

# Crime and Ethnicity in London\*

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## Abstract

We compare the spatial distribution of crime and the black population density across the London boroughs. Once endogeneity issues are taken into account, we find that the higher is the density of the black population in a given borough, the higher is the crime rate. This effect is still positive but lower for neighboring boroughs and ceases to exist beyond a 40 minute driving distance. Such results are consistent with models of social interactions where relationships are strongest between individuals of the same ethnic group and highly localized.

**Key words:** Crime, ethnic minorities, social interactions, spatial correlation, panel data.

**JEL Classification:** C21, K42, R12

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# 1 Introduction

The relationship between a community's ethnic population density and its crime rate is not a new question, at least not in the *non-economic* literature. Indeed, the connection between ethnic population density and spatial crime distributions is one of the oldest in criminology. In the early decades of the twentieth century, Shaw and McKay (1942) made this link a central component of their theory of social disorganization. Since then, there have been myriads of papers investigating this link in criminology and the relationship is in general found to be positive (see, for example, Bottoms and Wiles, 1997). However, the study of such a relationship in criminology, which is typically based on cross-sectional studies, is plagued by different econometric problems and therefore, it is difficult to interpret the result in terms of causality.

The contribution of this paper lies in the use of *panel data techniques* to identify the claimed effect and, in addition, in the use of *spatial regression techniques* to assess the spatial scale of such an effect. Once the influence of observable and unobservable factors defining the local context has been taken into account, we find that a significant and positive relationship between crime and ethnic density still holds. Such an effect is, however, quite localized. Our analysis provides a natural interpretation of the results in terms of *social interactions*. To be more precise, a mechanism consistent with our findings is that, in denser areas, individuals interact on average with more people, which facilitates the diffusion of information. When such an information is about crime opportunities, this mechanism is particularly strong for ethnic minorities. Indeed, ethnic minorities are overrepresented in criminal activities and social interactions between individuals of the same ethnic group are quite strong. If the information about crime opportunities is localized, it is then not surprising to find that the longer the physical distance between individuals of the same ethnic group, the lower is the impact of such peer effects on the local crime rate. Our data have, however, some limitations, mainly because we cannot separate the local crime rate per ethnicity. As a result, our analysis should be taken with caution. Nevertheless, it rules out some traditional explanations of the relationship between ethnicity and crime at the local level, such as those based on unobservable area characteristics, and suggests that peer effects might be at work.

It is, in fact, well documented that social interactions are important in explaining criminal activities. An individual is more likely to commit crime if his or her peers commit crime than if they do not (Glaeser et al., 1996; Calvó-Armengol and Zenou, 2004; Ballester et al., 2006, 2010; Calvó-Armengol et al., 2007). Different papers have tried to understand the role of peers in criminal activities. Using data from the 1989 NBER survey of youths living in low-

income Boston neighborhoods, Case and Katz (1991) find that the behavior of neighborhood peers appears to have a substantial effect on the criminal activities of young people. They find that the direct effect of moving a young person with given family and personal characteristics to a neighborhood where 10 percent more of the young people are involved in crime than in his or her initial neighborhood is to raise the probability that this young person will become involved in crime by 2.3 percent. Ludwig et al. (2001) and Kling et al. (2005) explore this last result using data from the Moving to Opportunity (MTO) experiment that relocates families from high- to low-poverty neighborhoods. They find that this policy reduces juvenile arrests for violent offences by 30 to 50 percent as compared to control groups. This also suggests very strong social interactions in crime behavior. Patacchini and Zenou (2008) test the role of weak ties in explaining criminal activities, revealing that weak ties have a statistically significant and positive effect on both the probability to commit crime and its level. Finally, Bayer et al. (2009) consider the influence of juvenile offenders serving time in the same correctional facility on each other's subsequent criminal behavior. They find strong evidence of peer effects in criminal activities since exposure to peers with a history of committing a particular crime increases the probability that an individual who has already committed the same type of crime recidivates with that crime.<sup>1</sup>

All the above-mentioned papers use American data. In Europe, however, the social analysis of crime is not widespread. There are few (and recent) economic studies in the UK (Hansen and Machin, 2002; Machin and Meghir 2004; Machin and Marie, 2006) that analyze the link between crime and low-wages. Their findings point to a strong positive correlation between crime and low wages, which is consistent with findings from the US. However, in their analysis, there are neither social nor spatial aspects of crime.<sup>2</sup>

To the best of our knowledge, this is the first paper in economics for the UK (and even for Europe) that provides evidence of the role of social interactions and spatial proximities for crime.<sup>3</sup> For this purpose, we use monthly data on crime for the 33 London boroughs. Distance is measured by travel times, as this is reasonably the best metric to represent how agents' contacts materialize. The distance between boroughs varies between 19 and 74 minutes' driving time, which means that people are typically not very far from each other,

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<sup>1</sup>In the crime literature, the positive correlation between self-reported delinquency and the number of delinquent friends reported by adolescents has proven to be among the strongest and most consistently reported findings (see e.g. War, 1996, 2002; Matsueda and Anderson, 1998).

<sup>2</sup>There are, however, British studies on spatial issues of crime in the non-economic literature (see, e.g. Bottoms and Wiles, 1992, 1997, Hirschfield and Bowers, 1997, Craglia et al., 2001 and Chainey and Ratcliffe, 2005).

<sup>3</sup>Even if, as noted above, the interpretation has to be interpreted with caution.

both within and between boroughs.

The ethnic population is restricted to the Black population only.<sup>4</sup> This choice mitigates issues related to cultural differences between ethnic groups.<sup>5</sup> However, because there is still a large diversity within the Black population, we will perform our empirical analysis separately for each group composing the Black population, namely the “Black Caribbeans”, the “Black Africans” and the “Other Blacks”. We will see that the evidence remains unchanged.

We begin our analysis by using the techniques of exploratory spatial data analysis and compare the spatial patterns of crime in London with those of a range of socio-economic variables (namely the unemployment rate, the percentage of skilled population, Black population density, ethnic commuting flows and a house price index). Our results reveal more marked similarities between the spatial structure of crime and the spatial structures of the ethnic variables (population density and commuting flows). This evidence is in line with the findings in Conley and Topa (2002), which investigates the spatial distribution of unemployment in Chicago using different social and economic distance metrics. Their results indicate a clear dominance of the racial/ethnic distance metric and the racial/ethnic composition variables in explaining the spatial correlation of unemployment rates.<sup>6</sup>

We then look more closely at the relationship between crime and the Black population density. To measure the strength of social interactions, we create a series of distance-based bands around each area and we measure the ethnic population density within each proximity band. When these new variables are included in a regression model, it is possible to assess both their overall impact on crime and the rate at which the effect attenuates with distance by comparing estimates across rings.

The use of a panel data regression model allows us to control for observable and unobservable area characteristics, thus enabling us to examine the relationship between crime and ethnic population net the clustering effect that may simply be due to the sorting of individuals into locations. The estimation results confirm the relevance of the role played by the ethnic residing population in explaining the observed spatial patterns of crime rate. It appears that the estimated effect is greatest within 20 minutes driving time, sharply diminishing with travel time and having virtually no effect beyond approximately 40 minutes.

Observe that these results are related to the predictions made by the theory in criminology

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<sup>4</sup>The Black population is composed of “Black Caribbeans”, “Black Africans” and “Other Blacks”.

<sup>5</sup>According to the Office of National Statistics, in 2004, roughly 62% of the UK Black population lived in London whereas this percentage was only 37% for Asians and it was even smaller for the other minority groups.

<sup>6</sup>See also Raphael and Sills (2006) for an overview on the relationship between urban crime and race in the United States.

and sociology called the *routine activity approach* (Cohen and Felson, 1979). This theory stipulates that in order for crime rates to be high in an area, it has to be that offenders are at the same places as targets (victims), without any effective controller (guardian) and with weak handlers.<sup>7</sup> Unfortunately, we cannot explicitly test this theory since we do not have information on victims (targets), guardians (police) and even on where the crime is committed. However, if we interpret our analysis under this approach, then we are testing the role of peers on criminal activities, once any “local context” effect is washed out by our panel-data estimation technique (that is controlling for everything which is unobservable at the borough level such as victims, police, etc.). In our empirical analysis, we define peers as people from the same ethnicity living in the same borough. Using the routine activity approach, peers can be defined in two different ways. First, peers (or neighbors) can be defined as “handlers”. In that case, the routine activity approach predicts that more handlers will reduce crime because they exert some “control” over their peers. Second, peers can be viewed as co-offenders and thus more opportunities to commit crime. Indeed, the opportunity to engage in crime depends not merely on the activities of any one person, but on the interconnecting activities of *several* persons. In that case, peers would have a positive effect on crime.<sup>8</sup> In our empirical analysis, we find that the higher the percentage of the Black population in a given area, the higher is the crime rate in that area. This is in accordance with the second prediction of the routine activity approach and with the fact that crime is a group phenomenon (War, 2002). Our explanation is that peers capture the diffusion of information about crime opportunities which is in accordance with the idea that crime is often committed by a group of individuals rather than alone.

The paper is structured as follows. The next section discusses the different econometric problems underlying the relationship between a community’s ethnic population density and its crime rate and the possible mechanisms driving such a relationship. Section 3 describes the data and provides some exploratory evidence. Section 4 presents the estimation results of our empirical model both with OLS and IV estimators. Finally, Section 5 concludes.

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<sup>7</sup>Handlers are people who are influential in the lives of potential offenders such as parents for young offenders, siblings, neighbors, peers, close friends, etc.

<sup>8</sup>Reiss and Farrington (1991), for example, demonstrated that propinquity, along with homophily, was an important element of co-offender selection in their sample of London males, suggesting that mobility and the local availability of ethnic peers are significant constraining influences on delinquency.

## 2 Relationship between a community's racial composition and its crime rate

### 2.1 Econometric problems

The assessment of the existence and the extent of the causal effect of local ethnic population density on local crime is a very difficult exercise. There are, in fact, at least three different issues that affect the finding of a positive relationship between a community's ethnic population density and its crime rate:

(i) A positive correlation between ethnic population density and crime can simply be driven by the presence of *unobservable factors* or/and by an *endogenous sorting of individuals into areas*, i.e. areas that attract ethnic populations may also have unobserved characteristics that induce criminal behavior. For instance, biased policing practices, low informal social control, lack of educational or economic opportunities, genetic differences etc., which are typically difficult-to-measure variables, might result in a spurious positive correlation between density of ethnic population and crime at the local level.

(ii) There is a *simultaneity/reverse causality bias* problem. Indeed, it may well be that higher ethnically dense areas produce more crime but it is also possible that areas with higher crime rates, which are typically poor areas, attract ethnic minorities, possibly because they cannot afford richer areas.

(iii) High (low) crime rate areas are usually surrounded by high (low) crime rate areas. This creates spatial correlation that needs to be accounted for. Traditional studies of the relationship between ethnic population and crime show an average effect, thereby ignoring possible spillover effects at the local level, i.e. the effect of the levels of the variables in neighboring areas.

The construction of panel data, i.e. the availability of information on the same areas at different points in time, enables us to:

(a) include *area-fixed effects* that control for the presence of *unobservable area-characteristics* in the regression models. Indeed, by using a within-group panel estimator, we purge our estimates from the possible existence of area characteristics that are constant over time, possibly correlated with the regressor of interest, i.e. ethnic population density, whose effects might otherwise be captured in the estimated coefficient of our regressor of interest.

(b) include *a dependent variable lagged in time* in the regression models that accounts for dynamic effects, which also arise from the presence of unobservable factors that are varying over time. Indeed, by assuming the crime level today to be a function of the crime level

in the previous period, we account for all factors contributing to the realization of such a level of crime in the previous period. Examples include education, unemployment level in the area, number of policemen, etc..

(c) find suitable *instrumental variables* for tackling a possible simultaneity bias and/or an endogenous sorting of individuals into areas. Indeed, panel data *for the contemporaneous level of a regressor* offer the values of this regressor appropriately lagged in time as natural instruments.

In addition, by explicitly taking into account the geographical location of the areas, which requires the use of *spatial data analysis techniques*, we are able to appreciate the range of action of the effects. Most importantly, by creating ethnic population proximity bands, we are able to appreciate to what extent such variables explain the spatial association between local crime and crime in neighboring areas.

## 2.2 Interpretation problems

Because of the econometric problems mentioned above, the positive relationship between ethnic population density and spatial crime obtained by criminologists and others is extremely difficult to interpret and therefore, no clear policy implication can be derived. The methodological achievements listed above allow us to rule out some possible interpretations and to highlight a mechanism that is consistent with the evidence. The relevant question is the following one. Given that we control for (i), (ii), (iii), how can we interpret a positive relationship between ethnic density and crime rate in a given area? In other words, if it is not the observed and unobserved characteristics of the area that explain this positive relationship, what can it be?

Our conjecture is that social interactions between people of the same ethnicity can explain this positive relationship. Indeed, the denser an area is, the more likely an individual is to interact with others. This is the well-known *quantity effect*. Moreover, there is a *quality effect*, which is due to ethnicity. The interaction is of better quality if people belong to the same ethnicity because social contacts are stronger. When interactions about crime opportunities are considered, the mechanism is emphasized. It is indeed well-established that ethnic minorities, and in particular Blacks, are overrepresented in criminal activities both in the United States (Freeman, 1999)<sup>9</sup> and in Europe (see e.g. Shute et al., 2005, for the

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<sup>9</sup>In the US, blacks constitute 13 percent of the total population but 30 percent of the people arrested are black, 49 percent of the prison inmates are black and 9 percent of all black adults are under some sort of correctional supervision (prison, parole or probation).

United Kingdom).<sup>10</sup> Hence, when there are more Black people around, it is more likely that crime increases. Furthermore, the higher is the population density of a given ethnic group, the more likely individuals of this ethnic group interact with each other. Such a relationship decreases with physical distance.

Let us now give some empirical evidence of these different issues.

First, it is well-established that in larger cities, i.e. in more populated areas, individuals are more likely to interact with others. Although those relationships may neither be personal nor strong, those contact are channels of information.<sup>11</sup>

Second, individuals interact more with those living in the same area and less with those residing in distant areas. Studying selected neighborhoods in Linköping, Sweden, Henning and Lieberg (1996) found neighborhood to be relatively unimportant for strong ties – three quarters of the contacts were outside the local area. But, there are three times as many contacts in the neighborhood when weak ties are considered, as compared to strong ties. Henning and Lieberg suggest that weak ties are important for the things they deliver and for the fact that they provide a type of relationship that can be most easily sustained in the neighborhood. Using Census Tract data for Chicago in 1980 and 1990, Topa (2001) also finds a significantly positive amount of social interactions across neighboring tracts, especially for areas with a high proportion of less educated workers and/or minorities. Bayer et al. (2008) also document that people who live close to each other, defined as being in the same census block, tend to work together, that is, in the same census block.<sup>12</sup>

Third, having more contacts increases the range of interactions and information is spread more efficiently and evenly throughout the economy. The mechanism is similar in spirit to many of the job network models (see e.g. Calvó-Armengol and Jackson, 2004, Calvó-Armengol et al., 2007) in that individuals pass on information to partners when received.

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<sup>10</sup>In 2000, even though African/Caribbean (black) people constitute 2 percent of the overall UK population, they are overrepresented in prison (10 percent of black males and 12 percent of black females).

<sup>11</sup>Sociologists argue that relationships in large cities are less personal. People in large cities, as compared to people in small towns or rural areas, experience general deficits in the quality of interpersonal relations (strong ties). This is the perspective of the so-called *social disorganization* theory and the *social capital* literature (see e.g. Wirth, 1938; Coleman, 1988 and Putman, 1993, 2001). People in small towns or rural areas base their social networks on the limited number of people who live nearby whereas people in large cities have a great deal of choice in constructing their social networks and can seek out others with similar values, interests and life-styles (weak ties). This is the so-called *subculture* theory (see e.g. Fisher 1976, 1982). As a result, urbanites are less likely than rural dwellers to base their personal networks on traditional sources (such as family) and are more likely to include voluntary sources, such as friends, coworkers and club members.

<sup>12</sup>See also Kan (2007) who shows that social capital tends to be very local.

Using the U.S. National Longitudinal Survey of Adolescent Health (AddHealth), which contains unique detailed information on friendships among teenagers, Patacchini and Zenou (2008) find that weak ties, as measured by friends of friends, have a positive impact on criminal activities. Having more weak ties increases the criminal activity of each individual.

Finally, there is plenty of evidence showing the higher quality of relationships between individuals belonging to the same ethnic group. For example, in the labor market, Falcon and Melendez (1996) and Elliott (2001) find that Latinos, especially newly arrived immigrants, are more likely to enter jobs through insider referrals than native-born whites. Munshi (2003) identifies network effects among Mexican migrants in the U.S. labor market and shows that the network improves the labor market outcomes for its members. There is also a growing literature in the fields of public finance, development and urban economics that shows that investments in public goods, tastes for redistribution, and other forms of civic behavior are more common in racially or ethnically homogenous communities.<sup>13</sup> Furthermore, there is a rich socio-economic literature on patterns of relations among agents documenting that social networks appear to be fairly homogeneous with regard to certain socio-demographic attributes: agents are likely to associate with people who are similar, i.e. *assortative matching*. This tendency is particularly strong among ethnic groups.<sup>14</sup>

To sum up, our conjecture is that in denser areas, individuals interact with more people and meet more random encounters than in sparsely populated areas. Moreover, they have a better quality relationship if they belong to the same ethnic group, especially when sharing information about crime opportunities. As a result, the higher the number of people of the same ethnicity living in the same area, the higher is the local crime rate. Furthermore, the strength of interactions decreases with physical distance.

Thus, we estimate a model where the crime rate in a given borough will be explained by the Black population density within this borough and the Black population density of the neighboring boroughs.

If our theoretical mechanism is correct, we will expect that the ethnic population density variables are able to explain spatial dependence in crime rates, since the diffusion of information is the driving factor, and that a higher ethnic population density in a given borough will increase the crime rate in this borough, because information about crime will circulate at a higher rate. This effect should still be positive but *weaker* for the population density of the neighboring boroughs because physical proximity is of importance for social interactions

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<sup>13</sup>See, in particular, Alesina et al. (1999); Alesina and La Ferrara (2000, 2005); Luttmer (2001); Vigdor (2004).

<sup>14</sup>See e.g. Moody (2001); Marmaros and Sacerdote (2006); Bayer et al. (2007).

and thus, for the diffusion of information about crime. As a result, the further people live from each other, the lower is the quality and diffusion of information about crime.

It is true, however, that there could be an alternative mechanism, that could give rise to a positive relationship between crime rate and ethnic population density. Importantly, such a mechanism is still based on social interactions. Imagine a model of peer effects and social interactions. Then, the perception that one's peers will or will not disapprove can exert a stronger influence than the threat of a formal sanction on whether a person decides to engage in a range of common offences – from larceny, to burglary, to drug use (Braithwaite, 1989; Lott and Mustard, 1997). If a person is surrounded by individuals who are themselves criminals, these social sanctioning effects may work to *increase* crime if delinquency is seen as a badge of honor in a population (Wilson and Herrnstein, 1985; Kahan, 1997; Silverman, 2004; Ballester et al., 2006). Indeed, when individuals see others from the same ethnic group committing crimes, they infer that their peers value law-breaking; they are then more likely to break the law themselves, which leads other individuals to draw the same inference and engage in the same behavior. In this respect, violence and crime can become status-enhancing. Thus, there can be social effects that could increase the crime rate. As noted above, both mechanisms (transmission of information about crime and badge of honor) are due to social interactions. We are not able to discriminate between these two mechanisms on the basis of our evidence. Nevertheless, their common feature is that the ethnic dimension could be crucial for understanding crime. This is why, as a first step of our empirical analysis, we will examine to what extent the spatial patterns of crime in London correlate with the spatial patterns of ethnicity-related variables.

Our empirical analysis proceeds as follows.

First, we use the techniques of exploratory spatial data analysis to examine to what extent the spatial patterns of crime in London correlate with the spatial patterns of a range of variables. We focus our attention on the analysis of local spatial association schemes. In other words, given an area with a high (low) crime rate surrounded by neighbors with similar high (low) levels of crime, we look at the variables sharing this spatial association scheme for the same area. Evidence in support of our theoretical mechanisms would be to find a more accentuated similarity in the spatial structures of variables such as Black population density or ethnic commuting flows.

Second, the impact of Black population density in explaining the spatial distribution of crime in London is investigated within a regression analysis framework, where the impact of observable and unobservable area characteristics is controlled for. Our aim here is mainly to examine the relationship between crime and ethnic population net the clustering effect that

may simply be due to the sorting of individuals into locations.

### 3 Exploratory spatial data analysis

Monthly data on crime for the 33 London boroughs are available on line from the London Metropolitan Police Service (LMPS).<sup>15</sup> The data cover the period January 2000 to December 2006. Thus, we have constructed a panel, which gives 2,772 observations. Crime rates are calculated on the basis of population estimates by borough level, supplied by the Office of National Statistics (ONS) on-line database. This database also provides information on the residing ethnic population (here restricted to the Black population only) in each borough for the corresponding time period.

Figure 1 depicts the spatial distribution of crime rate and Black population density data (average over the period).

*[Insert Figure 1 here]*

A visual inspection of Figure 1 reveals that the darker (clearer) areas in the crime map often correspond to the darker (clearer) areas in the Black population density map. The statistical significance of such associations is assessed using local tests of spatial autocorrelation. Indeed, our first exercise is to describe the degree of similarity of spatial patterns between crime and a set of socio-economic variables. We select variables that are typically responsible for crime differentials across space, that is the unemployment rate, the percentage of high-skilled population, i.e. the percentage of individuals aged above 18 holding an A-level<sup>16</sup> or a higher qualification, and a house price index.<sup>17</sup> We add the Black population density

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<sup>15</sup>The City of London runs its own police force. Data on crime can be obtained from the website [www.cityoflondon.gov.uk](http://www.cityoflondon.gov.uk).

<sup>16</sup>The A-level in UK is equivalent to the SAT in the US or the baccalaureat in France.

<sup>17</sup>Average house prices within London by individual borough are available on line from the UK Land Registry website. Unemployment rate, percentage of high skilled population and ethnic population density can be obtained from the on line data provided by the National On-line Manpower Information Service (NOMIS) located at University of Durham. Data on commuting flows are available from the Census Interaction Data Service (CIDS), located at University of Leeds and St. Andrew. Our data are taken from the special workplace statistics from the 2001 Census. They provide information on origin-destination journey-to-work flows within London. For each borough,  $i$ , we consider total commuting, which is defined as people aged 16 or above in employment that are resident in area  $i$  and work outside the area (out-flows) plus those residing outside area  $i$  and working in area  $i$  (in-flows). The flows are divided by total employment in each area.

and the ethnic commuting flows. Our sample descriptive statistics are reported in Table 1.

[Insert Table 1 here]

The techniques of exploratory spatial data analysis (ESDA) are then used to compare and contrast patterns of spatial association across these indicators. This approach provides valuable insights into the nature and extent of spatial clustering in crime in London.

To examine the nature of spatial linkages across areas at a local level, we use the local Moran's I and the Getis-Ord's  $G^*$  statistics.<sup>18</sup> The values of these statistics are reported in Table 2 for the different variables.

[Insert Table 2 here]

A significant and positive value for I indicates a local spatial clustering of similar values, either high or low. If instead the local Moran's statistic, I, is significant and negative, the value of the variable at the given borough and those of its neighbors are dissimilar. The spatial clustering of high values results in positive values for the  $G^*$  statistics, whereas negative values for  $G^*$  are indicative of a clustering of relatively low values. Statistically significant evidence of local spatial association is obtained for slightly less than half of the boroughs.<sup>19</sup> This is clear evidence of the existence of a spatial structure in the crime data, thus indicating that *crime is not randomly distributed across London boroughs*. Not surprisingly, local

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<sup>18</sup>Different statistics of local spatial correlation have been developed to assess spatial dependence in a particular sub-region of the sample. These statistics describe the relation between the value of the variable at a given site and that of its neighbors and between the value within the neighborhood set and that for the sample as a whole. Those more widely used are the Getis-Ord's  $G^*$  and the local Moran's I. The Getis-Ord's  $G^*$  statistic is based on a comparison of the average value within a given neighborhood set and the global average and, as such, may be used to identify local regimes of relatively high or relatively low values of a variable. The local Moran's I statistic measures the correlation between the value for a given area and that for its neighbors, and may be used to identify atypical localisations as well as clusters of high or low values (see Getis and Ord, 1992; Ord and Getis, 1995, and Anselin, 1995, for further details).

<sup>19</sup>Since the distribution of both the local Moran and the Getis-Ord statistics is affected by the presence of global spatial association, the assessment of statistical significance is based on the conditional randomisation assumption with 999 permutations which provides a more reliable basis for inference (Anselin, 1995). Along with the traditional 5% and 10% levels of significance, we consider an adjusted significance level of 0.1% based on the Bonferroni correction (computed as  $0.05/32$ , i.e., the standard 5% significance level adjusted by sample size). This adjustment accounts for the fact that the local statistics for any pair of locations are correlated whenever their neighborhood sets contain common elements, yielding to a possible overestimation of the extent of the local spatial association (Ord and Getis, 1995). However, in practice, for any given location, the number of other locations in the sample with correlated local statistics is likely to be considerably smaller than  $n$  and thus, this procedure is expected to be overly conservative.

clustering of high values of crime is particularly strong in boroughs mainly located in Inner London, i.e. in places such as Westminster, Hackney, Islington, Camden, Lambeth, Southwark and extending towards the North to include Haringey. Evidence of local clustering of low values is instead found in the South-West, i.e. Kingston upon Thames and Merton, and in the North-East, i.e. in Havering. Only one area is signaled as a borough with a value of crime significantly different from those of its neighbors. It is Croydon, in the South, which is a high-crime area with relatively low-crime neighbors.

Let us now turn to the question of identifying the related variables with (the most) similar spatial structures. For instance, strong similarities with the distribution of unemployment would be expected. According to the standard cost-benefit crime model (Becker, 1968), crime should be high when unemployment is high. Thus, clusters of areas where the average crime rate is high (low) relative to the global average are expected to also be clusters of areas where unemployment is high (low). Quite surprisingly, instead, the figures in Table 2 do not provide strong support for this view. For instance, areas with lower house prices, lower education level of the residing population and higher unemployment rates, such as Bexley, Sutton, are not always associated with statistically significant higher crime rates. The spatial structure of crime seems to be better reproduced in the Black population density or ethnic commuting flows data than in unemployment, high-skilled population and house price data. Even more, most of the local spatial association schemes in the crime data match those in the data for the ethnicity-related variables and, in particular, for Black population density.

Figure 2 reproduces such evidence. It depicts the boroughs with significant values for the local Moran's I statistic in the crime and Black population density data. At a first glance, it appears that the spatial regimes identified for crime are closely reproduced in the Black population density data. Indeed, all areas with significant local statistics in the LL scheme for crime, i.e. areas with a statistically significant low value of crime surrounded by areas with low values of crime, also show significant local statistics in the LL scheme when Black population density is considered, i.e. these are areas for which the Black population density shows a statistically significant low value surrounded by areas with low values. Observe that the only area associated with a statistically significant local indicator that shows a value of crime rate which is dissimilar from that of its neighbors (Croydon) displays the same results for the Black population density data. The HH cluster of areas for crime, i.e. high value areas surrounded by other areas with high values, is also partly reproduced in the Black population density data.<sup>20</sup>

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<sup>20</sup>As appears from the figures reported in Table 2,  $G^*$  statistic maps lead to similar pictures.

[Insert Figure 2 here]

The patterns reported in Table 2 thus appear to support the scenario where, besides economic incentives, the ethnic dimension may be important for explaining criminal activities.<sup>21</sup>

This evidence can, however, be driven by an endogenous sorting of people into boroughs and the Black population density variable may be capturing other area characteristics. To better understand these results, we then consider a panel data model where the relationship between crime and Black population density is more closely analyzed, once the effects of confounding factors have been controlled for.

## 4 Regression Analysis

Our main conjecture is that social interactions are a function of proximity. To implement this, we create proximity bands based on the driving time between areas and measure the density of Black population within each proximity band. We choose travel time as a distance measure because, as noted above, this is reasonably the best metric for representing how agents' contacts materialize.<sup>22</sup> The time distance between areas in the sample varies between 19 and 74 minutes, with a mean time distance of 39 minutes and a considerable dispersion around this mean value since the standard deviation is equal to 25 minutes.<sup>23,24</sup>

To be specific, we assume the population of each borough to be evenly distributed within each area and compute the density of the Black population residing within concentric rings

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<sup>21</sup>The ESDA analysis has also been performed for different types of crime and for the different minority groups that compose the Black population in London ( i.e. "Black Caribbean", "Black African" and "Other Black"). Our qualitative evidence, i.e. the more pronounced similarity of the spatial patterns of crime with the ethnic-related variables rather than with the other indicators of economic performance, remains roughly unchanged for all types of crime and for the three different groups composing the Black population.

<sup>22</sup>Driving time distances in minutes are estimated using Microsoft Autoroute 2002. We consider the shortest route, given the road network in 2002.

<sup>23</sup>It may be argued that ethnic minorities have less access to cars than natives so that the driving time may not correspond to their real time distance. Because we are focussing on the agglomeration of London where public transportation is very good (for example the tube), the time distances between and within boroughs should, in fact, be even lower for those using public transportation.

<sup>24</sup>The alternative use of spatially lagged ethnic population variables (i.e. first, second and third order contiguity matrices) does not change our qualitative results, however.

of a given radius (in minutes) drawn around the centroid of each borough.<sup>25,26</sup> Thus, we aim at examining whether the density of the Black population nearby influences the local rate of crime and how far this effect extends. Thus, we are able to assess the spatial scale of the Black population density effect by comparing estimates across rings. Unfortunately, we do not have any information on the crime rate per ethnicity. However, because Blacks are overrepresented in criminal activities, the total crime rate and that per Black should be highly correlated.

We estimate the following model:<sup>27</sup>

$$c_{b,t} = \alpha c_{b,t-1} + \sum_s \gamma_s d_{s,b,t}^B + \eta_b + \varepsilon_{b,t}, \quad |\alpha| < 1, \quad b = 1, \dots, N; t = 2, \dots, T, \quad (1)$$

where  $c_{b,t}$  is the crime rate in borough  $b$  at time  $t$ ,  $c_{b,t-1}$  is the same variable at time  $t - 1$ , and  $d_{s,b,t}^B$  denotes the density of Black population (superscript  $B$ ) in borough  $b$  within the proximity band  $s$  at time  $t$ . The error term is composed by a borough-specific fixed effect,  $\eta_b$ , controlling for cross-borough (observable and unobservable) differences that are constant across time and by a white noise error component,  $\varepsilon_{b,t}$ .

Because cultural differences within the Black population can be important, we perform our analysis for both the total Black population and each group that composes the Black population living in London, i.e. “Black Caribbeans”, “Black Africans” and “Other Blacks”. Indeed, using only the total Black population density might mismeasure social interactions at the local level if they operate, for instance, only within sub-groups.

Observe that the empirical model neither includes any measure of the average human capital characteristics of the different areas nor any other features of the local structure of the economy (such as the unemployment rate for example). Indeed, we assume the impact of these characteristics on the crime rate in each area to be captured through the inclusion of (time) lagged values of the crime rate, i.e.  $c_{b,t-1}$ . The inclusion of the lagged dependent variable is thus a purely modeling device to approximate the effects of other area characteristics on local crime. In other words, we use area (borough) fixed effects to purge our estimates

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<sup>25</sup>Since London boroughs are not necessarily circular and, in fact, have a rather irregular grid, it is likely that the rings include only parts of the boroughs. Thus, we compute the ring’s total population by summing the population shares of each borough according to the percentage of the borough area afferent to the ring. In other words, if only  $x$  percent of borough  $j$ ’s surface is included in a ring, the population of the latter will contain exactly  $x$  percent of borough  $j$ ’s population (see Rosenthal and Strange, 2008).

<sup>26</sup>The analysis has also been performed assuming that the population is concentrated at the economic center of each area (see Rice and al., 2006, for details). The results remain qualitatively unchanged.

<sup>27</sup>The condition  $|\alpha| < 1$  indicates (time) stationarity. In fact, this property is satisfied by crime series.

from the effects of area characteristics that are constant over time and we assume that the impact of time-varying variables on the crime rate in each location is captured through the inclusion of (time) lagged values of the crime rate. Such variables include, for example, the percentage of policemen in the area.<sup>28</sup>

## 4.1 OLS estimates

Table 3 reports the estimation results for the total Black population and for each sub-group obtained with five proximity bands; up to 20 min, 20 to 30 min, 30 to 40 min, 40 to 50 min and 50 to 60 min. We display the within group estimates, i.e. OLS where all variables are expressed in deviations from their area-specific means (taken over time).<sup>29</sup>

Let us begin by documenting to what extent the spatial Black population bands explain the spatial association between crime in a local area and its neighboring areas. The first column of each block of the table shows the results when the population density proximity bands (i.e., the term  $\sum_s \gamma_s d_{s,b,t}^B$ ) are not included in the specification of model (1)). Under this specification, the spatial dependence in crime rate (see Section 3.1) should result in an omitted spatially lagged dependent variable (i.e. the average crime rate in neighboring areas). We report the Lagrange Multiplier test for an omitted spatially lagged dependent variable (LM test) in the last row of the table. The null hypothesis is the absence of spatial dependence (i.e., that the effect of the spatially lagged dependent variable is zero). A significant value of the test provides evidence of the existence of spatial dependence in the data that is not fully captured by the model specification.

Looking at the results for the model specification without population density proximity bands (first column of each block), the test provides clear evidence of unexplained spatial dependence in all columns. This indicates that the model does not incorporate all channels of interdependence between areas.

Our theoretical mechanism postulates that such a contagion/spillover effect is explained by the diffusion of information (here measured by Black population density) between adjacent areas. Indeed, when we add the population density proximity bands to the model (second column of each column), the LM test now does not provide evidence of an omitted spatial lag in any column, thus revealing that the Black population density bands entirely capture the

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<sup>28</sup>The analysis has also been performed including a variety of (observable) area characteristics. The results on our target variables remain qualitatively unchanged.

<sup>29</sup>As T becomes large, the within-group estimator is consistent, even in the presence of lagged dependent variables (or other endogenous regressors). Thus, with our panel of 84 time periods, any bias from using within groups is likely to be minimal (see Nickell, 1981, for example).

spatial interactions in total crime.<sup>30</sup> If the Black population density is taken as a measure of the strength of social contacts, these results are consistent with our theoretical mechanisms where criminal activities depend on interactions between agents in social space. Table 3 shows that the results are almost unchanged across columns suggesting that issues related to cultural heterogeneity within the Black population are not a serious concern in our analysis. Social networks, as captured by the Black population density, seem to operate both between and within the Black population sub-groups.

Turning to the estimates of the spatial decay, we find positive and statistically significant effects, which are highest within 20 minutes driving time. Then, they decrease quite sharply with travel time. They have no effect beyond approximately 40 minutes. A one-point percentage increase in the density of Black population within 20 minutes driving time increases the total crime rate by roughly 0.12 percentage points. It has more than four times the impact of the density of the Black population 30 minutes away, and more than 15 times that of the density of the Black population 40 minutes away. Such a pattern is consistent with the idea that social interactions are very localized (Topa, 2001; Bayer et al, 2009). These results are common to the Black population as a whole and to each of the different subgroups composing the Black population.

[Insert Table 3 here]

## 4.2 IV estimates

If areas that attract an ethnic population also have exogenously determined characteristics (not directly observable) that affect crime, the population density variables will be correlated with the error term. In our analysis, the adoption of a panel data estimator with area fixed effects should remove any unobserved effects that are constant over time. However, it does not account for the effects of a possible endogenous sorting of a different nature. As is standard, we address this problem by employing an instrumental variable approach. We employ the Arellano and Bond (1991) instrumental variable estimator for dynamic panel data. This method consists of taking deviations from the area-specific time means to get

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<sup>30</sup>In the model specification with population bands, the null hypothesis of no spatial dependence is tested against an alternative of spatial dependence within a specified proximity. The tests are computed with spatial weight matrices  $W = \{w_{ij}\}$ , where  $w_{ij} = 1$  if the estimated driving time between area  $i$  and area  $j$  is less than  $d$  minutes and  $w_{ij} = 0$  otherwise, for values of  $d = \{30, 60, 90, 120, 150\}$ . The highest values are reported in the table in each case. When the bands are not considered, a simple first-order contiguity matrix (i.e. a spatial weight matrix  $W = \{w_{ij}\}$ , where  $w_{ij} = 1$  if area  $i$  and area  $j$  share a common border and  $w_{ij} = 0$  otherwise) is used.

rid of the unit-specific error term and combining valid instruments for the lagged dependent variable and the other endogenous variables in a GMM framework. Given the first-order autoregressive specification of our model, valid instruments for the (time) lagged dependent variable are variables that are lagged two-time periods or more. In addition, we instrument the actual Black population of each borough with the historical Black population as reported in the Census in 1951. The validity of these instruments rests on the assumption that the location decisions of the ethnic population more than fifty years ago are unrelated to the (unobserved) factors determining crime activity today, besides their effect through present-day ethnic population. The use of population density variables lagged in time as instruments for the contemporaneous values at least mitigates endogeneity issues. The Sargan test of overidentifying restrictions (Sargan, 1958) is used to choose the appropriate set of instruments in the case study (in particular the fact that we include the lags of the crime rate in the instrumental set).

Our instrumental variable results for the model that includes all the population bands are reported in Table 4 for both the Black population and each subgroup that composes it. The Sargan test does not reject the null of instruments' validity. In the last rows, we also report the tests for first-order and second-order serial correlation in the first-differenced residuals ( $M\_1$  and  $M\_2$ ). The consistency of the GMM estimators requires the absence of serial correlation in the original error term. In turn, this requires negative first-order, but no second-order correlation in the differenced error term. Table 4 reveals no evidence of misspecification. The results confirm the main findings from Table 3, thus revealing that possible endogeneity issues are properly accounted for by the inclusion of area-fixed effects. The magnitudes of the estimated effects are only slightly higher.

*[Insert Table 4 here]*

## 5 Concluding remarks

Using panel data techniques as well as spatial regression techniques, we assess the existence and the spatial decay of a relationship between Black population density and local crime rate across the London boroughs. We find positive and statistically significant effects, which are highest within 20 minutes driving time. Then, they decrease quite sharply with travel time and have no effect beyond approximately 40 minutes.

In this paper, we propose to interpret such evidence in terms of social interactions. Indeed, the methodological achievements of our analysis in the estimation of the relationship

between crime and ethnicity at a local level allow us go beyond the traditional explanations based on a cost-benefit analysis (Becker, 1968) and on unobservable area characteristics.

Our data are, however, limited for delivering conclusive results about the mechanisms at the basis of the complex relationship between crime and ethnicity. Our purpose here is to highlight that peer effects might be an important part of the story. If ethnic population density is interpreted as a proxy for the strength of social interactions, then our analysis suggests that they are quite localized and are relevant in explaining the spatial distribution of crime.

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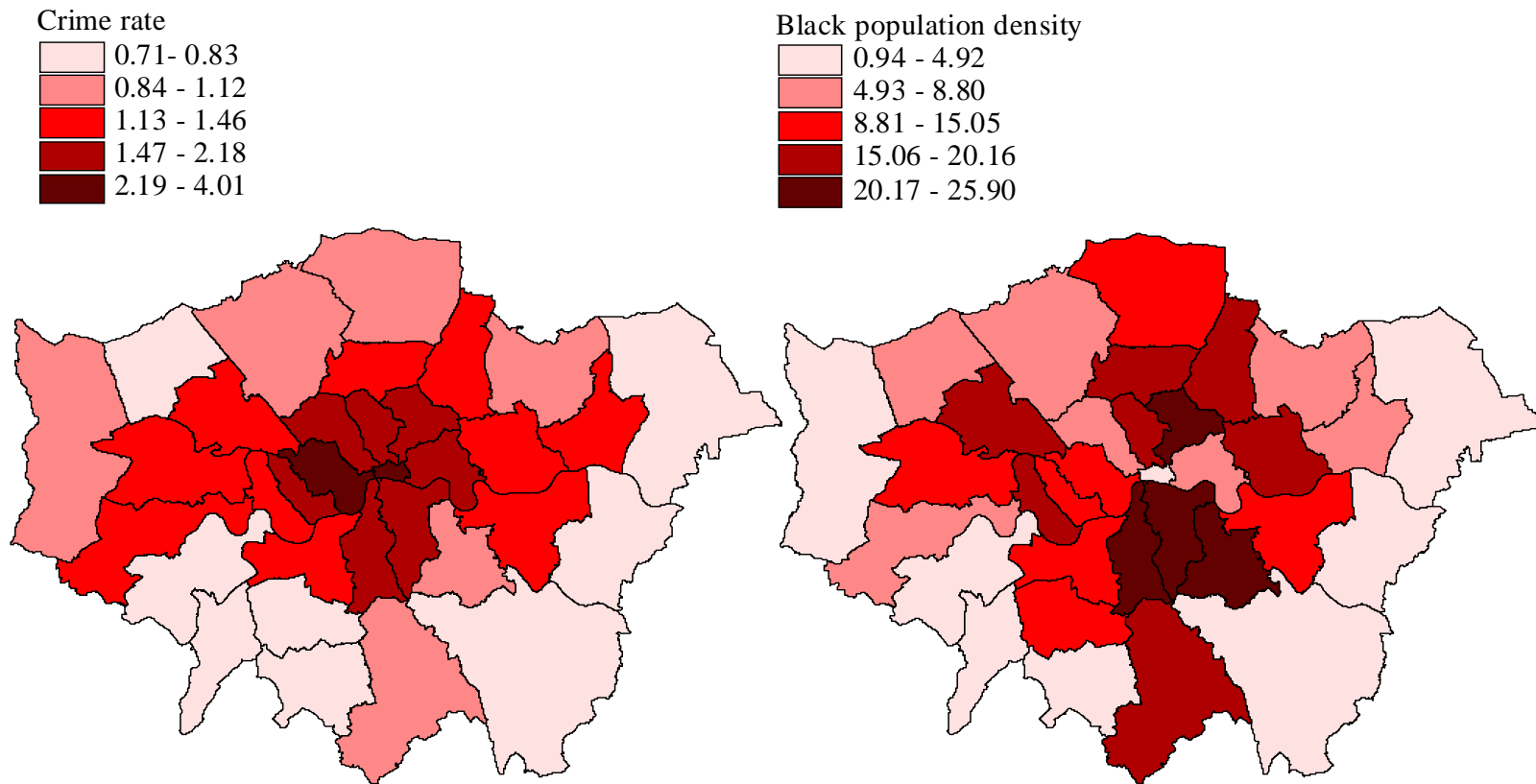
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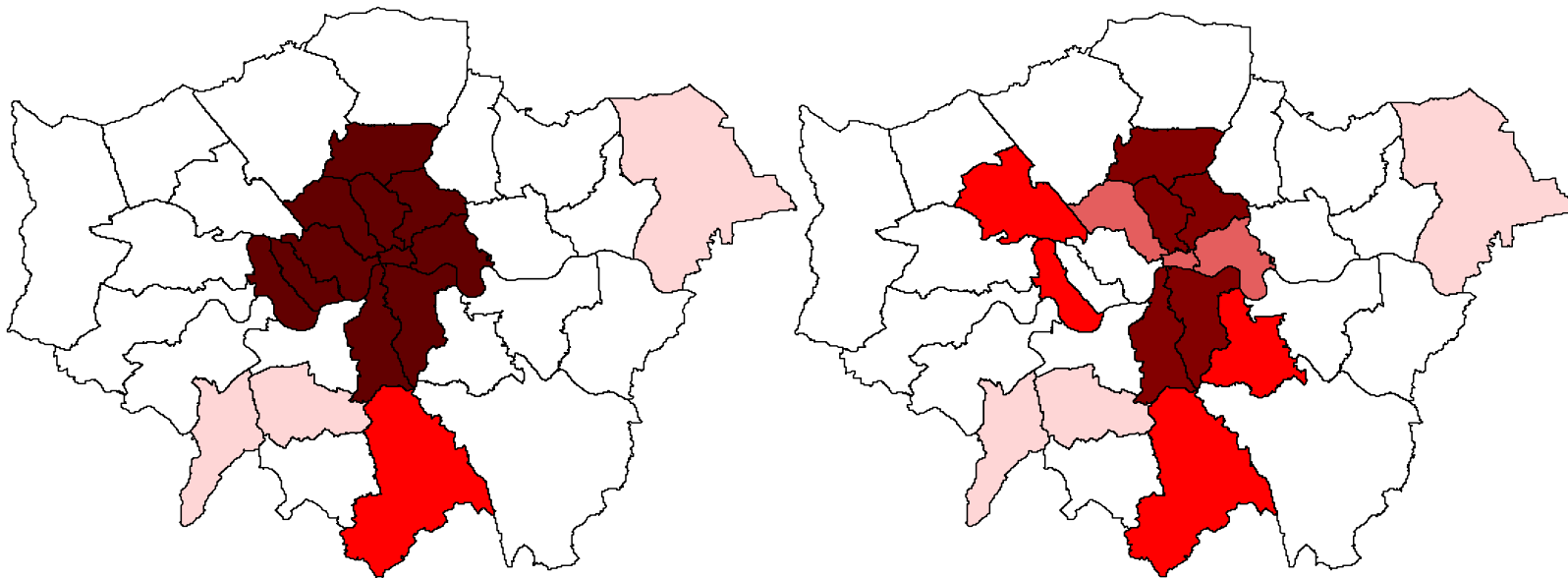
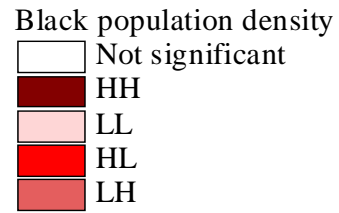
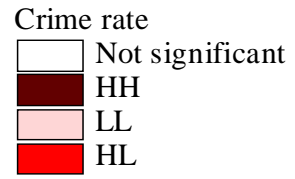
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**Figure 1. Spatial distribution of crime and Black-British population in London.**  
(average over the period 2000-2006)



**Figure 2. Local indicators of spatial association  
(significant at least at the 5% level)**



**Table 1. Descriptive Statistics**

Variable	Mean	Std. Dev.	Min.	Max.
Total crime rate (%)	1.22	0.65	0.71	4.01
Black pop. density (%)	10.18	7.50	0.94	25.90
Black Caribbean pop. density (%)	4.48	3.49	0.37	12.07
Black African pop. density (%)	4.92	3.82	0.48	16.07
Other Black pop. density (%)	0.79	0.62	0.08	2.39
High skilled population (%)	37.99	10.10	16.06	59.71
House price index (£)	309.66	173.55	202.02	586.07
Unemployment rate (%)	7.28	2.21	3.30	12.90
Ethnic commuting flows (%)	24.02	15.99	7.39	44.72

**Table 2: Local spatial correlation in crime and related socio-economic variables**

Borough	Crime rate		Black population density		Ethnic commuting flows		Unemployment rate		High-skilled population		House prices	
	I	G*	I	G*	I	G*	I	G*	I	G*	I	G*
Brent	0.85	-0.77	<b>-2.12</b>	-0.63	0.32	1.05	-0.36	0.74	0.11	0.74	<i>0.08</i>	1.19
Hillingdon	0.38	-1.30	0.66	-1.71	0.95	1.88	0.17	0.81	0.48	-1.49	<b>2.18</b>	<b>-2.50</b>
Harrow	-0.81	-0.57	-0.95	-0.21	-1.42	1.81	<b>2.22</b>	<b>2.75</b>	0.07	-0.78	<b>2.02</b>	<b>-2.42</b>
Ealing	0.15	-0.59	-1.56	-1.09	<b>2.29</b>	<b>2.07</b>	<b>2.15</b>	<b>2.27</b>	<b>1.95</b>	<b>-2.41</b>	<b>2.10</b>	<b>-2.60</b>
Hounslow	0.14	0.07	0.48	-0.50	-0.17	1.75	<b>2.05</b>	<b>2.02</b>	-0.13	0.04	<b>2.17</b>	<b>-1.95</b>
Kingston upon Thames	<b>4.65</b>	<b>-2.32</b>	<b>3.50</b>	<b>-3.84</b>	<b>2.24</b>	<b>-1.87</b>	1.30	1.12	0.12	0.71	0.13	0.11
Richmond upon Thames	1.01	-1.18	1.50	-1.77	<b>2.05</b>	<b>-1.79</b>	1.82	-1.33	<b>2.26</b>	<b>2.06</b>	<b>2.13</b>	<b>3.26</b>
Merton	<b>2.25</b>	<b>-2.19</b>	<b>2.05</b>	<b>-2.09</b>	<b>2.28</b>	<b>-2.12</b>	1.19	-1.51	0.22	1.84	1.16	1.40
Wandsworth	-0.09	-0.46	-0.83	0.37	0.01	-0.47	<b>-2.08</b>	<b>-2.04</b>	0.02	0.31	-0.46	1.67
Hammersmith and Fulham	<b>2.10</b>	<b>2.02</b>	<b>-2.53</b>	<b>1.96</b>	0.02	0.10	<b>2.05</b>	<b>2.15</b>	<b>2.22</b>	<b>2.79</b>	<b>-4.19</b>	<b>5.12</b>
Kensington and Chelsea	<b>1.72</b>	<b>1.99</b>	0.53	-0.69	<b>-2.60</b>	<b>2.16</b>	<b>3.02</b>	<b>-2.78</b>	<b>3.31</b>	<b>3.95</b>	<b>3.73</b>	<b>5.24</b>
Westminster	<b>5.16</b>	<b>4.64</b>	1.05	-0.75	1.44	1.75	<b>2.41</b>	<b>-2.22</b>	0.22	0.34	<b>3.40</b>	<b>3.31</b>
City of London	<b>6.12</b>	<b>5.05</b>	<b>-2.35</b>	-1.56	<b>2.05</b>	<b>2.12</b>	<b>-2.22</b>	<b>-2.30</b>	1.23	-0.75	<b>4.02</b>	<b>4.32</b>
Hackney	<b>2.60</b>	<b>2.10</b>	<b>3.51</b>	<b>3.90</b>	<b>3.14</b>	<b>3.90</b>	0.33	0.73	0.01	-0.79	0.33	-1.14
Islington	<b>3.29</b>	<b>3.68</b>	<b>2.69</b>	<b>2.49</b>	<b>2.38</b>	<b>2.24</b>	<b>2.02</b>	<b>2.42</b>	-1.14	-1.42	0.30	0.51
Camden	<b>3.59</b>	<b>3.42</b>	<b>-1.96</b>	1.11	<b>2.10</b>	<b>2.60</b>	0.20	0.88	0.09	-0.34	<b>-2.24</b>	<b>-1.78</b>
Tower Hamlets	<b>2.94</b>	<b>2.72</b>	<b>-3.13</b>	-1.16	<b>2.52</b>	<b>2.37</b>	<b>1.76</b>	<b>2.89</b>	0.38	1.15	-0.79	0.72
Newham	1.18	0.99	0.45	1.04	<b>2.50</b>	<b>2.36</b>	1.16	2.03	0.56	-0.66	<b>-2.15</b>	<b>2.91</b>
Southwark	<b>2.72</b>	<b>2.66</b>	<b>4.48</b>	<b>5.07</b>	<b>2.22</b>	<b>2.58</b>	1.36	1.81	<b>2.76</b>	<b>2.13</b>	<b>1.63</b>	<b>2.42</b>
Lambeth	<b>1.86</b>	<b>2.15</b>	<b>2.19</b>	<b>3.10</b>	0.93	0.27	<b>2.41</b>	<b>2.24</b>	-1.31	-0.85	0.04	-0.37
Croydon	<b>-2.89</b>	<b>-3.23</b>	<b>-1.95</b>	<b>-2.54</b>	<b>-2.06</b>	<b>-2.54</b>	0.06	0.46	0.67	-0.74	1.22	-1.97
Bromley	0.44	-0.91	0.69	-0.78	0.89	1.39	-0.89	-0.32	1.05	-1.04	0.64	-1.67
Sutton	1.32	-1.19	0.78	-1.51	0.59	-1.29	<b>2.04</b>	<b>1.95</b>	<b>2.61</b>	<b>-2.69</b>	<b>1.74</b>	<b>-2.08</b>
Lewisham	1.05	-0.98	<b>-2.15</b>	1.67	0.33	0.75	0.03	-0.33	0.28	-1.06	0.25	-0.26
Greenwich	0.99	-0.18	-1.15	-0.64	0.25	0.20	0.07	-0.18	1.24	1.89	0.01	-0.17
Bexley	0.21	-1.31	0.19	-1.80	0.25	-1.18	-0.47	1.33	<b>3.46</b>	<b>-4.26</b>	<b>3.04</b>	<b>-3.11</b>
Barking and Dagenham	-1.10	-1.69	-0.89	-1.03	-0.85	-0.54	-0.14	-0.06	<b>2.65</b>	<b>-2.54</b>	<b>2.37</b>	<b>-2.39</b>
Havering	<b>2.02</b>	<b>-1.88</b>	<b>2.89</b>	<b>-3.15</b>	0.67	-0.33	<b>2.26</b>	<b>1.17</b>	0.74	-1.14	0.00	-0.64
Redbridge	-0.10	-0.42	-0.46	-0.10	0.31	-1.19	0.05	0.50	1.18	-1.83	-0.22	-0.70
Waltham Forest	0.06	0.38	0.21	0.17	<b>2.09</b>	<b>2.28</b>	0.02	0.51	-0.54	-0.09	-1.94	-0.64
Haringey	<b>2.16</b>	<b>2.09</b>	<b>1.97</b>	<b>1.75</b>	<b>1.76</b>	<b>1.71</b>	<b>-3.12</b>	<b>2.23</b>	0.70	-1.77	-0.10	-0.61
Enfield	0.08	-0.16	-0.42	-0.08	0.64	0.26	0.38	1.13	0.14	-0.91	0.23	-1.15
Barnet	0.15	-0.59	0.09	-0.06	1.38	0.67	<b>-0.44</b>	<b>-2.31</b>	<b>2.16</b>	<b>1.78</b>	<b>2.20</b>	<b>2.00</b>

**Notes:** Boroughs are ordered according to their geographical location, going from West, Inner London, South, East to the North. Local Moran's I and Getis-Ord G\* statistics are reported. Statistics significant at the 0.05 level and using the Bonferroni correction (i.e. 0.0001) are marked in bold and bold-italics respectively. Significance levels are based on the conditional randomisation approach with 999 permutations. The analysis is performed in in SpaceStat 1.80 using the first-order contiguity matrix (i.e., areas are defined as neighbours if they share a common border).

**Table 3. Crime and Black population density  
- OLS estimates -**

	All Blacks		Black Caribbeans		Black Africans		Other Blacks	
Ethnic population density								
...within 20 min	-	0.1175 (2.69)	-	0.0915 (3.12)	-	0.1059 (2.60)	-	0.1246 (3.07)
... within 20-30 min	-	0.0268 (5.95)	-	0.0197 (3.50)	-	0.0201 (2.77)	-	0.0213 (6.16)
... within 30-40 min	-	0.0074 (2.98)	-	0.0032 (2.27)	-	0.0079 (2.50)	-	0.0077 (2.69)
... within 40-50 min	-	0.0043 (1.17)	-	0.0015 (1.39)	-	0.0039 (1.02)	-	0.0035 (1.09)
... within 50-60 min	-	0.0012 (0.25)	-	0.0005 (0.19)	-	0.0010 (0.45)	-	-0.0008 (0.25)
Time lag of dependent variable	0.5609 (4.03)	0.4533 (3.44)	0.5455 (5.03)	0.4501 (4.51)	0.5776 (3.96)	0.4855 (3.25)	0.5115 (4.32)	0.4319 (3.50)
R-squared	0.79	0.83	0.81	0.85	0.79	0.82	0.81	0.86
LM test	5.25 [0.00]	0.35 [0.55]	4.95 [0.00]	0.23 [0.63]	5.13 [0.00]	0.42 [0.52]	4.16 [0.00]	0.52 [0.47]

Notes:

The number of observations is 2,772 in all cases. Regional dummies are included.

Within-group parameter estimates and *t*-ratios in parentheses are reported. LM test: Lagrange multiplier test for a spatial lagged dependent variable, distributed as a chi-squared with 1 degree of freedom with associated probability level in squared brackets.

Estimation using SpaceStat v1.93 (Anselin, 1995).

**Table 4. Crime and Black population density  
- IV estimates -**

	All Blacks	Black Caribbeans	Black Africans	Other Blacks
Black population density				
...within 20 min	0.1335 (3.03)	0.1096 (2.26)	0.1294 (2.75)	0.1414 (3.73)
... within 20-30 min	0.0353 (2.86)	0.0230 (2.15)	0.0295 (2.38)	0.0401 (3.69)
... within 30-40 min	0.0120 (2.58)	0.0100 (2.00)	0.0118 (2.18)	0.0133 (2.79)
... within 40-50 min	0.0080 (0.99)	0.0061 (1.01)	0.0095 (1.12)	0.0057 (0.85)
... within 50-60 min	0.0016 (0.35)	0.0015 (0.34)	-0.0005 (0.10)	-0.0015 (0.34)
Time lag of dependent variable	0.5053 (4.13)	0.5438 (4.70)	0.4951 (5.16)	0.5501 (3.83)
Sargan test	544.69 [0.15]	440.50 [0.99]	545.02 [0.15]	521.40 [0.38]
M_1	5.5484 [0.00]	13.615 [0.00]	7.1399 [0.00]	5.74 [0.00]
M_2	1.05 [0.29]	-0.80 [0.42]	0.91 [0.36]	1.07 [0.28]

Notes:

The number of observations is 2,772 in all cases. Regional dummies are included. Arellano and Bond (1991) parameter estimates and *t*-ratios in parentheses are reported. Instruments: 1951 population in the area within 40 kilometers; within 80 kilometers; within 120 kilometers; within 160 kilometers; within 200 kilometers; lagged values of the dependent variable more than one year and up to three years. Sargan test: Sargan test of overidentifying restrictions, distributed as a chi-squared with degrees of freedom given by the number of overidentifying restrictions, which are 512. M\_1 and M\_2: tests for first-order and second-order serial correlation in the first-differenced residuals, distributed as N(0,1) under the null of no serial correlation. The associated probability levels of all tests are in squared brackets. Estimation using Ox version 3.0 (Doornik, 2001).