DISCUSSION PAPER SERIES

No. 6130

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LABOUR ECONOMICS and PUBLIC POLICY

Centre for Economic Policy Research

www.cepr.org

Available online at: www.cepr.org/pubs/dps/DP6130.asp

ISSN 0265-8003

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Discussion Paper No. 6130
February 2007

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CEPR Discussion Paper No. 6130

February 2007

ABSTRACT

Ethnicity and Spatial Externalities in Crime*

We develop a model where the decision to commit a crime in a neighboring area is a positive function of the percentage of same-race individuals residing in that area since they can provide crucial information on crime possibilities. The model then predicts a positive spatial correlation in crime between different contiguous areas; this correlation is higher the closer the distance between the areas. We empirically investigate these relationships using data from the crime statistics that are recorded by the police in Britain. We find results that are consistent with the model. In particular, the agglomeration of a given ethnic minority group is positively related to its crime activity and this effect declines quite sharply with distance between areas.

JEL Classification: C23, K42 and R12
Keywords: crime, ethnic minorities and social interactions

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* Yves Zenou thanks the Marianne and Marcus Wallenberg Foundation for financial support.

Submitted 29 January 2007

1 Introduction

It is well documented that there is more crime in big than in small cities (Glaeser and Sacerdote, 1999). For example, the rate of violent crime in cities with more than 250,000 population is 346 per 100,000 inhabitants whereas in cities with less than 10,000 inhabitants, the rate of violent crime is just 176 per 100,000 (Glaeser, 1998). Similar figures can be found for property crimes or other less violent crimes. It is also well documented that, within cities, crime is highly concentrated in a limited number of areas. For instance, South and Crowder (1997, Table 2) have shown that U.S. central cities have higher crime and unemployment rates, higher population densities and larger relative black populations than their corresponding suburban rings.

To our knowledge, three types of theoretical models have integrated space and location in crime behavior.[1] First, *social interaction* models that state that individual behavior depends not only on the individual incentives but also on the behavior of the peers and the neighbors are a natural way to explain the concentration of crime by area. An individual is more likely to commit crime if his or her peers commit than if they do not commit crime (Glaeser et al., 1996; Calvó-Armengol and Zenou, 2004; Ballester et al., 2006; Calvó-Armengol et al., 2007). This explanation is backed up by several empirical studies that show that indeed neighbors matter in explaining crime behaviors. Case and Katz (1991), using the 1989 NBER survey of young living in low-income, inner-city Boston neighborhoods, found that residence in a neighborhood in which many other youths are involved in crime is associated with an increase in an individual's probability of committing crime. Exploiting a natural experience (i.e. the Moving to Opportunity experiment that has assigned a total of 614 families living in high-poverty Baltimore neighborhoods into richer neighborhoods), Ludwig et al. (2001) and Kling et al. (2005) found that the behavior or characteristics of neighbors strongly influence juvenile criminal activity. Also, Calvó-Armengol et al. (2005) test whether the position and the centrality of each delinquent in a network of teenager friends has an impact on crime effort. They show that, after controlling for observable individual characteristics and unobservable network specific factors, the individual's position in a network is a key determinant of his/her level of criminal activity.[2]

Second, Freeman et al. (1996) provide a theoretical model that explains why criminals are concentrated in some areas of the city (ghettos) and why they tend to commit crimes in their own local areas and not in rich neighborhoods. Their explanation is based on the fact that,

[1] For an overview see Zenou (2003).

[2] See also Patacchini and Zenou (2006) who study the impact of friends and conformism on crime behaviors.

when criminals are numerous in an area, the probability to be caught is low so that criminals create a positive externality for each other. In this context, criminals concentrate their effort in (poor) neighborhoods where the probability to be caught is small. This explanation has also strong empirical support (see, e.g., O'Sullivan, 2000).

Finally, Verdier and Zenou (2004) show that prejudices and *distance to jobs* (legal activities) can explain crime behaviors, especially among blacks. If everybody believes that blacks are more criminal than whites -even if there is no basis for this- then blacks are offered lower wages and, as a result, locate further away from jobs. Distant residence increases even more the black-white wage gap because of more tiredness and higher commuting costs. Blacks have thus a lower opportunity cost of committing crime and become indeed more criminal than whites. Using 206 census tracts in city of Atlanta and Dekalb county and a state-of-the-art job accessibility measure, Ihlanfeldt (2002, 2006) demonstrates that modest improvements in the job accessibility of male youth, in particular blacks, cause marked reductions in crime, especially within category of drug-abuse violations. He found an elasticity of 0.361, which implies that 20 additional jobs will decrease the neighborhood's density of drug crime by 3.61%.

In this paper, we follow the first trend of research (i.e. social interactions) by highlighting the role of friends in influencing crime rates. We take here an explicit spatial approach by focussing on the (possible) interdependence of crime rates between adjacent areas.

We first develop a simple theoretical model where the social interactions in crime are captured by the fact that the probability to be arrested in a neighboring area depends on the percentage of individuals of same-race residing there. Indeed, when an individual of a certain race (white or nonwhite) wants to commit a crime in an area where he/she does not live, the information about crime possibilities in this area can only come from people of the same race. This obviously reduces the probability to be caught. We obtain three main predictions. First, assuming that nonwhites and whites have different wages, we find that if the difference in wages is large enough, then the number of nonwhite criminals is higher than that of white criminals in each area. Second, we show that there is spatial correlation in crime rates per ethnicity between two adjacent areas, i.e. if the crime rate of nonwhites is high (low) in one area, then it is also high (low) in the neighboring area. This spatial interactions effect depends negatively on the distance between the two areas. Finally, the percentage of individuals of same-race influences crime decisions. The direction of the impact is ambiguous, but is more likely to be positive the more spread the wage distribution (between nonwhites and whites) is.

The predictions of this model are tested on area-level data in Britain.[3] In particular, we examine how ethnic crime relates to proximity to ethnic residing population adopting a spatial approach.[4] In doing so, we analyze and characterize the spatial distribution of our target variables across the police force areas in Britain. Firstly, we estimate the crime spatial autocorrelation function by ethnic group, and the portion attributable to the own ethnic group population residing in adjacent areas, in a non-parametric way, following the approach by Conley and Topa (2002). Secondly, we model the spatial structure of the ethnic population by creating a series of distance-based bands around each area. By comparing estimates across those rings it is possible to assess both their overall impact on crime and the rate at which these effects attenuate with distance.[5] Distance is measured here by travel times, as this is reasonably the best metric to represent how agents' contacts materialize.

Our results are consistent with the predictions of our theoretical model of local interactions. In particular they appear to support the scenario where social interactions and social networks are important in explaning crime activities for ethnic minorities. The estimation of a panel data model then confirms the relevance of the role played by the ethnic residing population in explaining the observed spatial patterns of local ethnic crime rate. It appears that the estimated effects are greatest within 30 minutes driving time, diminishing sharply with travel time and having virtually no effect beyond approximately 90 minutes.

The next section contains the theoretical model. Section 3 bridges our theoretical analysis into the empirical investigation, describes the data and provides some exploratory evidence. Section 4 presents the estimation results of our empirical model both with OLS and IV estimates. Finally, section 5 concludes.

[3] We resort to aggregate data because, unlike the US, it is very rare in Europe to find surveys with individual data on crime (victimization data).

[4] Unlike the US, there are few (and recent) papers modelling crime in the UK. Most notably, Machin and Meghir (2004) and Hansen and Machin (2002) 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. Despite the strong link between "place" and crime, however, these studies are not based on spatial models of crime, i.e. on models using explicitly the spatial dimension of the local crime markets. Therefore a possible cross-sectional dependence is not considered and the mechanisms that originate such a pattern are not identified.

[5] This second empirical exercise has been recently used to estimate the spatial scale of agglomeration effects on (aggregate) productivity and wages by Rice et al. (2006) and Rosenthal and Strange (2006), respectively.

2 Theoretical analysis

There are two areas and a continuum of black and white individuals.[6] In each area $a = 1, 2$, the mass of individuals of type $r = B, W$ (B stands for "black" and W for "white") is denoted by N_{ra}. Blacks and whites are assumed to be totally identical but differ in terms of human capital. We assume that human capital levels and wages are perfectly correlated. In this context, the distribution of wages (i.e. human capital) for individuals of type $r = B, W$ is described by a cumulative distribution function (cdf) $F_r(w)$ with support $[\underline{w}_r, \overline{w}_r]$. We assume that

$$\underline{w}_B < \underline{w}_W < \overline{w}_B < \overline{w}_W \tag{1}$$

There are very strong evidence that blacks (or more generally nonwhites) have lower human capital levels and lower wages than whites both in the US and in Europe (see e.g. Neal, 2006). For simplicity and without loss of generality, we focus on a uniform distribution[7] so that, for an individual of type $r = B, W$,

$$F_r(w) = \frac{w - \underline{w}_r}{\overline{w}_r - \underline{w}_r} \qquad \text{if } \underline{w}_r < w < \overline{w}_r$$

$$f_r(w) = \frac{1}{\overline{w}_r - \underline{w}_r} \qquad \text{if } \underline{w}_r < w < \overline{w}_r$$

and

$$\mathbb{E}(w_B) = \frac{\underline{w}_B + \overline{w}_B}{2} < \frac{\underline{w}_W + \overline{w}_W}{2} = \mathbb{E}(w_W)$$

where $\mathbb{E}(.)$ is the expectation operator. We focus here on a model where the location of each individual is given so that the total number of people living in an area N_{ra} is fixed. Each individual w_{ra}, i.e. individual with human capital w of race $r = B, W$ and living in area $a = 1, 2$, has to decide whether he/she will commit a crime by comparing the utility of committing a crime and his/her (potential) wage corresponding to his/her human capital level. Each individual, when deciding to be a criminal or not, can commit a crime in the two areas. The key assumption that we are making is that someone who decides to commit a crime in an area when he/she does not live can do it only if he/she has some contact with people of the same race.

To be more precise, the utility of a criminal $r1$ (i.e. of race $r = B, W$ and living in area

[6] The term "black" refers here to all individuals who are nonwhites.

[7] It is easy to verify that all our results are not altered if we assume a general distribution function $F_r(.)$ instead of a uniform one.

1) is given by:

$$
\begin{aligned}
V_{r1}^{C} &= (1-p_{11})\, b(C_1) + p_{11}\left[b(C_1) - P\right] \\
&\quad + \left[1 - p_{12}\left(d, \delta_r n_{r2}\right)\right] b(C_2) + \delta_r p_{12}\left(d, \delta_r n_{r2}\right)\left[b(C_2) - P\right] \\
&= b(C_1) + b(C_2) - p_{11}\, P - \delta_r p_{12}\left(d, \delta_r n_{r2}\right) P
\end{aligned}
$$

where $0 \leq \delta_r \leq 1$. Let us explain this utility function. When an individual r_1 engages in crime, he/she can commit his/her deeds in both areas. The proceeds from crime or booty is denoted by $b(.)$ and is a negative function of the number of criminal in the area C_a. We thus have $b(C_a)$, with $b(C_a) > 0$, $\forall C_a$, and $b'(C_a) < 0$. Indeed, when there are more criminals operating in an area $a = 1, 2$, the less remains for a particular criminal (think for example of thieves where more thieves implies that there is less to steal for a particular thief) so that the return per criminal must eventually fall. As a result, the booty per criminal is a decreasing function of C_a (see for example Freeman et al., 1996, for a similar assumption). Each individual can be caught and convicted with some probability. The probability to be caught in the same area where the individual lives (here area 1) is exogenous and denoted by $p_{11} \in]0, 1[$. This probability just reflects for example the number of policemen in the area. What is crucial here is that the probability p_{12} to be caught in the area where the individual does not live (here area 2) is a increasing function of the distance d between the two areas and a negative function of the percentage of people of the same race in the area. Indeed, when someone wants to commit a crime in an area where he/she does not live, he/she needs some information about the crime possibilities in this region. So if the two areas are very far away, then information about crime opportunities is not very good and the probability to be caught is then very high. Moreover, the information about crime opportunities depends on the social network of each individual. Here we capture it by the percentage of people of the same race in the area, i.e. $n_{r2} = N_{r2}/N_2$.[8] So basically if a black individual wants to commit a crime in another area, then his/her probability to be caught will decrease with the percentage of black individuals living there. The parameter δ_r, which is race specific, determines the quality of the information transmitted by the social network. Since whites belong to the majority group so that n_{W2} is usually very high, the percentage of white persons in area 2 is certainly not a very good indication of social network and the transmission of crime information is certainly not very good within this group; we should thus expect that δ_W is very small and maybe close to zero. On the contrary, for blacks, since

[8] In their empirical analysis on Egypt, Wahba and Zenou (2005) also use population density as a proxy for the size of the social network of individuals. They show that it has a strong impact on the way workers find jobs.

they belong to the minority group, the percentage of same-ethnic group in the other region is certainly a better indicator of transmission of crime information and thus δ_B should not be too small. To summarize, we have

$$\frac{\partial p_{12}\left(d,\delta_r n_{r2}\right)}{\partial d}<0 \text{ and } \frac{\partial p_{12}\left(d,\delta_r n_{r2}\right)}{\partial n_{r2}}<0$$

Finally, the public penalty, when convicted, is P. On top of that he/she is sent to prison and therefore cannot participate to the labor market. In this formulation, a criminal activity is full time so that criminals are not able to work. The expected payoff of a non criminal is equal to:

$$V_{wr}^{NC}=w$$

where w is the wage.

Therefore, an individual w_{r1} chooses to be criminal if and only if $V_{r1}^{C}>V_{wr}^{NC}$, i.e.

$$b(C_1)+b(C_2)-p_{11}\,P-p_{12}\left(d,\delta_r n_{r2}\right)P>w$$

So the value of $\widetilde{w}_{r1}$ making an individual indifferent between crime and non crime is given by:

$$\widetilde{w}_{r1}=b(C_1)+b(C_2)-p_{11}\,P-p_{12}\left(d,\delta_r n_{r2}\right)P$$

Thus the number of criminals of race r in region 1 is given by:

$$C_{r1}=F(\widetilde{w}_{r1})=\frac{\widetilde{w}_{r1}-\underline{w}_r}{\overline{w}_r-\underline{w}_r}$$

Since

$$C_1=C_{B1}+C_{W1}$$
$$C_2=C_{B2}+C_{W2}$$

we have the following definition

Definition 1 *An equilibrium is a 4-tuple (C_{B1}, C_{W1}, C_{B2}, C_{W2}) such that the following equations are satisfied*

$$C_{B1}=\frac{b(C_{B1}+C_{W1})+b(C_{B2}+C_{W2})-p_{11}\,P-p_{12}\left(d,\delta_B n_{B2}\right)P-\underline{w}_B}{\overline{w}_B-\underline{w}_B} \tag{2}$$

$$C_{B2}=\frac{b(C_{B1}+C_{W1})+b(C_{B2}+C_{W2})-p_{22}\,P-p_{21}\left(d,\delta_B n_{B1}\right)P-\underline{w}_B}{\overline{w}_B-\underline{w}_B} \tag{3}$$

$$C_{W1}=\frac{b(C_{B1}+C_{W1})+b(C_{B2}+C_{W2})-p_{11}\,P-p_{12}\left(d,\delta_W n_{W2}\right)P-\underline{w}_W}{\overline{w}_W-\underline{w}_W} \tag{4}$$

$$C_{W2}=\frac{b(C_{B1}+C_{W1})+b(C_{B2}+C_{W2})-p_{22}\,P-p_{21}\left(d,\delta_W n_{W1}\right)P-\underline{w}_W}{\overline{w}_W-\underline{w}_W} \tag{5}$$

We are now able to state our first result.

Proposition 1 *If the difference in wages is large enough between blacks and whites, then the number of black criminals is higher than that of white criminals in each area, i.e.*

$$C_{Ba} > C_{Wa} \qquad \textit{for } a = 1, 2.$$

This result is standard and stems from the fact that whites have on average higher wages than blacks and thus are on average less likely to be criminal than blacks. The next result is new and shows the spatial correlation in crime for each ethnic group.

Proposition 2

(i) *There is spatial correlation in crime rates per ethnicity between the two areas, i.e.*

$$\frac{\partial C_{r1}}{\partial C_{r2}} > 0 \qquad \textit{for } r = B, W.$$

(ii) *The effect of distance d on crime rates per ethnicity is ambiguous.*

The spatial correlation in crime rates per ethnicity stems from the fact that the probability to commit crime in the area where the criminal does not live is the function of the percentage of individuals of same race in that area. So ethnic criminals in area 1 are affected by ethnic people living in area 2 and vice versa. As a result, crime rates are correlated between the two areas. The extend of the effect depends on the distance d between the two areas, but its sign is ambiguous, since the distance d affects equally blacks and whites. So when d increases, both blacks and whites living in one area tend to be less criminal because the probability to be caught in the other area increases but at the same time this reduces the congestion in crime and thus increases the booty, which in turn increases the crime activities.

We have a final result.

Proposition 3

(i) *For $r = B, W$, $\frac{\partial C_{r1}}{\partial n_{r2}}$ is an increasing function of δ_r and is equal to zero if $\delta_r = 0$. Furthermore,*

$$\frac{\partial C_{B1}}{\partial n_{B2}} \gtreqless 0 \Leftrightarrow \frac{2}{\overline{w}_W - \underline{w}_W} + \frac{1}{\overline{w}_B - \underline{w}_B} \lesseqgtr -\frac{1}{b'(.)}$$

$$\frac{\partial C_{W1}}{\partial n_{W2}} \gtreqless 0 \Leftrightarrow \frac{2}{\overline{w}_B - \underline{w}_B} + \frac{1}{\overline{w}_W - \underline{w}_W} \lesseqgtr -\frac{1}{b'(.)}$$

(*iii*) *The cross effect of distance* d *and ethnic population* n_{r2} *on ethnic crime* C_{r1}*, i.e.* $\frac{\partial^2 C_{r1}}{\partial d \partial n_{r2}}$*, is ambiguous.*

The effect of n_{r2}, the percentage of same-race individuals in region 2, has an impact on crime activities. However, this impact should be very small for whites since δ_W is very low because the percentage of white people in an area is not a good proxy for information about crime opportunities. Focussing on blacks, where δ_B should be a priori quite high we find that the effect of n_{B2} on blacks' crime activities in area 1 is ambiguous. However, if the distribution of wages for whites or for blacks is sufficiently spread, then the impact is positive. Since distance d had an ambiguous effect on C_{B1}, the cross effect $\frac{\partial^2 C_{r1}}{\partial d \partial n_{r2}}$ can also not be signed.

3 Empirical strategy

We would like to test these different effects using UK data. In summary, our model predicts the existence of a positive spatial correlation of crime, which is a function of distance. It is either increasing or decreasing with distance according to the relative importance of congestion and social networks effects, respectively. Secondly, taking the density of own-race residents as a measure of local contacts, the crime rate for whites should not be affected by the own-race residing population in adjacent areas, or to a lesser degree than the crime rate of blacks. Thirdly, for nonwhites, the effect of the density of nonwhite residing population is a function of distance. This effect cannot be theoretically signed, as the impact of distance of crime is ambiguous as well. Observe, however, if the basic mechanism underlying our model is at work, i.e. if social networks are important in explaining criminal behavior, spatial correlation in crime should be a negative function of distance, and the effect of the residing population on crime rate should sharply decrease with distance (as social interactions are quite localized), and, this should be particularly true for ethnic minorities.

Our empirical analysis proceeds as follows. First, in Section 3.2, we examine the existence of a positive spatial correlation in crime rates and whether it is a function of distance (Prop. 2, results (*i*) and (*ii*)). In doing so, we also estimate the contribution of our indicator of social networks in shaping this trend. A non-parametric approach is adopted. A cross-race comparison will shed some light on the (ambiguous) qualitative theoretical predictions in Prop. 3, results (*i*) and (*ii*). In Section 4, we test more explicitly the model. In particular, we quantify these effects by assessing the impact of own-race residing population on crime for each rate and the spatial scale of the results. A panel data model specification is adopted.

3.1 Data

The crime data we use comes from the crime statistics that are recorded by the police. They are compiled and published annually by the Home Office. Consistent area-level crime data by ethnicity are available for the 43 police force areas of England and Wales since 1992.[9] We thus construct a panel of police force areas covering the period 1992-2005. We use the information on total arrests for notifiable offences divided between "White", "Black", "Asian", and "Other" races of the arrested persons.[10] The data on the ethnic composition of the population residing in each area is available for the corresponding period through the Office of National Statistics (ONS). They derive from the Census data, which are updated yearly using the ONS mid-year population estimates. We use the percentage of each ethnic group population over total residing population.

We measure distance between areas in terms of both time and physical distance. We use both the average road journey time (in minutes) and the actual road distance (in kilometers) between the centres of the areas.[11] The estimated road journey time between areas in the sample varies between 23 minutes and 471 minutes, with a median journey time of approximately 229 minutes. The distance between areas in the sample varies between roughly 20 and 688 kilometers, with a median distance of 350 kilometers.

3.2 Spatial correlation in crime by ethnicity and ethnic population density

We begin our empirical analysis by providing some evidence on the spatial patterns of crime rate by ethnic group across police force areas in Britain, and on the contribution of the (average) percentage of population of each ethnic group residing in adjacent (police force) areas in shaping this trend.

We estimate the crime spatial autocorrelation as a function of distance using non-parametric techniques as described, for instance, in Conley and Topa (2002). Let $(c_i - c^m)$ be the deviation of each area i crime rate from the sample (national) mean. The estimated autocorrelation function (ACF) is obtained running a kernel regression of $(c_i - c^m)(c_j - c^m)$ on the distance

[9] Police areas in Britain are slightly bigger than NUTS 3 areas.

[10] "Black" includes Black British, Black Caribbean and Black Africans; "Asian" includes Indian, Pakistani, Bangladeshi; "Other races" is mainly Chinese (see, e.g., Home Office (2005), Appendix B).

[11] Distances in travel times and kilometers are estimated using Microsoft Autoroute 2002. The Microsoft Autoroute software computes the driving time between two locations on the basis of the most efficient route given the road network in 2002, and allowing for different average speeds of travel depending on the type of road. Distances in kilometers are calculated considering the shortest route, given the road network in 2002.

between areas i and j, which provides an estimate of the autocovariance function, and then normalizing it by dividing by the sample variance.[12] This approach permits to investigate how spatial dependence declines with distance without defining the neighborhood set of each location i, i.e. the areas that potentially interact with area i. When the regression includes the average percentage of each ethnic group population in the areas confining with area i as explanatory variable, this procedure also allows us to distinguish the portion of spatial dependence that is attributable to this variable.

We consider average values of crime rates over five -year periods (four in the last slot), i.e., 1992-1996, 1997-2001, 2002-2005, in order to eliminate short-run noise.[13]

Figures 1 and 2 contain the estimation results for the last four-year period for the different ethnic groups in the different panels, measuring spatial proximity in terms of travel time and road distance, respectively.[14] In each plot, we represent both the estimated autocorrelation function for the raw crime rate (solid line) and the one for the residuals of the regression of crime on the average population of each ethnic group residing in adjacent areas (dotted line). The values of the functions that are statistically significant at the 5 percent level are marked with circles.

[*Insert Figures* 1 *and* 2 *here*]

Looking at the solid lines in Figure 1, it appears that, for all races, the crime spatial autocorrelation decreases with distance, losing statistical significance for distances beyond approximately 100 kilometers. The estimates for the ethnic minorities then show some significant and negative values for distances around 130-140 kilometers. When looking at the contribution of our indicator of social networks in explaining this spatial autocorrelation (i.e. dotted lines), one can notice important differences across races. For whites, the estimated effects is negligible, whereas for all ethnic minorities, social interactions seem to play an important role. Indeed, in the first panel, the dotted line is still decreasing and shows significant values, while in the rest of the panels the degree of spatial correlation indicated by the dotted line disappears altogether.

The evidence collected in Figure 2, i.e. when measuring distance in terms of travel time, remains qualitatively unchanged, thus indicating its robustness to different choices of metrics. The different importance of our indicator of social networks in explaining the

[12] The smoothing function used is the one proposed by Cleveland (1979). Standard errors are based on bootstrapping 200 replications.

[13] If measurement error is an issue, to the extent that measurement error is temporary, the fact that the values have been averaged over a period of five years should mitigate this problem.

[14] The pictures for the other time-periods are similar, and the qualitative results remain unchanged.

observed patterns of local spatial correlation in crime rates between whites and nonwhites is even more evident, and the magnitude of its effect for all the ethnic minorities is larger. This is probably due to the fact that this second metric better represents how agents' contacts develop.

These findings are consistent with our theoretical model, which is based on social interactions. In particular, spatial correlation in crime appears to be positive and quite localized. The percentage of same-race individuals in neighboring areas seems to play an important role in explaining this trend for nonwhites. This relationship is further investigated and quantified in the next section.

4 Empirical model and estimation results

The main mechanism highlighted in the theoretical model is based on the idea that interactions are a function of proximity. To implement this, we create proximity bands based on driving time between areas, and measure the population by ethnic group residing within each proximity band. We choose travel time as a distance measure because, as noted above, this is reasonably the best metric to represent how agents' contacts materialize. To be specific, for each area a in our sample, we form new variables containing the percentages of ethnic population within 30 minutes driving time from area a; within 30-60 minutes, and so on. In doing so, we aim at examining whether the density of own-race individuals nearby influences the criminal activity of this ethnic group and how far this effect extends. We assume that the population of each area is massed at the economic centre of the area, so that each time band (e.g., 30-60 minutes) contains the population densities of all areas whose centre is in the band (e.g., within 30-60 minutes from the centre of area a).[15] We exploit the panel structure of our data to control for unobserved heterogeneity between areas. For each ethnic group ($r = 1, ...4$), we estimate the following model:

$$c_{a,t} = \alpha c_{a,t-1} + \sum_{s} \gamma_s n_{s,a,t} + \eta_a + \varepsilon_{a,t}, \qquad |\alpha| < 1, \qquad a = 1, ..., N;\ t = 2, ..., T, \quad (6)$$

where $c_{a,t}$ is the crime rate in area a at time t and $n_{sa,t}$ denotes the density of population within the proximity bands s. The error term is composed by an area-specific fixed effect, η_a, controlling for cross-area differences constant across time and by a white noise error

[15] The analysis has also been performed assuming that the population is evenly distributed within the area (see Rice et al., 2006, for details). The results remain qualitatively unchanged.

component, $\varepsilon_{a,t}$.[16] Observe that the empirical model does neither include any measure of the average human capital characteristics of the different areas, nor other features of the local structure of the economy (such as the unemployment rate or percentage of policemen for example). Indeed, we assume that the impact of these characteristics on the crime rate in each area is captured through the inclusion of (time) lagged values of the crime rate. The inclusion of the lagged dependent variable is thus a purely modelling device to approximate the effects of other area characteristics on local crime. In other words, we use area fixed effects to purge our estimates 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.

4.1 OLS estimates

Model (6) is estimated for each ethnic group separately. Table 1 reports the results obtained with five proximity bands; up to 30 min, 30 to 60 min, 60 to 90 min, 90 to 120 min, 120 to 150 min. In each block of the table, we display the within groups estimates, i.e. OLS where all variables are expressed in deviations from their area specific means (taken over time) for the model with and without the regional dummies.[17] In the last rows, we report the values of diagnostic tests for possible misspecification of the spatial structure of the data; one for a spatial process in the error term of the model (LM (spatial error)) and another for an omitted spatially lagged dependent variable (LM (spatial lag)).[18] In each case, the null hypothesis of no spatial dependence is tested against an alternative of spatial dependence within a specified proximity.[19] Both tests are valid only under the assumption of normality and so we show also the value of the Jacques–Bera test statistic for normality of the errors. Those tests provide evidence on the existence of spatial dependence in the data that is not fully captured by the population density bands.

For whites, we find clear evidence of misspecification, both for an omitted spatial lag and, to a lesser degree, for spatial dependence in the error term. This indicates that other factors, beyond the population density proximity bands, are important to explain the spatial

[16] The condition $|\alpha| < 1$ indicates (time) stationarity. In fact, the crime series satisfies this property.

[17] 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 15 years time-lenght any bias from using within groups is likely to be minimal (see Nickell, 1981 for example).

[18] For theoretical details on these spatial test statistics see Anselin (1992).

[19] 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 $w_{ij} = 1$ otherwise, for values of $d = \{30, 60, 90, 120, 150\}$. The highest values are reported in the table in each case.

distribution of crime for whites. For the ethnic minorities, on the contrary, the diagnostic statistics show no evidence of misspecification once regional dummies are included (second column in each block). Thus, the ethnic population density bands seem to capture entirely spatial interactions in ethnic crime.

If we compare the results for whites (first block) with those for the various ethnic minorities (second, third and fourth block), it appears that the density of white population has no effect on white crime, whereas the density of ethnic population shows a significant effect on ethnic crime for all the ethnic minorities' groups. In addition, the specification for whites is less well-determined (the figures of the $R-$squared in the first block are roughly one half of those in the other blocks). This confirms the intuition we had in the model, that is δ_W is extremely low, even close to zero, whereas for nonwhites, δ_B is strictly positive and quite high.

[*Insert Table* 1 *here*]

Focusing on the estimates of the spatial decay for the different ethnic minorities, we find positive and statistically significant effects, which are greatest within 30 minutes driving time. They then decrease quite sharply with travel time and have no effect beyond approximately 90 minutes. This pattern remains unchanged across the different ethnic minority groups. The magnitude of the effects is also similar, showing for Asians the highest values as well as the highest rate of attenuation. A one point percentage increase in the density of Asian population within 30 minutes driving time increases Asian crime rate by roughly 0.12 percentage points. It has more than four times the impact of the density of Asian population 60 minutes away, and 15 times that of the density of Asian population at 90 minutes. These patterns are consistent with our theoretical model of local interactions. In particular they appear to support the scenario where social networks, as opposed to economic incentives (congestion effects in the theoretical model), are the major driving of criminal activities. The density of own-race population seems to be a good proxy for these effects, as it is signalled by the different results obtained for whites and nonwhites.

4.2 Instrumental variable estimates

If areas that attract ethnic population also have exogenously determined characteristics (not directly observable) that affect crime then 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 constant over time. It does not account, however, for the effects of a possible endogenous sorting of a different nature. As it is standard, we address this problem by employing an instrumental variable approach. For each area, we instrument the actual population with the historical population as reported in the Census 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, apart from their effect through present-day ethnic population. We employ the Arellano and Bond (1991) instrumental variable estimator for dynamic panel data. This method consists in taking deviations from the area-specific time means to get rid of the unit-specific error term and in combining valid instruments for the lagged dependent variable and for the other endogenous variables in a GMM framework. Distributional assumptions are not needed. Given the first order autoregressive specification of our model, valid instruments for the (time) lagged dependent variable are two-time or more periods lagged variables. The Sargan test of overidentifying restrictions (Sargan, 1958) is used to choose the appropriate set of instruments, and in particular the number of lags of the dependent variable to be included in the instrumental set. Our best instrumental variable estimates for the basic specification with regional dummies are reported in Table 2. The Sargan test does not reject the null of instruments' validity. In the last rows, we also report 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 2 reveals no evidence of misspecification. The results confirm the main findings from Table 1. The magnitudes of the estimated effects are only slightly higher in magnitude.

[*Insert Table* 2 *here*]

5 Conclusion

In this paper, we focus on the analysis of spatial correlation patterns in crime for whites and nonwhites. For that, we first develop a theoretical model where social interactions in crime are captured by the fact that the probability to be arrested in a neighboring area depends on the percentage of individuals of same-race. We obtain three main predictions. First, assuming that whites and nonwhites have different wages, we find the standard result that if the difference in wages in large enough, then the number of nonwhite criminals is higher than that of white criminals in each area. Second, we show that there is spatial correlation in crime rates per ethnicity between two adjacent areas, i.e. if the crime rate of nonwhites is high (low) in one area, then it is also high (low) in the neighboring area. These spatial interactions effects depend on the distance between the two areas. Finally, the percentage of individuals of same-race influences crime decisions. The direction of the impact is ambiguous, but is more likely to be positive the more spread the wage distribution (for whites and nonwhites) is. We then test this model using data from the crime statistics that are recorded by the police in Britain. We find results that are consistent with the model. In particular, the agglomeration of a given ethnic minority group is positively related to its crime activity. Second, this effect declines quite sharply with distance.

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APPENDIX

Proof of Proposition 1. By combining (2)−(5), we easily obtain:

$$\begin{aligned}
b(C_1)+b(C_2) &= C_{B1}\left(\overline{w}_B-\underline{w}_B\right)+p_{11}\,P+p_{12}\left(d,\delta_B n_{B2}\right)P+\underline{w}_B \\
&= C_{B2}\left(\overline{w}_B-\underline{w}_B\right)+p_{22}\,P+p_{21}\left(d,\delta_B n_{B1}\right)P+\underline{w}_B \\
&= C_{W1}\left(\overline{w}_W-\underline{w}_W\right)+p_{11}\,P+p_{12}\left(d,\delta_W n_{W2}\right)P+\underline{w}_W \\
&= C_{W2}\left(\overline{w}_W-\underline{w}_W\right)+p_{22}\,P+p_{21}\left(d,\delta_W n_{W1}\right)P+\underline{w}_W
\end{aligned}$$

This implies that

$$C_{B1}=\left(\frac{\overline{w}_W-\underline{w}_W}{\overline{w}_B-\underline{w}_B}\right)C_{W1}+\frac{\overline{w}_W-\underline{w}_B}{\overline{w}_B-\underline{w}_B}+\frac{\left[p_{12}\left(d,\delta_W n_{W2}\right)-p_{12}\left(d,\delta_B n_{B2}\right)\right]}{\left(\overline{w}_B-\underline{w}_B\right)}P \tag{7}$$

$$C_{B2}=\left(\frac{\overline{w}_W-\underline{w}_W}{\overline{w}_B-\underline{w}_B}\right)C_{W2}+\frac{\overline{w}_W-\underline{w}_B}{\overline{w}_B-\underline{w}_B}+\frac{\left[p_{21}\left(d,\delta_W n_{W1}\right)-p_{21}\left(d,\delta_B n_{B1}\right)\right]}{\left(\overline{w}_B-\underline{w}_B\right)}P \tag{8}$$

and the results follow. ▮

Proof of Proposition 2. If we subtract the two first equations (2) and (3), we obtain a relationship between C_{B1} and C_{B2}:

$$C_{B1}=C_{B2}+\frac{p_{22}-p_{11}+p_{21}\left(d,\delta_B n_{B1}\right)-p_{12}\left(d,\delta_B n_{B2}\right)}{\overline{w}_B-\underline{w}_B}\,P \tag{9}$$

If we subtract the two last equations (4) and (5), we have:

$$C_{W1}=C_{W2}+\frac{p_{22}-p_{11}+p_{21}\left(d,\delta_W n_{W1}\right)-p_{12}\left(d,\delta_W n_{W2}\right)}{\overline{w}_W-\underline{w}_W}\,P \tag{10}$$

This shows the spatial correlation in crime rates per ethnicity between the two regions, i.e. $\frac{\partial C_{r1}}{\partial C_{r2}}>0$ for $r=B,W$. ▮

Proof of Proposition 3. By adding (9) and (10), we obtain:

$$\begin{aligned}
C_{B2}+C_{W2} &= C_{B1}+C_{W1} \\
&\quad -\frac{p_{22}-p_{11}+p_{21}\left(d,\delta_B n_{B1}\right)-p_{12}\left(d,\delta_B n_{B2}\right)}{\overline{w}_B-\underline{w}_B}\,P \\
&\quad -\frac{p_{22}-p_{11}+p_{21}\left(d,\delta_W n_{W1}\right)-p_{12}\left(d,\delta_W n_{W2}\right)}{\overline{w}_W-\underline{w}_W}\,P
\end{aligned}$$

Now by plugging the value of $C_{B2}+C_{W2}$ from this equation in (2), we get:

$$C_{B1}\left(\overline{w}_B-\underline{w}_B\right)=b(C_{B1}+C_{W1})-p_{11}\,P-p_{12}\left(d,\delta_B n_{B2}\right)P-\underline{w}_B \tag{11}$$
$$+b\left(\begin{array}{c} C_{B1}+C_{W1}-\frac{p_{22}-p_{11}+p_{21}(d,\delta_B n_{B1})-p_{12}(d,\delta_B n_{B2})}{\overline{w}_B-\underline{w}_B}P \\ -\frac{p_{22}-p_{11}+p_{21}(d,\delta_W n_{W1})-p_{12}(d,\delta_W n_{W2})}{\overline{w}_W-\underline{w}_W}P \end{array}\right)$$

Now observe that equations (7) and (8) can be written as:

$$C_{W1}=C_{B1}\left(\frac{\overline{w}_B-\underline{w}_B}{\overline{w}_W-\underline{w}_W}\right)-\left(\frac{\overline{w}_W-\underline{w}_B}{\overline{w}_W-\underline{w}_W}\right)+\frac{\left[p_{12}\left(d,\delta_W n_{W2}\right)-p_{12}\left(d,\delta_B n_{B2}\right)\right]}{\left(\overline{w}_W-\underline{w}_W\right)}P \tag{12}$$

Now by plugging the values of C_{W1} from equation (12) into (11), we can define implicitly the equilibrium value of C^*_{B1} as follows:

$$C^*_{B1}\left(\overline{w}_B-\underline{w}_B\right)$$

$$\begin{aligned}
= \; & b\left(C^*_{B1}+C^*_{B1}\left(\frac{\overline{w}_B-\underline{w}_B}{\overline{w}_W-\underline{w}_W}\right)-\left(\frac{\overline{w}_W-\underline{w}_B}{\overline{w}_W-\underline{w}_W}\right)+\frac{\left[p_{12}\left(d,\delta_W n_{W2}\right)-p_{12}\left(d,\delta_B n_{B2}\right)\right]}{\left(\overline{w}_W-\underline{w}_W\right)}P\right) \\
& -p_{11}\,P-p_{12}\left(d,\delta_B n_{B2}\right)P-\underline{w}_B \\
& +b\left(\begin{array}{c} C^*_{B1}+C^*_{B1}\left(\frac{\overline{w}_B-\underline{w}_B}{\overline{w}_W-\underline{w}_W}\right)-\left(\frac{\overline{w}_W-\underline{w}_B}{\overline{w}_W-\underline{w}_W}\right) \\ +\frac{\left[p_{12}(d,\delta_W n_{W2})-p_{12}(d,\delta_B n_{B2})\right]}{\left(\overline{w}_W-\underline{w}_W\right)}P-\frac{p_{22}-p_{11}+p_{21}(d,\delta_B n_{B1})-p_{12}(d,\delta_B n_{B2})}{\overline{w}_B-\underline{w}_B}P \\ -\frac{p_{22}-p_{11}+p_{21}(d,\delta_W n_{W1})-p_{12}(d,\delta_W n_{W2})}{\overline{w}_W-\underline{w}_W}P \end{array}\right)
\end{aligned}$$

By differentiating this equation, it is easy to show:

$$\begin{aligned}
\frac{\partial C^*_{B1}}{\partial n_{B2}} &= -\delta_B\frac{b'(.)\left[-\frac{p'_{12}(d,\delta_B n_{B2})}{(\overline{w}_W-\underline{w}_W)}P\right]+b'(.)\left[-\frac{p'_{12}(d,\delta_B n_{B2})}{(\overline{w}_W-\underline{w}_W)}P-\frac{p'_{12}(d,\delta_B n_{B2})}{(\overline{w}_B-\underline{w}_B)}P\right]-p'_{12}\left(d,\delta_B n_{B2}\right)P}{2b'(.)\left[1+\left(\frac{\overline{w}_B-\underline{w}_B}{\overline{w}_W-\underline{w}_W}\right)\right]-\left(\overline{w}_B-\underline{w}_B\right)} \\
&= \delta_B\frac{p'_{12}\left(d,\delta_B n_{B2}\right)P\left[\frac{2b'(.)}{(\overline{w}_W-\underline{w}_W)}+\frac{b'(.)}{(\overline{w}_B-\underline{w}_B)}+1\right]}{2b'(.)\left[1+\left(\frac{\overline{w}_B-\underline{w}_B}{\overline{w}_W-\underline{w}_W}\right)\right]-\left(\overline{w}_B-\underline{w}_B\right)}
\end{aligned}$$

so that

$$\frac{\partial C_{B1}}{\partial n_{B2}}\gtreqless 0\Leftrightarrow\frac{2}{\overline{w}_W-\underline{w}_W}+\frac{1}{\overline{w}_B-\underline{w}_B}\lesseqgtr-\frac{1}{b'(.)}$$

Following the same procedure for whites, we can define implicitly the equilibrium value of C^*_{W1} as follows:

$$
\begin{aligned}
& C^*_{W1}\left(\overline{w}_W-\underline{w}_W\right) \\
= \; & b\left(C^*_{W1}+C^*_{W1}\left(\frac{\overline{w}_W-\underline{w}_W}{\overline{w}_B-\underline{w}_B}\right)+\left(\frac{\overline{w}_W-\underline{w}_B}{\overline{w}_B-\underline{w}_B}\right)-\frac{\left[p_{12}\left(d,\delta_W n_{W2}\right)-p_{12}\left(d,\delta_B n_{B2}\right)\right]}{\left(\overline{w}_B-\underline{w}_B\right)}P\right) \\
& +b\begin{pmatrix} C^*_{W1}+C^*_{W1}\left(\frac{\overline{w}_W-\underline{w}_W}{\overline{w}_B-\underline{w}_B}\right)+\left(\frac{\overline{w}_W-\underline{w}_B}{\overline{w}_B-\underline{w}_B}\right)-\frac{\left[p_{12}(d,\delta_W n_{W2})-p_{12}(d,\delta_B n_{B2})\right]}{\left(\overline{w}_B-\underline{w}_B\right)}P \\ -\frac{p_{22}-p_{11}+p_{21}(d,\delta_B n_{B1})-p_{12}(d,\delta_B n_{B2})}{\overline{w}_B-\underline{w}_B}P \\ -\frac{p_{22}-p_{11}+p_{21}(d,\delta_W n_{W1})-p_{12}(d,\delta_W n_{W2})}{\overline{w}_W-\underline{w}_W}P \end{pmatrix} \\
& -p_{11}P-p_{12}\left(d,\delta_W n_{W2}\right)P-\underline{w}_W
\end{aligned}
$$

By differentiating this equation, we finally obtain:

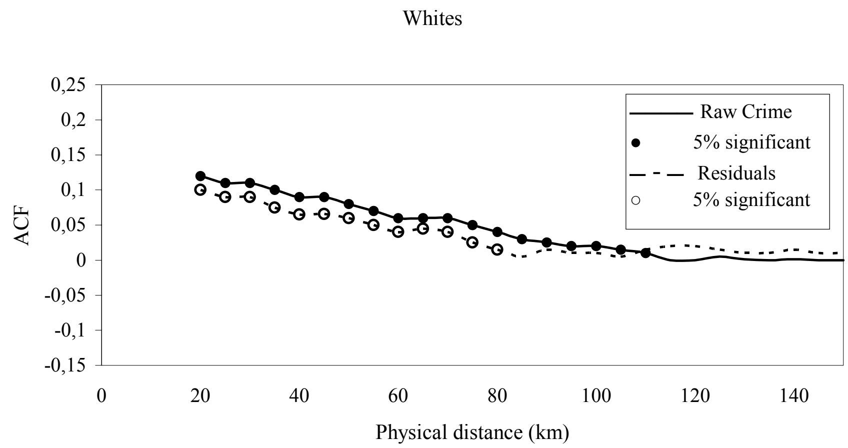
$$
\begin{aligned}
\frac{\partial C^*_{W1}}{\partial n_{W2}} &= -\delta_W\frac{b'(.)\left[-\frac{p'_{12}(d,\delta_W n_{W2})}{(\overline{w}_B-\underline{w}_B)}P\right]+b'(.)\left[-\frac{p'_{12}(d,\delta_W n_{W2})}{(\overline{w}_B-\underline{w}_B)}P-\frac{p'_{12}(d,\delta_W n_{W2})}{(\overline{w}_W-\underline{w}_W)}P\right]-p'_{12}\left(d,\delta_W n_{W2}\right)P}{2b'(.)\left[1+\frac{\overline{w}_W-\underline{w}_W}{\overline{w}_B-\underline{w}_B}\right]-\left(\overline{w}_W-\underline{w}_W\right)} \\
&= \delta_B\frac{p'_{12}\left(d,\delta_W n_{W2}\right)P\left[\frac{2b'(.)}{\overline{w}_B-\underline{w}_B}+\frac{b'(.)}{\overline{w}_W-\underline{w}_W}+1\right]}{2b'(.)\left[1+\left(\frac{\overline{w}_B-\underline{w}_B}{\overline{w}_W-\underline{w}_W}\right)\right]-\left(\overline{w}_B-\underline{w}_B\right)}
\end{aligned}
$$

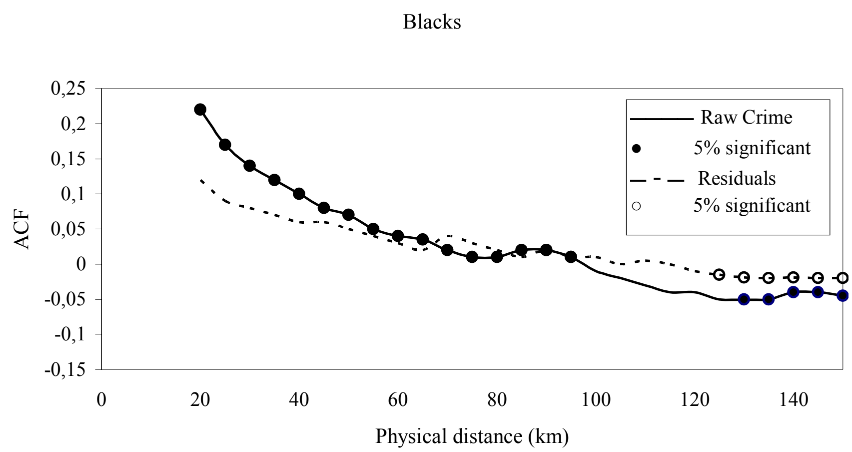
and thus

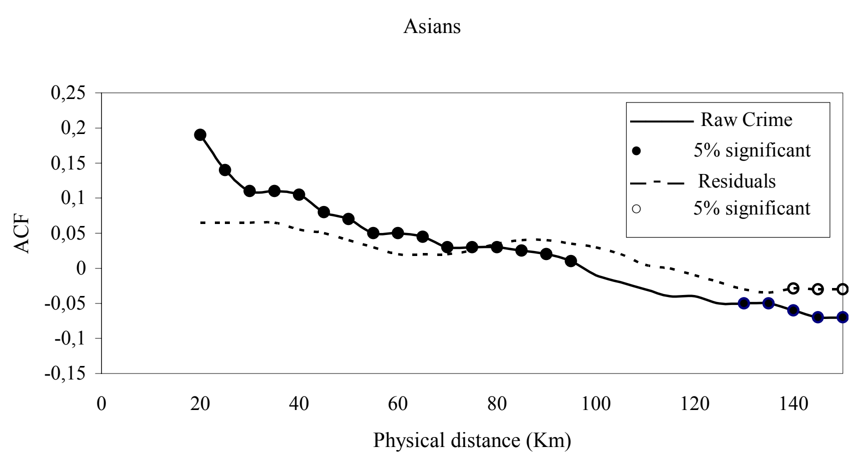
$$
\frac{\partial C^*_{W1}}{\partial n_{W2}} \gtreqless 0 \Leftrightarrow \frac{2}{\overline{w}_B-\underline{w}_B}+\frac{1}{\overline{w}_W-\underline{w}_W} \lesseqgtr -\frac{1}{b'(.)}
$$

∎

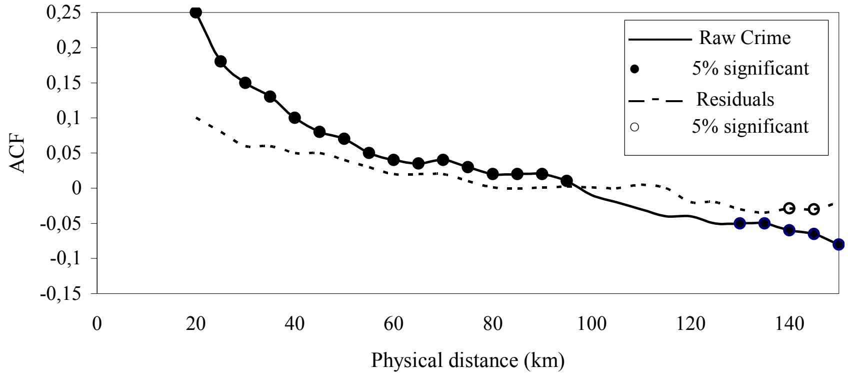
Figure 1. ACFs of crime rates by race (years 2002-2005)
- distance in kilometers-





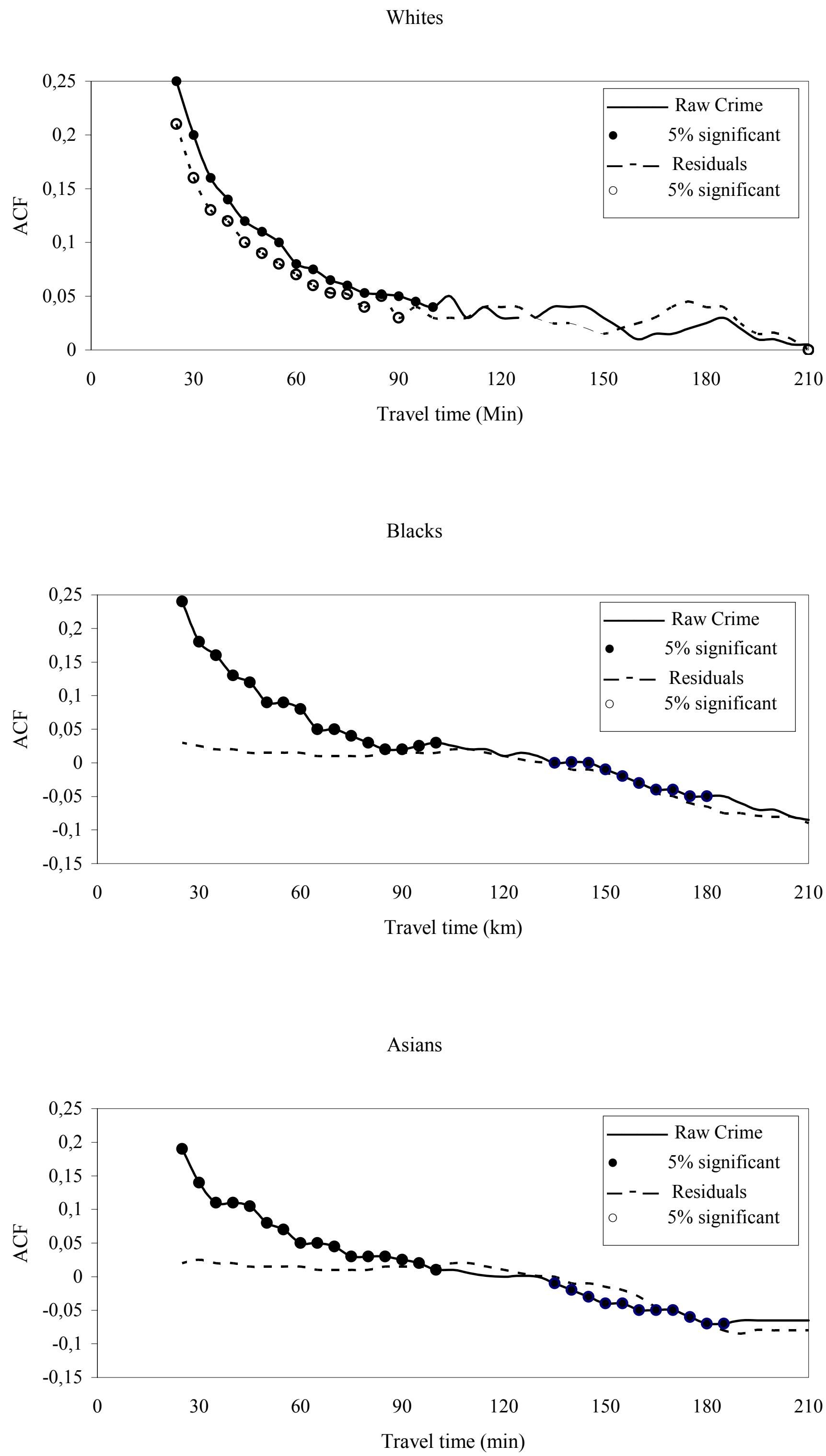


Other races



0,25
0,2
0,15
0,1
0,05
0
-0,05
-0,1
-0,15
ACF
0
20
40
60
80
100
120
140
Physical distance (km)
Raw Crime
5% significant
Residuals
5% significant

Figure 2: ACFs of crime rates by race (years 2002-2005)
- distance in minutes of road journey -



Other races

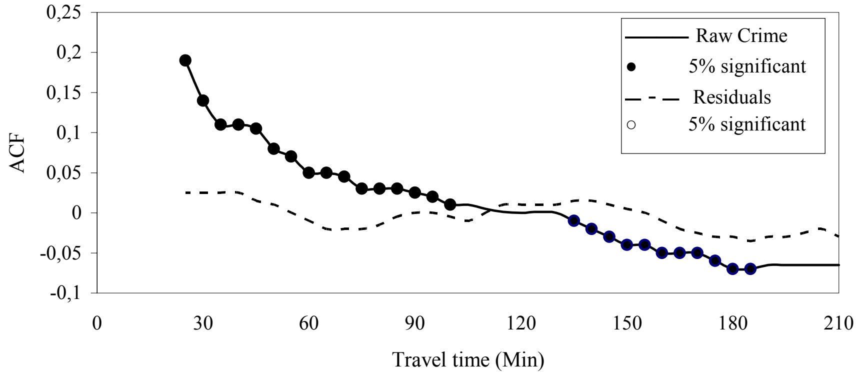

0,25
0,2
0,15
0,1
0,05
0
-0,05
-0,1
ACF
0
30
60
90
120
150
180
210
Travel time (Min)
Raw Crime
5% significant
Residuals
5% significant

Table 1. Crime and population density by ethnic group
- OLS estimates -

	Whites		Blacks		Asians		Other races	
Own group population density								
…within 30 min	0.0091 (0.30)	0.0143 (0.65)	0.0994 (3.69)	0.0967 (4.01)	0.1096 (3.41)	0.1229 (2.98)	0.0841 (3.00)	0.0904 (3.14)
… within 30-60 min	0.0204 (1.01)	0.0105 (1.16)	0.0372 (3.81)	0.0330 (4.98)	0.0204 (5.67)	0.0255 (6.84)	0.0399 (3.78)	0.0350 (3.55)
… within 60-90 min	0.0132 (1.02)	0.0096 (1.10)	0.0182 (2.07)	0.0105 (2.52)	0.0132 (2.90)	0.0080 (2.82)	0.0141 (3.00)	0.0089 (2.84)
… within 90-120 min	0.0032 (0.22)	0.0023 (0.42)	0.0093 (0.96)	0.0063 (1.16)	0.0025 (0.52)	0.0032 (1.02)	0.0052 (0.45)	0.0069 (0.95)
… within 120-150 min	0.0014 (0.10)	0.0010 (0.19)	0.0095 (0.12)	-0.0038 (0.15)	0.0004 (0.16)	-0.0008 (0.22)	0.0024 (0.10)	0.0018 (0.13)
Time lag of dependent variable	0.5098 (4.25)	0.5516 (5.32)	0.4384 (3.22)	0.4538 (3.65)	0.4109 (2.22)	0.3985 (4.35)	0.4987 (2.29)	0.4355 (3.12)
Regional dummies	no	yes	no	yes	no	yes	no	yes
R-squared	0.3865	0.4890	0.8655	0.8904	0.8655	0.9275	0.8565	0.9054
Normality	1.6254 (0.44)	1.3935 (0.50)	3.364 (0.19)	2.8750 (0.24)	1.0909 (0.58)	1.9061 (0.39)	1.1658 (0.56)	2.0113 (0.37)
LM (spatial error)	6.8752 (0.00)	4.0485 (0.00)	11.934 (0.00)	0.6125 (0.43)	9.8752 (0.00)	0.3937 (0.53)	9.3412 (0.00)	0.5355 (0.46)
LM (spatial lag)	25.040 (0.00)	17.060 (0.00)	0.5156 (0.47)	0.7388 (0.39)	0.9807 (0.32)	0.2357 (0.63)	0.1355 (0.71)	0.8583 (0.35)

Notes:
The number of observations is 645 in all cases.
Within groups parameter estimates and *t*-ratios in parentheses are reported.
The reported diagnostic test statistics with the associated probability level in parentheses are the following ones.
Normality: Jacque–Bera test for non-normal errors, distributed as chi-squared with 2 degrees of freedom; LM (spatial error): robust version of the Lagrange multiplier test for spatial autoregressive or spatial moving average errors, distributed as chi-squared with 1 degree of freedom; LM (spatial lag): robust version of the Lagrange multiplier test for spatial lag dependent variable, distributed as a chi-squared with 1 degree of freedom.
Regional dummies are at the NUTS 1 level.
Estimation using SpaceStat v1.93 (Anselin, 1995).

Table 2. Crime and population density by ethnic group
- IV estimates -

	Whites	Blacks	Asians	Other races
Own group population density				
…within 30 min	0.1701	0.1196	0.1472	0.1109
	(1.06)	(4.66)	(3.19)	(3.61)
… within 30-60 min	0.1050	0.0530	0.0425	0.0535
	(1.16)	(5.56)	(5.38)	(3.69)
… within 60-90 min	0.0095	0.0310	0.0118	0.0108
	(1.04)	(3.52)	(2.78)	(2.98)
… within 90-120 min	0.0052	0.0161	0.0095	0.0076
	(0.94)	(1.22)	(0.92)	(0.95)
… within 120-150 min	0.0022	-0.0095	-0.0015	-0.0018
	(0.21)	(0.34)	(0.12)	(0.26)
Time lag of dependent variable	0.7095	0.5938	0.5140	0.5539
	(5.23)	(3.70)	(7.12)	(6.39)
Regional dummies	yes	yes	yes	yes
R-squared	0.4890	0.8904	0.9275	0.9054
Sargan test	2.1413	1.4085	0.9854	1.0833
[7]	(0.95)	(0.98)	(0.99)	(0.99)
M_1	-5.5484	-13.615	-7.1399	-10.555
	(0.00)	(0.00)	(0.00)	(0.00)
M_2	1.064	0.8873	-0.5023	-1.0856
	(0.2874)	(0.3750)	(0.6154)	(0.2776)

Notes:
The number of observations is 645 in all cases.
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 up to (t-6); regional dummies.
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 difference between the number of overidentifying restrictions and the number of parameters;
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.
Regional dummies are at the NUTS 1 level.
Estimation using Ox version 3.0 (Doornik, 2001).