indexed by $i = 1, 2$ and is *predetermined*. That is, we assume that (in the short run), criminals are *exogenously* allocated to an area l and need to decide where to commit their crimes. There is a continuum of criminals in each location, and the total mass of criminals in the economy is normalized to 1. Let β_j represent the proceeds from crime from area j, $p \in [0,1]$ the probability of being arrested, and σ the cost of punishment.

There are two types of areas, denoted as $l \in \{K, H\}$, where K represents a key-player area, and H represents a hot-spot area. Without loss of generality, assume that a criminal resides in area 1. Committing a crime in the neighboring area (area 2) incurs a cost. This cost could arise from commuting expenses as well as from the inherent advantage of familiarity with one's area of residence. Criminals typically have better knowledge of their home area, such as the locations of CCTV cameras and police patrol routes, compared to other areas. Consequently, the cost of committing a crime outside one's area of residence (area 2) is expressed as:

$$t(\theta) = t_0^l - \tau(\theta), \tag{5}$$

where $t_0^l > 0$, and $\theta \in \Theta := [0,1]$ represents represents the inverse ability of committing crimes in areas other than the area of residence. We assume that θ follows a uniform distribution over Θ. The cost function satisfies the following properties: $\tau(0) = 0$, $\tau(1) < t_0$, and $\tau'(\theta) > 0$, where t_0^l represents the maximum cost faced by any individual in area l.

Criminals residing in key-player areas (K) experience lower costs when committing crimes outside their area of residence compared to those residing in hot-spot areas (H). Formally, this implies $t_0^K < t_0^H$. This distinction highlights the relative ease with which criminals in key-player areas operate in neighboring locations.

A criminal i (of type θ) residing in area 1 will choose to engage in criminal activities *externally* (i.e., in area $j = 2$) rather than locally (i.e., in their area of residence, $j = 1$) if and only if:

$$(1-p)\beta_1 - p\sigma \leq (1-p)\beta_2 - p\sigma - \left(t_0^l - \tau(\theta)\right).$$

For simplicity, assume $\tau(\theta) = \overline{\tau}\theta$, with $0 < \overline{\tau} < t_0^l$. The inequality can be written as:

$$t_0^l \leq (1-p)\left(\beta_2 - \beta_1\right) + \overline{\tau}\theta.$$

Since criminals in our dataset reside in poorer areas, they are motivated to commit crimes in neighboring, wealthier areas. Thus, we assume $\beta_2 > \beta_1$. This assumption also captures a psychological distaste for committing crimes in one's own neighborhood. For instance, individuals may feel more comfortable stealing from strangers rather than from someone familiar, such as the local shopkeeper or someone they often see at the pub. In Table 4, we observe that hot-spot areas tend to have a higher concentration of public transport infrastructure, including bus stops, metro stations, tunnels, and bridges, which enhances their connectivity and accessibility. These features likely make such areas more attractive for criminal activity. In contrast, key-player areas have fewer of these features, potentially limiting local opportunities for crime and encouraging offenders to operate in nearby areas that offer better prospects.

Therefore, criminals face a trade-off between committing crimes locally—where the cost of committing a crime is lower due to familiarity with the area, but the proceeds from crime are also lower—and committing crimes externally—where the cost of committing a crime is higher due to unfamiliarity, but the potential proceeds are greater. Solving this trade-off equation leads to

$$\theta \geq \frac{t_0^l - (1-p)(\beta_2 - \beta_1)}{\overline{\tau}}.$$

Let $t_0^l > (1-p)(\beta_2 - \beta_1)$ for $l \in \{K, H\}$ and define the critical threshold as follows:

$$\widetilde{\theta}^l = \frac{t_0^l - (1-p)(\beta_2 - \beta_1)}{\overline{\tau}}.$$

Proposition 1.

(*i*) *Assume* $\beta_2 > \beta_1$ *and* $(1-p)(\beta_2 - \beta_1) < t_0^l < (1-p)(\beta_2 - \beta_1) + \overline{\tau}$. *Then, all criminals with* $\theta \geq \widetilde{\theta}^l$ *will commit crimes externally in neighboring areas, while those with* $\theta < \widetilde{\theta}^l$ *will commit crimes internally within their area of residence.*

(*ii*) *Further assume* $t_0^K < t_0^H$. *In this case, criminals residing in key-player areas will commit a higher proportion of their crimes externally compared to criminals residing in hot-spot areas.*

This proposition illustrates that, in equilibrium, criminals in both key-player areas and hot-spot areas commit crimes both locally and outside their area of residence. However, a higher proportion of criminals commit crimes outside their area of residence in key-player areas due to their greater accessibility. This pattern is reflected in the ratio of crimes committed in neighborhood to the number of crimes by residents, as shown in Table 5. Indeed, key-player areas act as crime dissipators, characterized by a ratio of crimes committed within the area to the number of crimes by residents falling below 1 (0.769). This suggests that offenders residing in these areas are more inclined to commit crimes outside their home area. Conversely, hot-spot areas function as crime attractors, with a ratio exceeding 1 (1.571).

This indicates their capacity to draw offenders from neighboring areas, making them focal points for criminal activity.

7 Conclusions

Our paper introduces a novel framework for crime reduction, shifting from conventional hot spot policing to a network-based approach that targets key player neighborhoods – areas most influential in the diffusion of crime. Using London as a case study, we establish the presence of substantial spatial spillovers in property crime, demonstrating that reallocating resources from hot spots to these key nodes could lead to greater reductions in overall crime. Based on simulations that target the 500 most affected areas, we estimate that such a reallocation could achieve a 5.8 percentage point greater reduction in property crime, translating into financial savings exceeding £130 million annually. Our results show that these effects are driven by property crime, with no significant impact on violent offenses. This suggests that crime diffusion mechanisms primarily operate through economically motivated crimes rather than violent ones.

Crucially, our analysis highlights a fundamental distinction between conventional hot spot policing and the key player strategy. Hot spots act as attractors, concentrating crime in specific locations, whereas key player areas function as diffusors, shaping how crime propagates through the network. By targeting the latter, our approach disrupts the underlying transmission mechanisms of crime, offering a more strategic and cost-effective alternative to traditional enforcement strategies.

This shift in focus from crime concentration to crime propagation has important implications for policing efficiency, particularly in an era of rising crime and constrained budgets. Rather than reacting to crime where it is most visible, targeting key player neighborhoods addresses its root causes, amplifying the impact of enforcement efforts and maximizing public safety benefits.

Beyond immediate crime reduction, this network-based approach challenges conventional policing paradigms. While hot spot methods effectively suppress crime in specific locations, they may overlook broader structural dynamics that sustain crime across urban areas. By accounting for spatial dependencies, reallocating resources to key player neighborhoods generates wider spillover effects, creating more durable and systemic reductions in crime.

These findings provide a strong policy insight: optimizing police deployment through a network-based approach not only enhances cost-effectiveness but also strengthens the long-term resilience of urban crime prevention strategies. This perspective offers a more holistic framework for rethinking crime control in complex urban environments, aligning enforcement strategies with the underlying structure of criminal activity.

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