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ABSTRACT

Crime and Ethnicity in London*

This paper studies the relationship between a community's ethnic population density and its crime rate. We compare the spatial distribution of crime and the black population across the 32 London boroughs. Once endogeneity and sorting issues are taken into account, we find that the higher is the density of the ethnic population in a given borough, the higher is the crime rate. This effect is still positive but lower for neighbouring boroughs and ceases to exist beyond a 40 minute driving distance. Social interactions between individuals of the same ethnic group are the most likely explanation for this positive relationship.

JEL Classification: C21, K42 and R12
Keywords: crime, ethnic minorities, panel data, social interactions and spatial correlation

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1 Introduction

The aim of this paper is to investigate the relationship between a community's ethnic population density and its crime rate. This is not a new question, at least not in the non-economic literature. Indeed, the connection between ethnic heterogeneity 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 plenty 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. Our analysis provides a natural interpretation of the results in terms of *social interactions*. To be more precise, the mechanism put forward in our analysis is that in denser areas, individuals interact with more people, especially from the same ethnic group, who can provide information about crime. Although those relationships may neither be personal nor strong, those weak ties provide the best information about crime. Quite naturally, the strength of weak ties decreases with the physical distance between individuals.

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; 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. (2007b) 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.[1]

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 (Machin and Meghir, 2004, Machin and Marie, 2006, and Hansen and Machin, 2008) that analyze the link between crime and low-wages. Their findings point to a strong negative 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.[2]

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. For this purpose, we use monthly data on crime for the 32 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, both within and between boroughs.

The ethnic population is restricted to Black-British only, which is the major ethnic group in London, with a substantial difference in size with respect to the other minorities. This choice avoids issues related to cultural differences between ethnic groups.

We begin our analysis by using the techniques of exploratory spatial data analysis as compared to 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, ethnic 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 unemploy-

[1] 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).

[2] However, there are 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).

ment 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.

We then look more closely at the relationship between crime and ethnic 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.

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 the paper and discusses some policy implications of our results.

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 heterogeneity 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 (area) 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 (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 due to 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 (for example, the education or unemployment level in the area, the 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 interpret the results in a more satisfactory way and thus, to derive some policy implications. 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 and the (observed and unobserved) characteristics of the people that explain this positive relationship, what might it be?

Our conjecture is that *social interactions* between people of the same ethnicity constitute the key for understanding this positive relationship. Let us explain why. The strength of the relationship (ties) between individuals can be weak or strong (Granovetter, 1973, 1983). We define a *weak tie* (as opposed to a *strong tie* in which the relationship is repeated over time, for example members of the same family or very close friends) when social interaction between two individuals is *transitory* (such as random encounters, for example) What is crucial is that relationships with weak ties occur at a *very local level* and depend on population density while those with strong ties are typically not location dependent and do not depend on population density (see the evidence below).

Our theoretical mechanism works as follows. Individuals have strong and weak ties that can provide information about crime, but only weak tie relationships depend on location and density. So the denser (in terms of population density) an area is, the more an individual is likely to interact with weak ties. This is the *quantity effect*. Moreover, there is a *quality effect*, which is due to ethnicity. The interaction between weak ties is of better quality if people belong to the same ethnicity, which means that the information about crime is of better quality. It is indeed well-established that ethnic minorities are overrepresented in criminal activities both in the United States (see e.g. Freeman, 1999)[3] and in Europe (see e.g. Shute et al., 2005, for the United Kingdom).[4] Hence, when there are more people of the same ethnic group around, it is more likely that crime increases. Furthermore, the higher is the population density of a given ethnic group, the more people of this ethnic group interact

[3] 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).

[4] 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).

with each other.

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 meet weak ties than strong ties.[5]

Second, individuals interact more with weak ties 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. (2005) 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.[6]

Third, weak ties provide important information about crime. 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. Indeed, having more friends increases the range of interactions and information is spread more efficiently and evenly throughout the economy. 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

[5]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.

[6]See also Kan (2007) who shows social capital to be very local.

weak ties 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 (see, in particular, Alesina et al., 1999; Alesina and La Ferrara, 2000, 2005; Luttmer, 2001; Vigdor, 2004). 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 (*assortative matching*). This tendency is particularly strong among ethnic groups (see e.g. Moody, 2001; Marmaros and Sacerdote, 2006; Bayer et al., 2007a).

To sum up, 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. Although those relationships may neither be personal nor strong, those weak ties provide the best information about crime. As a result, the higher the number of weak ties of the same ethnicity living in the same area, the higher is the individual crime rate. Furthermore, the strength of weak ties decreases with physical distance.

Thus, we estimate a model where the crime rate in a given borough will be explained by the ethnic population density within this borough and the ethnic 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 between weak ties 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.

2.3 An alternative mechanism

So far, we have put forward the crucial role of information about crime opportunities in explaining the positive relationship between crime rate and ethnic population density. There is, in fact, an alternative mechanism, still based on social interactions, that could give rise to a positive relationship between crime rate and ethnic population density.

Indeed, 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 (see, e.g., 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 (through weak ties) that could increase the crime rate.

Both mechanisms (transmission of information about crime and badge of honor) are due to social interactions and postulate that the ethnic dimension is crucial for understanding crime. This is why, as a first step, we will examine to what extent the spatial patterns of crime in London correlate with the spatial patterns of ethnicity. We will not, however, be able to discriminate between these two mechanisms on basis of our evidence.

3 Empirical analysis

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 ethnic population density or ethnic commuting flows.

Second, the impact of ethnic 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 controled 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.

3.1 Exploratory spatial data analysis

Monthly data on crime for the 32 London boroughs are available on line from the London Metropolitan Police Service (LMPS)[7]. The data cover the period January 2000 to December 2006. Thus, we have constructed a panel giving 2,688 observations. Crime rates are calculated on 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 be only Black British) in each borough for the corresponding time period.

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

[*Insert Figure* 1 *here*]

A visual inspection of Figure 1 reveals that the darker (clearer) areas on the crime map are typically also the darker (clearer) areas on the ethnic 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. These are the unemployment rate, the percentage of high skilled population (that is the percentage of individuals aged above 18 holding an A-level[8] or a higher qualification) and a house price index.[9] We add ethnic population density and

[7] The City of London is not included because it runs its own police force. However, its inclusion does not qualitatively change our results.

[8] The A-level in UK is equivalent to the SAT in the US or the baccalaureat in France.

[9] 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

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 employed 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.[10] 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 roughly half the boroughs.[11] This is clear

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.

[10] 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 [not sure I understand the use of the word "regime" here] 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).

[11] 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.

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 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 and extending towards the North to include Waltham Forest and Haringey and towards the East to include Newham. Evidence of local clustering of low values is instead found in the South-West (i.e. Kingston upon Thames, Richmond upon Thames and Merton) and, to a lesser extent, 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 any strong support for this view. For instance, areas with lower house prices, a 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 ethnic population density or ethnic commuting flows data than in unemployment, high-skilled population and house price data. Even more, almost all local spatial association schemes in the crime data accurately match those in the data for the ethnicity-related variables and, in particular, for 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 ethnic population density data. At a first glance, it appears that the spatial regimes identified for crime are closely reproduced in the ethnic population density data. Indeed, roughly all areas with significant local statistics in the HH scheme for crime (i.e. areas with a statistically significant high value of crime surrounded by areas with high values), also show significant local statistics in the HH scheme when ethnic population density is considered (i.e. these are areas for which the ethnic population density shows a statistically significant high value surrounded by areas with high values). The areas in the LL scheme for crime (i.e. low value areas surrounded by other areas with low values) are also the areas in the LL scheme for ethnic population density, and 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) has the same nature in the ethnic population density data.[12]

[*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 criminal activities.[13]

Clearly, however, this evidence can be driven by an endogenous sorting of people into boroughs and the ethnic 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 ethnic population density is more closely analyzed, once the effects of confounding factors have been controled 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 ethnic 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.[14] 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 (the standard deviation is equal to 25 minutes).[15,16]

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

[12] As appears from the figures reported in Table 2, G* statistic maps lead to similar pictures.

[13] The ESDA analysis has also been separately performed for the different types of crime. However, 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.

[14] Driving time distances in minutes are estimated using Microsoft Autoroute 2002. We consider the shortest route, given the road network in 2002.

[15] 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.

[16] 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.

a given radius (in minutes) drawn around the centroid of each borough.[17,18] Thus, we aim at examining whether the density of ethnic 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 ethnic population density effect by comparing estimates across rings.

We perform our analysis for different types of crimes. The information provided by the London Metropolitan Police Service (LMPS) is disaggregated by type of crime. We break down the crime data into five categories, namely violent and sexual crime (type 1), robbery and burglary (type 2), theft and handling (type 3), drug-trafficking (type 4) and criminal damage (type 5). Descriptive statistics are reported in Table 1.

For each crime category ($r = 1, ...5$), we estimate the following model:[19]

$$c^r_{b,t} = \alpha c^r_{b,t-1} + \sum_s \gamma_s d^e_{s,b,t} + \eta_b + \varepsilon_{b,t}, \qquad |\alpha| < 1, \qquad b = 1, ..., N;\ t = 2, ..., T, \qquad (1)$$

where $c^r_{b,t}$ is the crime rate[20] of type r in borough b at time t and $d^e_{s,b,t}$ denotes the density of ethnic population within the proximity band s at time t. The error term is composed by a borough-specific fixed effect, η_b, controling for cross-borough (observable and unobservable) differences that are constant across time and by a white noise error component, $\varepsilon_{b,t}$. 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 from the effects of area characteristics that are constant over time and we assume that the impact

[17] 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, 2006).

[18] 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.

[19] The condition $|\alpha| < 1$ indicates (time) stationarity. In fact, this property is satisfied by crime series.

[20] Unfortunately, we do not have any information on the crime rate per ethnicity. However, because ethnic minorities are overrepresented in criminal activities, the total crime rate and that per ethnicity should be highly correlated.

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.[21]

4.1 OLS estimates

Model (1) is estimated both for total crime and each crime category separately. Table 3 reports the results (in different blocks) 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).[22]

Let us begin by documenting to what extent the spatial ethnic 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 $\sum_s \gamma_s d^e_{s,b,t}$) 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). Then, we report Lagrange Multiplier tests for an omitted spatially lagged dependent variable (LM (spatial lag)) 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). Significant values of these tests provide evidence of the existence of spatial dependence in the data that is not fully captured by the model specification.

[*Insert Table* 3 *here*]

Looking at the results for the model specification without population density proximity bands (first column of each block), all tests provide 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 model postulates that such a contagion/spillover effect is explained by the diffusion of information (here measured by ethnic population density) between adjacent areas.

[21] The analysis has also been performed including a variety of (observable) area characteristics. The results on our target variables remain qualitatively unchanged.

[22] As T becomes large, the within groups 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).

We then add the population density proximity bands to the model (second column of each block). The diagnostic tests now provide evidence of an omitted spatial lag only for type 1 and type 2 crimes (i.e., violent and sexual crime, and robbery and burglary), whereas the ethnic population density bands seem to entirely capture the spatial interactions in total crime and type 3, 4 and 5 crimes (i.e., theft and handling, drug-trafficking and criminal damage, respectively).[23] These are the types of crime most likely to be affected by local social interactions. However, the spatial distribution of other types of crime is likely to be explained by other factors, beyond the population density proximity bands (here used as a proxy for local interactions). These results are thus consistent with our theoretical mechanisms where criminal activities depend on interactions between agents in social space. Indeed, our geographical approximation reveals that spatial autocorrelation in crime, which measures the extent of spatial interactions between areas is (at least partly) explained by ethnic population density, where the latter is taken as a measure of the strength of social contacts.

Turning to the estimates of 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. For total crime, they have no effect beyond approximately 40 minutes. A one-point percentage increase in the density of ethnic 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 ethnic population 30 minutes away, and more than 15 times that of the density of the ethnic population 40 minutes away. Quite interestingly, for the different types of crime, we find that the larger is the magnitude of the effects, the shorter is their spatial range. These patterns are consistent with the idea that social interactions are very localized (Topa, 2001; Bayer et al, 2005).

4.2 Instrumental variable 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 corre-

[23] 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.

lated 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 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. The Sargan test of overidentifying restrictions (Sargan, 1958) is used to choose the appropriate set of instruments in the case study, i.e., the lags of the crime rate to be included in the instrumental set.

Our instrumental variable results are reported in Table 4.[24] 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*]

4.3 The endogeneity of location choices: A discussion

As discussed in the previous section, the density of ethnic population may be endogenous with respect to the level of crime committed. However, when we compare the different effects of the density of ethnic population on the level of different types of crime, our qualitative (differential) results remain valid even if people with a criminal propensity choose to reside in specific areas. In this context, the effect of the social interactions they develop in the area

[24] The analysis has also been performed by instrumenting the actual ethnic population of each borough with the historical ethnic 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. Our qualitative results remain unchanged.

on their decision to commit *a specific type of crime* is the target relationship of our analysis. Certainly, we need to assume that criminals' residential location decisions are not driven by their willingness to commit *a specific type of crime*. This assumption is not strong and, in addition, the effect of such a scenario is also controled for in our analysis by the use of area-specific fixed effects. Indeed, the effects of area characteristics (constant over time) that might affect a particular type of criminals (e.g., some residential areas might be targeted for burglars or robbers) are removed by the adoption of a panel data estimator with area fixed effects.

5 Conclusion and policy implications

The aim of this paper is to investigate the link between a community's racial composition and its crime rate. We test this relationship using monthly data on crime for the 32 London boroughs for the period January 2000 to December 2006. Using panel data techniques as well as spatial regression techniques, we find a positive relationship between ethnic density and crime rate. Focusing on the estimates of 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 and have no effect beyond approximately 40 minutes.

The mechanism put forward in our analysis is that, in denser areas, individuals interact with more people, especially from the same ethnic group, who can give information about crime. Although those relationships may neither be personal nor strong, those weak ties provide the best information about crime. As stated in Section 2.3, it may also well be that status within a community can explain the positive relationship between these two variables. Indeed, when delinquency is seen as a badge of honor in a population, committing a crime is a way of being accepted by a local community. Since we find a positive relationship between crime rate and ethnic population density in our empirical analysis, peer effects seem to be what is driving the results, but we are not able to disentangle the two different mechanisms mentioned above. However, since both are based on peer effects (whether peers provide information on crime opportunities or put social pressure to commit crime), the policy implications are quite similar. In particular, an effective policy should not only be measured by the possible crime reduction it implies but also by the group interactions it engenders.

If social interactions are crucial for understanding local criminal activities, then a targeted policy identifying "key players" in a given area (Ballester et al., 2006, 2008) may be an effective way of reducing crime. A key player (or a key group) is an individual (or a group

of persons) belonging to a network of criminals who, once removed, leads to the highest aggregate delinquency reduction. In practice, the planner may want to identify optimal network targets to concentrate (scarce) investigatory resources on some particular individuals, or isolate them from the rest of the group, through leniency programs, social assistance programs, or incarceration. The success of such policy depends on the ability to identify a social network and this task may not be as difficult as it seems. For instance, Haynie (2001) and Calvó-Armengol et al. (2005) use friendship data to identify delinquent peer networks for adolescents in 134 schools in the U.S. that participated in an in-school survey in the 1990's. Sarnecki (2001) provides a comprehensive study of co-offending relations and corresponding network structures for football hooligans and right-wing extremists in Stockholm. Baker and Faulkner (1993) reconstruct the structure of conspiracy networks for three well-known cases of collusion in the heavy electrical equipment industry in the U.S. Finally, Krebs (2002) maps the network of terrorist cells behind the tragic event of September 11, 2001. In all these cases, the available data may be directly used to determine the key player or group players.

Another effective policy would be not to target individuals but instead neighborhoods. Social mixing between minorities and non-minorities could be a good way of reducing criminality in certain "ethnic" neighborhoods. The Moving to Opportunity" (MTO) programs in the United States are a good example of such policies. By giving housing assistance (i.e. vouchers and certificates) to low-income families, the MTO programs help them relocate to better and richer neighborhoods. The results of most MTO programs (in particular for Baltimore, Boston, Chicago, Los Angeles and New York) show a clear improvement of the well-being of participants and a reduction in arrest rates (see, in particular, Ladd and Ludwig, 2001; Katz et al. 2001; Rosenbaum and Harris, 2001, and Kling et al. 2005). Observe that the MTO programs are not targeted at minority families (such as blacks) but rather at poor families. But since the two are correlated, this is a good example of an integration policy.

Instead of moving people, the quality of areas characterized by a large concentration of ethnic minorities could be improved. Neighborhood regeneration policies (see, e.g. Schill et al., 2002; Weber and Smith, 2003) would then be the right tool to use. Policies like enterprise zone programs (Papke, 1994; Boarnet and Bogart, 1996; Mauer and Ott, 1999; Bondonio and Engberg, 2000; Bondonio and Greenbaum, 2007) which consist of designating a specific urban (or rural) area, which is depressed, and targeting it for economic development through government-provided subsidies to labor and capital, would also be an effective way of reducing crime.

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

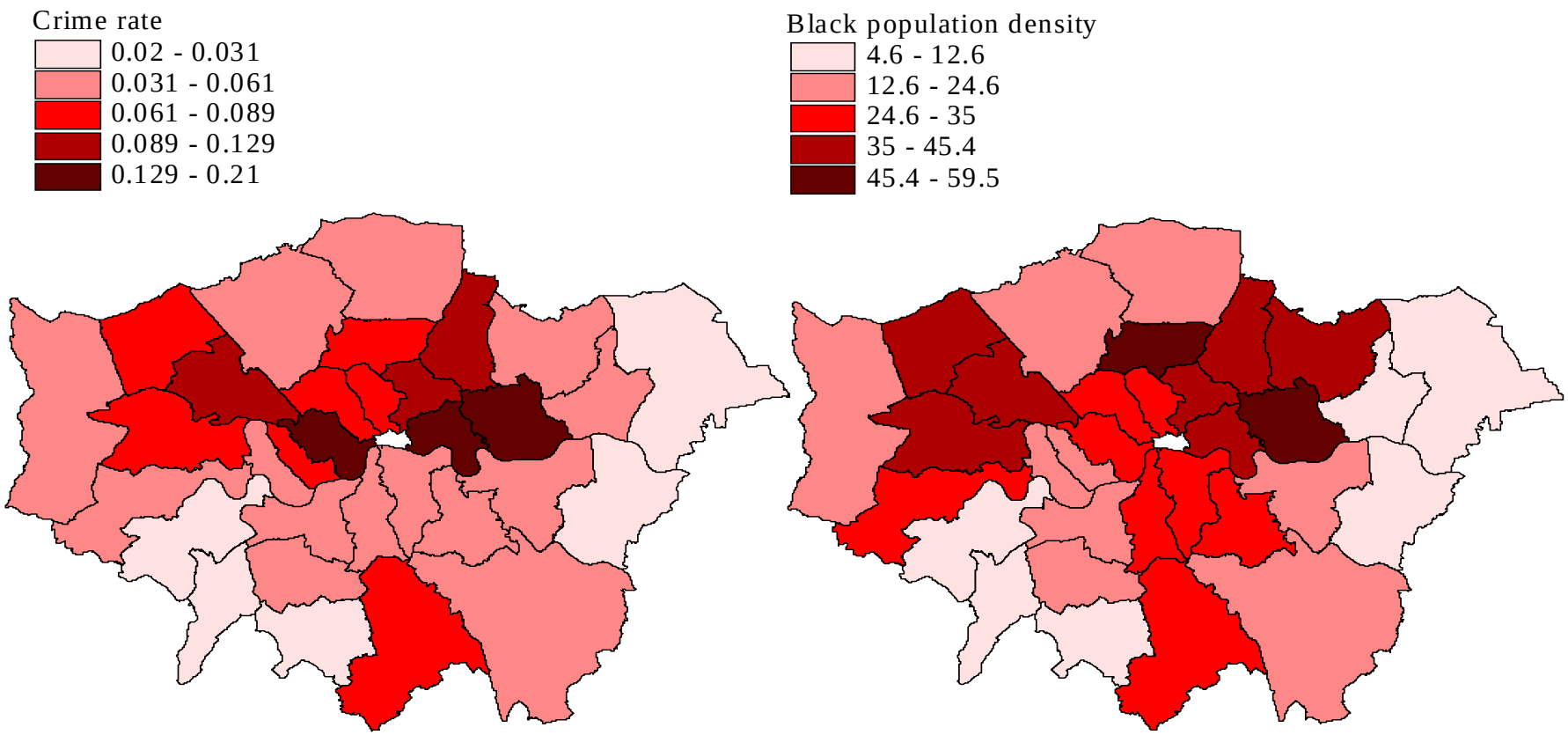

Figure 2. Local indicators of spatial assoication
(significant at least at the 5% level)

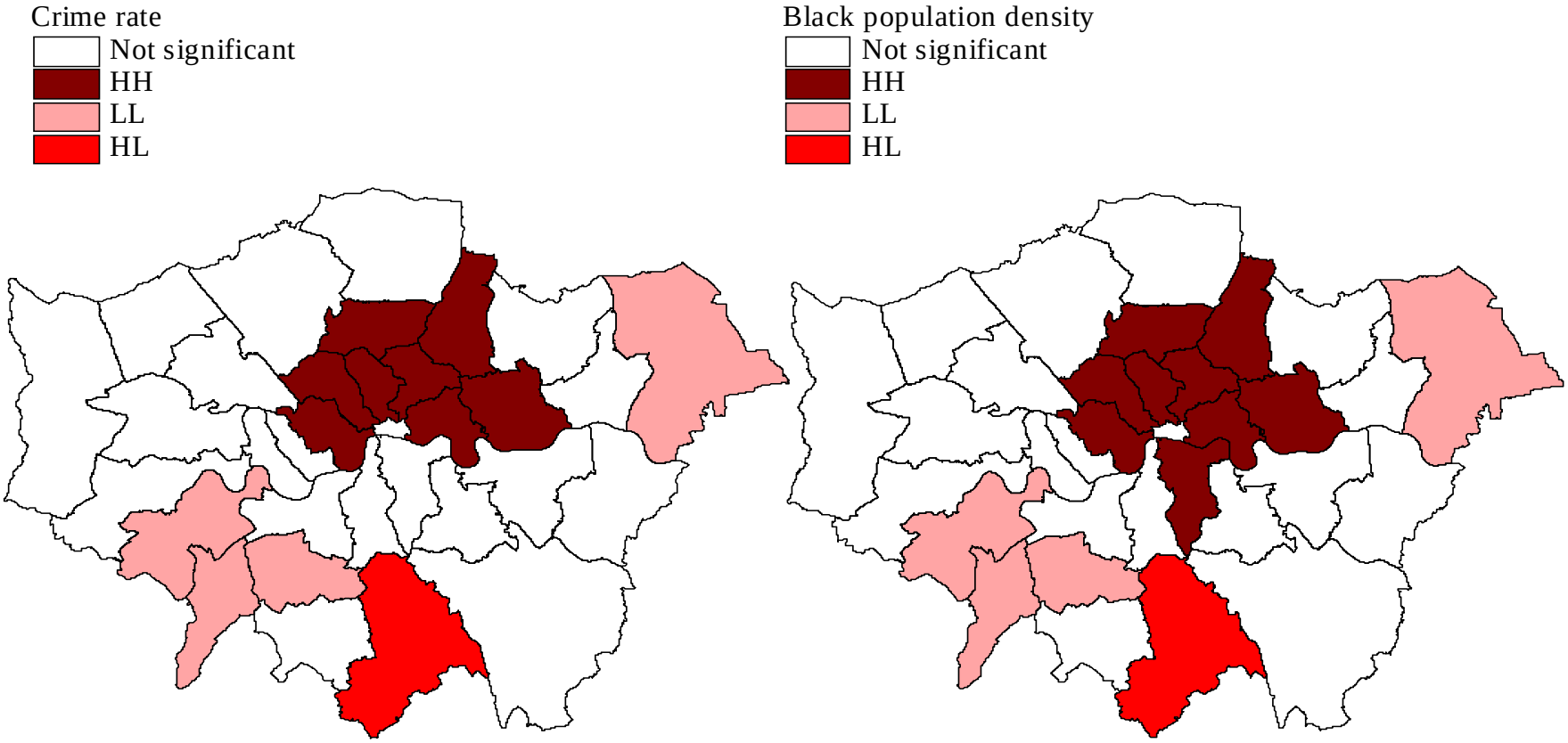

Table 1. Descriptive Statistics

Variable	Mean (%)	Std. Dev. (%)	Min. (%)	Max. (%)
Unemployment rate	7.28	2.21	3.30	12.90
High skilled population	37.99	10.10	16.06	59.71
House price index (£)	309.66	173.55	202.02	586.07
Ethnic population density	27.93	14.09	4.60	59.50
Ethnic commuting flows	24.02	15.99	7.39	44.72
Total crime rate	0.07	0.04	0.02	0.21
Violent and sexual crime	0.02	0.03	0.01	0.09
Robbery and burglary	0.06	0.09	0.03	0.18
Theft and handling	0.05	0.08	0.04	0.17
Drug-trafficking	0.12	0.10	0.04	0.32
Criminal damage	0.15	0.09	0.05	0.31

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

	Crime		Eth. pop.density		Eth. comm. flows		Unempl. rate		High skilled pop.		House prices	
Borough	**I**	**G***	**I**	**G***	**I**	**G***	**I**	**G***	**I**	**G***	**I**	**G***
Brent	0.54	0.51	0.16	0.35	0.32	1.05	-0.36	0.74	0.11	0.74	*0.08*	1.19
Hillingdon	0.50	-1.13	0.40	1.77	0.95	1.88	0.17	0.81	0.48	-1.49	***2.18***	***-2.50***
Harrow	-0.85	0.77	-1.00	1.10	-1.42	1.81	***2.22***	***2.75***	0.07	-0.78	***2.02***	***-2.42***
Ealing	1.50	1.69	1.64	1.72	**2.29**	**2.07**	***2.15***	***2.27***	**1.95**	**-2.41**	***2.10***	***-2.60***
Hounslow	-0.04	0.73	0.06	0.50	-0.17	1.75	***2.05***	***2.02***	-0.13	0.04	***2.17***	***-1.95***
Kingston upon Thames	**4.46**	**-2.26**	**3.23**	**-3.86**	***2.24***	***-1.87***	1.30	1.12	0.12	0.71	0.13	0.11
Richmond upon Thames	***2.14***	***-2.87***	***2.59***	***-1.52***	***2.05***	***-1.79***	2.01	-1.33	**2.26**	**2.06**	**2.13**	**3.26**
Merton	***2.29***	***-2.02***	***2.40***	***-2.43***	***2.28***	***-2.12***	2.11	-1.51	0.22	1.84	1.16	1.40
Wandsworth	-0.03	-0.57	-0.13	-0.66	0.01	-0.47	***-2.08***	***-2.04***	0.02	0.31	-0.46	1.67
Hammersmith and Fulham	-0.09	0.52	0.09	1.80	0.02	0.10	***2.05***	***2.15***	***2.22***	***2.79***	**-4.19**	**5.12**
Kensington and Chelsea	1.12	1.91	0.13	-0.54	***-2.60***	***2.16***	**3.02**	**-2.78**	***3.31***	***3.95***	**3.73**	**5.24**
Westminster	**3.53**	**3.27**	***2.25***	***2.72***	1.44	1.75	**2.41**	**-2.22**	0.22	0.34	**3.40**	**3.31**
Hackney	***2.52***	***2.04***	**3.10**	**3.77**	**3.14**	**3.90**	0.33	0.73	0.01	-0.79	0.33	-1.14
Islington	**2.95**	**2.50**	***3.23***	***3.85***	**2.38**	**2.24**	**2.02**	**2.42**	-1.14	-1.42	0.30	0.51
Camden	**5.12**	**4.74**	**4.01**	**4.13**	**2.10**	**2.60**	0.20	0.88	0.09	-0.34	***-2.24***	***-1.78***
Tower Hamlets	***1.98***	***2.26***	***2.16***	***2.64***	**2.52**	**2.37**	**1.76**	**2.89**	0.38	1.15	-0.79	0.72
Newham	**1.87**	**2.28**	***2.15***	***2.07***	***2.50***	***2.36***	1.16	2.03	0.56	-0.66	***-2.15***	***2.91***
Southwark	1.72	2.08	***2.29***	***2.97***	***2.22***	***2.58***	1.36	1.81	**2.76**	**2.13**	***1.63***	***2.42***
Lambeth	0.33	1.13	0.01	0.06	0.93	0.27	***2.41***	***2.24***	-1.31	-0.85	0.04	-0.37
Croydon	***-1.94***	***-2.34***	***-2.33***	***-2.45***	***-2.06***	***-2.54***	0.06	0.46	0.67	-0.74	1.22	-1.97
Bromley	0.33	0.95	0.40	0.69	0.89	1.39	-0.89	-0.32	1.05	-1.04	0.64	*-1.67*
Sutton	0.25	-1.10	0.45	-1.14	0.59	-1.29	**2.04**	**1.95**	***2.61***	***-2.69***	***1.74***	***-2.08***
Lewisham	1.06	0.87	0.11	1.52	0.33	0.75	0.03	-0.33	*0.28*	-1.06	0.25	-0.26
Greenwich	0.38	1.18	0.59	1.57	0.25	0.20	0.07	-0.18	1.24	1.89	0.01	-0.17
Bexley	0.11	-1.31	0.17	1.88	0.25	-1.18	-0.47	1.33	***3.46***	***-4.26***	***3.04***	***-3.11***
Barking and Dagenham	-1.09	-1.64	-0.53	-1.07	-0.85	-0.54	-0.14	-0.06	**2.65**	**-2.54**	**2.37**	**-2.39**
Havering	***2.40***	***-1.68***	***2.11***	**-1.59**	0.67	-0.33	***2.26***	***1.17***	0.74	-1.14	0.00	-0.64
Redbridge	0.12	-0.50	0.04	-0.13	0.31	-1.19	0.05	0.50	1.18	*-1.83*	-0.22	-0.70
Waltham Forest	***2.65***	***2.37***	***2.05***	***2.25***	***2.09***	***2.28***	0.02	0.51	-0.54	-0.09	-1.94	-0.64
Haringey	***2.10***	***2.79***	***2.17***	***1.78***	***1.76***	***1.71***	***-3.12***	***2.23***	0.70	-1.77	-0.10	-0.61
Enfield	-0.29	0.99	-0.02	0.05	0.64	0.26	0.38	1.13	0.14	-0.91	0.23	-1.15
Barnet	-0.41	-1.05	-0.01	-0.02	1.38	0.67	***-0.44***	***-2.31***	**2.16**	**1.78**	***2.20***	***2.00***

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 permutazions. It gives the same results for both statistics. 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 ethnic population density
- OLS estimates -

	All Crimes		Type 1: Violent and sexual crime		Type 2 robbery burglary		Type 3 theft and handling		Type 4 drug-trafficking		Type 5 criminal damage	
Ethnic population density												
…within 20 min	-	0.1229	-	0.0091	-	0.0154	-	0.0997	-	0.0746	-	0.1969
		(2.98)		(2.11)		(2.65)		(3.96)		(4.05)		(6.54)
… within 20-30 min	-	0.0255	-	0.0072	-	0.0105	-	0.0569	-	0.0330	-	0.1020
		(6.84)		(2.01)		(2.17)		(3.85)		(4.95)		(1.06)
… within 30-40 min	-	0.0080	-	0.0032	-	0.0089	-	0.0198	-	0.0109	-	0.0492
		(2.82)		(2.02)		(2.10)		(1.18)		(2.52)		(0.90)
… within 40-50 min	-	0.0032	-	0.0013	-	0.0032	-	0.0094	-	0.0063	-	0.0202
		(1.02)		(1.98)		(2.02)		(0.96)		(1.16)		(0.52)
… within 50-60 min	-	-0.0008	-	0.0004	-	-0.0010	-	0.0062	-	-0.0038	-	0.0170
		(0.22)		(0.10)		(0.51)		(0.24)		(0.55)		(0.31)
Time lag of dependent variable	0.5098	0.3985	0.5516	0.5091	0.5665	0.5519	0.4384	0.3438	0.5519	0.4438	0.4987	0.3941
	(4.25)	(3.35)	(5.32)	(4.12)	(5.32)	(5.22)	(5.12)	(4.05)	(5.22)	(3.65)	(2.77)	(2.02)
R-squared	0.8080	0.8499	0.7226	0.7583	0.7921	0.8222	0.7878	0.8336	0.7995	0.8505	0.8088	0.8655
LM (spatial lag)	0.2357	0.1353	5.005	4.1010	6.1314	4.2211	0.7725	0.5156	0.8582	0.7388	1.2515	0.9807
	(0.63)	(0.72)	(0.00)	(0.00)	(0.00)	(0.00)	(0.38)	(0.47)	(0.35)	(0.39)	(0.26)	(0.32)

Notes:
The number of observations is 2,688 in all cases. Regional dummies are included.
Within groups parameter estimates and *t*-ratios in parentheses are reported.
LM (spatial lag): robust version of the Lagrange multiplier test for a spatial lag of the dependent variable, distributed as a chi-squared with 1 degree of freedom.
Estimation using SpaceStat v1.93 (Anselin, 1995).

Table 4. Crime and ethnic population density
- IV estimates -

	All Crimes	Type 1 violent sexual crime	Type 2 robbery burglary	Type 3 theft and handling	Type 4 drug-trafficking	Type 5 criminal damage
Ethnic population density						
…within 20 min	0.1509	0.0196	0.0204	0.1099	0.0799	0.2011
	(3.61)	(2.26)	(2.75)	(3.19)	(4.25)	(7.61)
… within 20-30 min	0.0535	0.0130	0.0125	0.0605	0.0369	0.1505
	(3.69)	(2.15)	(2.38)	(3.00)	(4.05)	(1.39)
… within 30-40 min	0.0108	0.0100	0.0118	0.0219	0.0158	0.0508
	(2.98)	(2.00)	(2.18)	(1.21)	(2.79)	(1.09)
… within 40-50 min	0.0076	0.0061	0.0095	0.0099	0.0106	0.0276
	(0.95)	(2.01)	(2.12)	(0.99)	(1.10)	(0.65)
… within 50-60 min	-0.0018	0.0015	-0.0005	0.0056	-0.0013	0.0180
	(0.36)	(0.34)	(0.10)	(0.35)	(0.25)	(0.29)
Time lag of dependent variable	0.5539	0.5438	0.4951	0.3554	0.4013	0.3902
	(6.39)	(4.70)	(6.61)	(3.25)	(3.76)	(6.69)
Sargan test	521.41	500.25	450.25	461.38	440.98	438.33
[498]	(0.23)	(0.46)	(0.94)	(0.88)	(0.98)	(0.97)
M_1	5.5484	13.615	7.1399	6.5513	5.9955	10.555
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M_2	1.064	0.8873	-0.5023	0.7088	0.7350	-1.0856
	(0.2874)	(0.3750)	(0.6154)	(0.4785)	(0.4623)	(0.2776)

Notes:
The number of observations is 2,688. Regional dummies are included.
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 two year and up to four years.
The reported test statistics with the associated probability level in parentheses are the following ones.
Sargan test: Sargan test of overidentifying restrictions, distributed as a chi-squared with degrees of freedom (reported in squared brackets) given by the number of overidentifying restrictions;
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.
Estimation using Ox version 3.0 (Doornik, 2001).