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Commuting for crime

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Abstract
People care about crime, with the spatial distribution of both actual and perceived crime affecting the amenities from living in different areas and residential decisions. The literature finds that crime tends to happen close to the offender's residence but does not clearly establish whether this is because the location of likely offenders and crime opportunities are close to each other or whether there is a high commuting cost for criminals. We use a rich administrative dataset from one of the biggest UK police forces to disentangle these two hypotheses, providing an estimate of the cost of distance and how local socio-economic characteristics affect both crimes that are committed and the offenders' location. We find that the cost of distance is very high and has a great deterrence effect. We also propose a procedure for controlling for the selection bias induced by the fact that offenders' location is only known when they are caught.

Key words: crime, commuting
JEL codes: K42

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1. Introduction

Fear of crime and actual crime rates matter to people. Political campaigns often focus on crime. In 2019 about 25% of UK respondents said that "Crime/law and order/antisocial behaviour" was their biggest concern recently, with only Brexit and the NHS named by more people[1]. There is evidence that crime rates have an important influence on economic decisions e.g. consumption decisions (Mejia and Restrepo, 2016), house prices (Gibbons, 2004), the type of economic activity in the area (Rosenthal and Ross, 2010), and satisfaction with the area (Langella and Manning, 2019a).

Crime rates[2] vary greatly across areas, being typically higher in cities than in rural areas and, within cities, higher in the inner city than the suburbs (Glaeser and Sacerdote, 1999; Zenou, 2003; Verdier and Zenou, 2004; Almeida da Matta and Viegas Andrade, 2011; Gaigne and Zenou, 2015). These differences are very persistent (Glaeser et al., 1996) and are potentially related to the socio-economic conditions of the areas e.g. many of these studies have related crime rates to local employment rates (Zenou, 2003; Verdier and Zenou, 2004; Gaigne and Zenou, 2015).

In this paper we investigate the spatial distribution of crimes and the people who commit them, in particular the role of distance in the commuting to crime patterns, and the role of socio-economic local conditions in shaping this relationship and in explaining the crime and offenders' rates in a given small area. We use unique administrative data from the Greater Manchester Police (GMP) on all crimes recorded by the police between April 2008 and March 2018. The dataset also contains information on all the known offenders, who are matched to the crimes in the dataset. The known offenders are not the universe of offenders, as not all crimes are solved and matched to an offender. This can be a source of bias, and modelling selection to solve for this bias is very important, as we will discuss later. The GMP area covers a population of 2.6 million, which makes it one of the biggest police forces in the UK in terms of population. We model the number of crimes committed in every neighbourhood by residents of every neighbourhood as a function of the distance between them, crime and offender location fixed effects. We then model the fixed effects obtained from the distance model as functions of the characteristics of these areas such as the age composition, industrial structure, and deprivation. Our approach offers several advantages relative to the existing literature.

[1] Source: Ipsos Mori, October 2019
[2] Crime rates refer to crimes per 1,000 population, similarly, offenders' rates are the number of offenders per 1,000 population.

First, it allows to investigate the reason why crime is a very local phenomenon, with most offences being committed only a short distance from the offender's home. The average car time distance in our offender-crime dataset is in fact about 10 minutes[3]. The literature on 'Journey to Crime' (JtC) started in the 1920s (Park and Burgess, 1925; Lind, 1930; White, 1932)[4] and finds that most crime is short distance. A new work by Khanna et al. (2020) exploits public transport variation in Medellin to analyse the role of segregation on crime diffusion finding that being better connected generates better labour market opportunities to criminals, reducing criminality in the area, while potentially favouring the spreading of criminal activities to other areas. This literature has also documented how JtC varies with the offenders' characteristics (among others, Capone and Nichols, 1976; Van Koppen and De Keijser, 1997; Rengert et al., 1999; Carmichael and Ward, 2001; Bernasco and Block, 2009; Townsley and Sidebottom, 2010; Andresen et al., 2014; Ackerman and Rossmo, 2015). For example, Andresen et al. (2014) show that young offenders have shorter JtC. One limitation of this literature is that it does not address why JtCs are short. It could be, for instance, that there is a high cost of distance or that more attractive locations for offenses - or more vulnerable victims or lucrative targets - tend to be close to the offender's home. Our approach allows us to disentangle the two possibilities as we obtain a separate estimate of the cost of distance and of the attractiveness of different places for offenders.

Second, our formulation allows to estimate a separate measure of the incentive to commit crimes by different people and the returns to crime in different areas. Since the seminal work of Becker (1968), the empirical research in the economics of crime has focused on factors that affect the returns to crimes. Among the most studied there are unemployment (Cantor and Land, 1985; Gould et al., 2002; Freeman, 1999; Raphael and Winter-Ebmer, 2001; Lin, 2008; Buonanno et al., 2014; Bender and Theodossiou, 2016; Hémet, 2020), job opportunities (Engelhardt, 2010; Bell et al., 2018), wage levels (Gould et al., 2002; Entorf and Spengler, 2000; Machin and Meghir, 2004), and crime revenues (Draca and Machin, 2015; Draca et al., 2019)[5]. One of the issues in estimating the impact of economic conditions on crime is that it is hard to disentangle changes in the return to crime from changes in the opportunity cost of crime. For instance, those in poorer areas with worse job opportunities

[3] We will analyse and compare different measures of distance.

[4] Ackerman and Rossmo (2015) for a thorough review of the criminology literature on this topic.

[5] Revenues and job opportunities are not the only aspects named as potential drivers of criminal activities. Among others, the literature has focused on risk attitudes and specialisation in criminal activities (Ehrlich, 1973, 1996; Viscusi, 1986); the probability of punishment, both actual (Bell et al., 2014; Buonanno et al., 2011; Chalfin and McCrary, 2017; DeAngelo, 2012; Doleac, 2017; Fisman and Miguel, 2007), and perceived (Lochner, 2007); the probability of incarceration (Barbarino and Mastrobuoni, 2016); the diffusion of self-protection tools as security systems (Vollaard and Van Ours, 2011).

may have greater incentive to become a criminal but there might be ‘less to steal’ so the returns to crime might be lower (Kang, 2016). Our approach distinguishes these two effects as we estimate separately fixed effects on the offenders’[6] and on the crime location side.

Third, we propose a method to adjust for the selection induced by the fact that offenders are only observed if found by the police and most crimes are not solved. The selection problem is acknowledged by the existing literature[7], but as far as we know, this is the first paper to control for it. It is important to adjust for this source of selection as it is most likely non-random and a potential cause of bias. For instance, the extent to which crime is local will be mis-measured if the probability solving a crime – i.e. matching an offender to a crime - is correlated with distance, which is not an unlikely hypothesis. For this reason, we model selection using response time of the police and other crime characteristics as an exogenous variation (Blanes i Vidal and Kirchmaier, 2018). The police response time is, in fact, an important determinant of the probability of solving a crime (i.e. matching a crime to an offender), it is not likely to be related to how far the offender is coming from, though, in particular in a mostly urban area as Greater Manchester where heterogeneities in terms of area remoteness are limited.

All the analysis in this paper will take into account that the described mechanisms can be different by crime type. Our analysis will be conducted separately for violent, property, and other crimes, and robustness checks will further differentiate across narrower crime type definitions.

Our main conclusions are that controlling for selection is important, and not taking it into account leads to an overestimate the ‘cost of distance’ as offenders are more likely to be found if they live closer to the crime location. However, the cost of distance still remains very high and crime a very local phenomenon. Increasing distance by just 10 minutes of car time reduces the probability of committing a crime in a given place by 92 percent for violent crimes, 83 percent for property crimes, and 93 percent for other crimes. We also find evidence that areas that are better-connected through public transport tend to have higher crime links. Halving the ratio between public transport time and car time increases the probability of observing a crime by 36 percent for violent crimes, 16 percent for property crimes, and 24 percent for other crimes.

[6] It may be that the impact of the local economic conditions varies with offender characteristics e.g. young men seem in general more sensitive to economic conditions (Fougère et al., 2009, Grogger, 1997, Grönqvist, 2011).

[7] Thaler (1977) discusses how State-level analysis is likely not to capture the local dimension of crime and finds a negative relation between the probability of being arrested and travel time to commit a crime. Deutsch et al. (1987) provide a model to explain crime location dynamics and how they change with age. Deutsch and Epstein (1998) construct a model to explain clustering of criminal activities and show that spillover effects to other areas are likely to be driven by the police activity.

We find some similarities and some differences in the impact of socio-economic characteristics of an area on the probability of observing an offender and on the probability of observing a crime. Unemployment has a positive relationship with both the probability of observing an offender and of observing a crime, though the relation is not very robust across specifications. The level of education is strongly negatively related with offenders' rates across all crime types, while it has no significant relation with crime rates in a given area.

We also analyse heterogeneities in our results both in terms of area and individual characteristics.

Our results overall suggest that crime is a local phenomenon not much because offenders live close to attractive targets, rather because of the high opportunity cost of travelling.

The plan of the paper is as follows. Section 2 describes the dataset; Section 3 discusses the model for the location of crime and our procedure for dealing with the selection bias. This model delivers a 'cost of distance' function and fixed effects for the offence and offender location. The estimated cost of distance function is also described in this section. We investigate how these parameters vary by the type of crime and offender. Section 4 then models the offender and offence area fixed effects as functions of the characteristics of the area. Section 5 provides some extensions to our main cost of distance analysis, and Section 6 concludes.

2. Data

We use administrative data from the Greater Manchester Police on all crimes handled by GMP between April 2008 and March 2018. The police initially record all cases received as incidents; a subset is then assessed to be criminal activities and coded as crimes. In this work, we focus only on crimes. GMP is one of the biggest police forces in the United Kingdom, covering an area with a population of approximately 2.6 million people with approximately 6,200 police officers (Blanes i Vidal and Kirchmaier, 2018).

The dataset contains information on over 2 million crimes. It records precise information on the timing of the crime and on its location, so we can assign each criminal offence to one of the 214 GMP CAS Wards in our analysis[8]. The dataset provides information on the type of location where the crime took place[9], and some characteristics of the crime e.g. the type of

[8] CAS Wards are population-based areas designed for the 2001 census that accounted for, at the time of creation, approximately 5,000 people, so they are relatively small areas. They are comparable to US Census Tracts.
[9] We group this information in 6 categories – in a house, in a shop or another similar commercial activity, in any other 'indoor' public place (included offices), in any 'outdoor' public place, transportation, and a residual category. In addition, a 7th category groups all non-stated types of location. Figure A1 in the Appendix illustrates the distribution of crimes by type of location.

crime. Figure 1 illustrates the distribution of crimes by type[10]. Property crimes - burglaries in particular - are the most frequently recorded crimes[11]. We exclude domestic abuse from our study as these crimes have specific features that make them difficult to compare with other crime types, for instance they tend to be perpetrated inside the house, and crime dynamics are different from other violent offences. Domestic abuse is a small proportion of the crimes in our dataset and results are not sensitive to their exclusion. We also exclude fraud from our dataset as their definition and codification has changed over time. Cyber-crimes are also excluded as they raise different spatial considerations, and we are interested in more 'traditional' type of crimes where the offender needs to be physically at the crime location.

The dataset contains very detailed administrative information on the crime and on the police response. We know the time that the police take to respond to the offence, which has been shown to have a strong impact on the probability of solving a crime (Blanes i Vidal and Kirchmaier, 2018), as well as other information on who reported the crime, how the crime was reported to the police, and the degree of importance initially attributed to the crime by the call handlers, generally based on assessment of vulnerability, threat, and risk of harm. As we will discuss in the following Section, this allows us to model the selection in the dataset and to correct for the selection bias in estimation.

The dataset contains detailed information also on the offenders and on their residential location, though obviously only for the known offenders. 22.7 percent of the crimes observed in the dataset have at least one offender matched. We have information on approximately 170,000 unique offenders with a known residence, which translates into approximately 402,000 offender-crime pairs with known crime location and offender's residence. In some instances, solved crimes do not have an address for the offender and we have to exclude these data points from our analysis. This may happen for various reasons, as, for example, if offenders have no fixed abode. The final crime-offenders dataset corresponds to approximately 362,000 individual crimes. For modelling purposes, we will treat the GMP area as a self-contained environment and therefore exclude offenders – and the related crimes

[10] If a crime falls into multiple categories, the closing code of the crime will correspond to the most serious one, so there are no duplicates by crime identifier (Home Office, 2016). For the classification of crime types we rely on the Level 3 definition used by the police (https://www.justiceinspectorates.gov.uk/hmicfrs/media/crime-tree.pdf) illustrated in Figure A2 in the Appendix.

[11] Throughout the main analysis we aggregate crime types as follows. We refer to as violent crimes to the following Level 3 categories: homicide, violence with injury, violence without injury, other sexual offences, and rape. As property crimes we refer to robbery of business property, robbery of personal property, burglary, all other theft offences, vehicle offences, theft from the person, bicycle theft, shoplifting. As a remainder category, other types of crimes will be criminal damage and arson offences, trafficking of drugs, possession of drugs, possession of weapon offences, miscellaneous crimes against society, public order offences. The 19th type of crime in the Crime Tree Level 3 classification (Figure A2) - frauds – is also excluded from our study.

– who live outside the GMP area as well as GMP residents who commit crimes in other areas[12].

As Figure 2 shows, there is a substantial heterogeneity in the solving rates across crime categories attributable to a combination of investigative effort and definition, with drug related crimes, homicides, and possession of weapon offences showing the highest matching rates. On average violent crimes tend to show higher matching rates than property crimes, with the exception of shoplifting, which is frequently a 'caught in the act' crime.
Most of the offenders are known to have committed only one crime in our observation period (Figure 3), but the distribution of the number of crimes per offender has a long right tail. Figure 4 shows the monthly trends in the overall number of crimes registered, and in the number of crimes matched to an offender. Crime numbers show a mildly decreasing trend in the first half of the period we observe, then the trend flips after 2013/2014, with an increase in the crime numbers in 2017 and in the first months of 2018. The number of crimes solved – i.e. matched to an offender - have instead been steadily decreasing during the observed period. Figure 5 shows the same graph by crime types – violent, property, and other crime. It shows that the increasing pattern in the number of crimes is driven by the trends in violent and other crimes[13], while property crimes numbers remained more stable over time. Property crimes have a lower solving rate than violent and other crimes, though the decreasing trend in solved crimes is similar across types.

The dataset contains detailed information on the residential location of the offender, which we use to construct measures of distance from the crime location. It also collects information on some characteristics of the offender, as the age, gender, ethnic group, nationality, as well some information on the charges and the court outcomes. Table 1 describes the composition of the offenders in our dataset. Looking at Panel A, which shows descriptive statistics for the full sample of matched crime-offender instances, offenders are quite young – 28 years old on average, and only a minority of offenders – 19 percent – are women. Offenders are predominantly white-Northern European (73 percent) and UK nationals (75 percent). Panel B shows the same descriptive statistics only for offenders at their first offence. The average age is slightly higher than in Panel A, 28.7 years, suggesting that younger offenders may be more likely to commit multiple offences. Figure 6 shows the age distribution of offenders at their first offence. In addition, men seem to re-offend more, as

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[12] This is approximately 5 percent of solved crimes that have a non-missing offender address. Crimes located outside GMP represent less than the 1 percent of the whole crime sample.
[13] Figure A3 in the Appendix isolates the matched crimes time series for a clearer vision of the trends.

the share of women goes up for first time offenders – 24% - the share of white-Northern European goes down instead, similarly to the share of UK nationals.

Table 2 shows some demographic characteristics[14] of the GMP area, compared to the whole of England and Wales. The demographic composition of the GMP area is in similar to the rest of England and Wales, although there are some differences. The GMP area accounts for approximately 12 percent of the total population in England and Wales, and is slightly younger, has a higher proportion of students, a lower proportion of migrants, and white people. The proportion of people with a university degree is lower than the average of the country, while the unemployment rate is higher. Fewer people are married or in a stable couple. Table 2 is interesting also in comparison to Table 1. Compared to the census demographics and reweighting the ethnic group distribution to exclude the unknown ethnicity group – so implicitly assuming that people in that category homogeneously distribute across groups – the share of whites among offenders is remarkably similar to the share in the census of population (approximately 83-85 percent). In terms of nationality, the two tables are not directly comparable, as the offender's data refer to nationality, while the census of population refers to the country of birth. In the Appendix, Table A1, we also report offenders' characteristics by type of crime. Type of crimes are quite heterogeneous both in terms of frequency and matching rate, as already shown in Figures 1 and 2, and in terms of offenders' characteristics, with property crimes being committed by, on average, younger offenders, and with a slightly higher incidence of women and of UK nationals with respect to violent crimes. Robberies and burglaries are the crimes that show the lower incidence of first offences, reflecting a higher incidence of multiple offenders.

Crimes are not homogeneously distributed across areas. Figure 7 highlights how crimes are more frequent in the Manchester city centre and in some other urban centres. Solved crimes have a slightly different spatial distribution (Figure 8) and are concentrated where crime is less frequent. Figure 9 shows the geographical distribution of the offenders to crimes ratio, a simple measure of whether an area 'exports' or 'imports' offenders. There is a lot of variation in this with no clear pattern emerging. Figures A4 to A6 in the Appendix replicate the same figures separately for the three crime categories, violent, property, and other crimes.

We now discuss our model of the location of crime.

[14] From the 2011 Census of Population, source: Nomis.

3. The Model

3.1 The Number of Crimes

Suppose that the number of crimes committed by people from area a (which we refer to as the origin area) in area b (which we refer to as the destination area) - $\widetilde{N}_{ab}$ - is given by a the following model:

$$E\left(\ln(\widetilde{N}_{ab})\right) = \beta_1 x_a + \beta_2 x_b + \beta_3 x_{ab} \tag{1}$$

i.e. is influenced by some origin area factors x_a, some destination area factors x_b and some factors varying at the origin-destination level x_{ab}, with distance being the most obvious example. One might also distinguish by the type of crime and the characteristics of the criminal e.g. their age. The Poisson model is the most natural way of estimating this model because there are a large number of zeroes for many destination-origin pairs.

This type of model can be micro-founded using a discrete-choice model in which an individual criminal is deciding in which of many areas to commit a crime. The model for the area to commit a crime can then be combined with a model for the number of criminals in an area to have a model for the total number of crimes. The multinomial logit model (McFadden, 1978)[15] is well-known to be equivalent to the Poisson model (Aitkin and Francis, 1992, Baker, 1994, Guimaraes, 2004, among others). Our model also has affinities to other origin-destination models e.g. gravity models of trade (Overman et al., 2003, among others), commuting for work (Manning and Petrongolo, 2017; Monte, et al., 2018; Amior and Manning, 2019) and residential mobility (Langella and Manning, 2019b).

However, one difference between our context and these other studies is that we only observe the location of the offender when the offender is caught and recorded. So, the number of *observed* crimes by people living area a committed in area b will be a function not just of the number of crimes committed but also of the probability of being caught. If the probability of being caught is random this does not affect the estimated model coefficients (apart from the intercept) but, if there is selection correlated with regressors there needs to be some adjustment for this as commuting for crime estimates would be biased. Non-random selection seems plausible. For example, the police may find it easier or harder to solve crimes that involve local offenders, because people in the neighbourhood may help in recognising them or, in the opposite direction, people might be afraid to collaborate due to the presence of the offender in the neighbourhood. Another example of how selection can be relevant is if high ability or highly specialised offenders are both less likely to be tracked by the police and

[15] Dahl, 2002; Kennan and Walker, 2011 among many others. Greenwood (1997) for an early review of the literature

may be choosing where to operate differently from the average offender. We now discuss how we deal with the selection problem.

3.2 Selection

The number of crimes observed committed in area b by people living area a is the number of crimes committed in area b multiplied by the probability of being detected so that the number of crimes observed to have been committed by from a in b can, modifying (1), be written as:

$$E(\ln(N_{ab})) = \beta_1 x_a + \beta_2 x_b + \beta_3 x_{ab} + \ln(\Pr(c_{ab} = 1)) \tag{2}$$

where c_{ab} is a binary indicator with 1 representing that an offender located in a being caught for an offence committed in b. This probability appears logged in (2) with a unit coefficient because it can be thought of as an offset factor in the Poisson model.

Assume that the probability of being detected is a function of an index that can be written as:

$$c^*_{ab} = \gamma_1 x_a + \gamma_2 x_b + \gamma_3 x_{ab} + \gamma_4 z_b + u_{ab} \tag{3}$$

where z_b are factors that affect the probability of being caught like whether an officer is in the vicinity, though are exogenous to (1). As usual in binary choice models, there is no need to specify a variance for u_{ab}. The expected probability may affect the number of crimes committed in (1), here we are just modelling the actual probability of being caught. The probability of being caught can be written as a function of c^*_{ab}:

$$\Pr(c_{ab} = 1) = \Pr(c^*_{ab} \geq 0) = F(\gamma_1 x_a + \gamma_2 x_b + \gamma_3 x_{ab} + \gamma_4 z_b) \tag{4}$$

Probit or logit would be common choices for this model. (4) with (3) is not estimable because both x_a and x_{ab} are not observed for those crimes where the offender is not caught.

What can be estimated is the following. Write the linear projection of x_{ab} on x_b as:

$$x_{ab} = \delta_1 x_b + v_{ab} \tag{5}$$

Substituting (5) into (3)[16] leads to a 'reduced-form' equation for the index for the probability of being caught:

$$c^*_{ab} = (\gamma_1 + \gamma_2 + \gamma_3\delta_1)x_b + \gamma_4 z_b + u_{ab} + \gamma_3 v_{ab} \tag{6}$$

This is an equation that can be estimated. Though note that the variance of the error will no longer be 1 – denote this by σ_1.

$$c^*_{ab} = \gamma_3[x_{ab} - \delta_1 x_b] + \sigma_1 \hat{c}_{ab} + u_{ab} = \gamma_3 v_{ab} + \sigma_1 \hat{c}_{ab} + u_{ab} \tag{7}$$

[16] Formally, one is also required to project the origin dummies on all the destination dummies but this does not have to be estimated as it leads to a model with a perfect fit in which the origin dummy for a ward is explained by the destination dummy for that ward, so it leads to an identity between the two set of location fixed effects.

In which case (2) can be written as:

$$E(\ln(N_{ab})) = \beta_1 x_a + \beta_2 x_b + \beta_3 x_{ab} + \ln\left(F(\gamma_3 v_{ab} + \sigma_1 \hat{c}_{ab})\right) \quad (8)$$

We take a first-order Taylor series expansion of (8) about the value $v_{ab} = 0$ so that (8) can be written as:

$$E(\ln(N_{ab})) = \beta_1 x_a + \beta_2 x_a + \beta_3 x_{ab} + \ln\big(F(\sigma_1 \hat{c}_{ab})\big) + \frac{F'(\sigma_1 \hat{c}_{ab})}{F(\sigma_1 \hat{c}_{ab})}\gamma_3 v_{ab} \quad (9)$$

If F has a logistic form, then this can be written as:

$$E(\ln(N_{ab})) = \beta_1 x_a + \beta_2 x_a + \beta_3 x_{ab} + \ln\big(F(\sigma_1 \hat{c}_{ab})\big) + [1 - F(\sigma_1 \hat{c}_{ab})]\gamma_3 v_{ab} \quad (10)$$

The best estimate of the probability of being caught based on crime location factors alone appears as an off-set factor but the final term reflects the fact that there may also be a correlation of the probability of being caught with some of the criminal location factors e.g. it may be correlated with distance. The error term v_{ab} is simply a linear function of the other regressors so separate identification is problematic. Our approach is to note that the extent of selection depends on the probability of being caught – if this is one there is no selection. So, we identify the underlying effect by using this result.

This suggests using the estimated log probabilities of being caught as an offset parameter, and the residual from the projection of x_{ab} on x_b interacted with one minus the probability of being caught as a control in the model. We now turn to our empirical implementation.

4. Results

4.1 Empirical specification

Our basic empirical implementation of (1) includes a full set of origin and destination area fixed effects. CAS Wards are our area of interest, and there are 214 of them in the GMP area[17]. We include a broad set of time effects[18].

We also include a measure of the distance between each pair of wards. One question is whether the CAS Ward is a small enough area definition to fully capture the variation in distance. Figure 10 shows the comparison between the cumulative distribution of crime and offender location pairs with two different distance measures. The first is the exact distance between the crime and offender's locations[19], the second is the distance between the CAS

[17] We define crime location as the CAS Ward where the crime took place. CAS Wards are areas defined according to the 2001 Census of population. They were initially designed to account for approximately 5,000 people each. There are 214 CAS Wards in the GMP area, each of them accounted for approximately 13,000 people in 2011.

[18] We include fixed effects for year, month, day of the month, day of the week, hour of the day, day of the week interacted with month, and hour interacted with day of the week. The time refers to the opening time of the crime log. The hour of the day*week interaction is important as, some hours of the day, in some particular days are likely to be busier, and this could potentially influence the response time and the probability of finding an offender.

[19] We have the Easting and Northing of both the crime location and of the offender's residence.

Ward centroids of the crime and offender's locations. The closeness of the two distributions is remarkably high. We therefore can use CAS Wards distance without too much information loss.

The distance between two points can be defined in various ways. We can calculate the Euclidean distance between two points, or we can compute the travel distance or time between locations using different modes of transport (e.g. car, walking or public transport)[20]. As we are studying a self-contained urban area, the correlation between the different distance measures is very high (Table 3). In our main analysis we use a combination of car time and public transport time. Namely, in our main model, we include a linear car time term and the ratio between public transport time and car time, to capture the level of connection of a given area via the public transport network. The reason to do so is twofold. First, according to the 2011 Census of Population, 88% of people commuting within GMP area are doing so by car, so car time is relevant for the general commuting in this area. Public transport time though may also carry some additional variation, being the measure that is less correlated with the other distance measures (Table 3). So having a measure that combines both of them thus may be a good balance of different proxies. Second, transport time - either by car or by public transport - is a measure that is easier to interpret in economic terms compared to physical distance.

As illustrated by Equation (6), to address selection we need controls z_b that influence the probability of finding an offender for a given crime, while being exogenous to the commuting for crime model. The GMP dataset provides some variation that fits these conditions. Namely, we have information on the police response time to the crime, which is likely to affect the probability of matching a crime to an offender. The identification assumption is that the police response time is not directly connected to the distance to crime.

We follow Blanes i Vidal and Kirchmaier (2018) and we construct the response time as the difference, in minutes, between the time when the case is open and the time when the police arrives on the crime scene. As expected, the response time is on average lower for the matched crimes, as Table 4 shows. There are cases where the police are not required to arrive on the crime scene. For these crimes the time when the police arrive to the crime scene is not available. This happens for 43 percent of all crimes, but only for 14 percent of matched crimes. As we want to have a proxy for all crimes, we will impute the response time for these cases using the closing time of the crime as recorded by the GMP police. We include this

[20] We obtained car and public transport distance (in km) between CAS Ward centroids, as well as car and public transport time (in minutes), calculated using average traffic conditions, using HERE technologies.

imputed measure in the selection model, controlling for the imputed records with a dummy indicator.

We also include a set of controls that are likely to affect the probability of tracking an offender. For instance, we include the priority degree assigned to the incident by the call handler. According to the GMP Graded Response Policy (Blanes i Vidal and Kirchmaier, 2018), grades prescribe policies for the time to response of the police officers. For example, Grade 1 corresponds to events that require immediate response (within 15 minutes). Table 4 shows the distribution of the first 3 degrees of priority for both all crimes (Panel A) and only for the crimes matched to an offender (Panel B). As one may expect, priority grades 1 and 2 are overrepresented among matched crimes.

We also include variables on how the crime was reported to the police, who reported the crime, and the type of crime location. Crimes reported directly by the police are overrepresented among matched crimes, while crimes reported by the victim are less frequent in this group. The distribution of the type of location where the crime happened is instead quite similar across all crimes and matched ones, with the exception of shops/commercial location, that are overrepresented among matched crimes, perhaps related to the higher incidence in these locations of ‘caught in the act’ crimes as shoplifting.

4.2 The first stage: the probability of being caught

We estimate the model for the probability of being caught separately for violent, property, and other crimes, as in our main analysis we keep these as three separate categories. As controls we include the crime sub-categories as there is a great deal of heterogeneity in the share of matched crimes depending on the type of crime, as shown in Figure 2. The highest matching rates are the ones of possession of drugs and drugs trafficking, homicides, and for possession of weapon offences. We also control for the type of location where the crime occurred. As Figure A7 in the Appendix shows, crimes that happen in shops or other commercial locations are the ones with a higher matching rate.

Table 5 shows the estimated results for the selection model of Equation (6), separately for the different crime categories. All variables included are in general significant and of the expected sign. As expected, the higher the response time is, the lower is the probability of matching a crime to an offender. The response time has a slightly smaller influence on the probability of finding an offender for violent crimes than for other crime types. From these three models we derive the predicted matching probabilities of that will be used to control for selection in the distance cost function model as illustrated by Equation (10).

4.3 The estimated 'cost of distance'

As for our first stage model, we separately study property crimes, which include robberies[21], burglaries, vehicle thefts, shoplifting, and other thefts; violent crimes, which include homicides, sexual offences, and other violence against the person; and other crimes, which we define as a residual category that include criminal damage and arson, drug use and drug trafficking, and other crimes against society. Different types of crimes are likely to have different commuting patterns (Rossmo, 2005), and also to have different origin and destination area effects. As mentioned in the Section 2, we exclude from this study domestic abuse, as it tends not to be related to any commuting; moreover, our data do not include cyber-crimes, which also pose some issues in the commuting definition, as well as we exclude crimes committed by people with no fixed abode. Table 6 shows the average distance by crime type, while Figure 11 the distribution of crime numbers by our measure of distance.

Table 7 shows our main results for the commuting for crime models. Panel A shows the results for models that do not control for selection. As illustrated in Section 4.1, in our main specification we include both car time and a measure of the ratio between public transport time and car time. Figure A8 in the appendix visually compares different functional forms. All functional forms illustrated in Figure A8 include public transport over car time ratio while modifying the functional form of the car time term. The linear car time functional form does similarly well than other functional form, with the advantage of being simpler both for the estimation and for the interpretation, so we stick to this specification throughout our paper.

For all the three crime categories, the impact of distance is large and highly significant, implying a fast decay of the probability of committing a crime in a specific place with the increase of car time. The negative sign implies that most of the crimes tend to be very local. For instance, for violent crimes, just increasing car time distance by 10 minutes - while fixing, in a simplifying exercise, the public transport to car time ratio - brings down the probability of committing a violent crime in that area by approximately 95 percent. A very similar effect is found for other crimes. Property crimes are slightly less sensitive to distance, as increasing distance by 10 minutes brings down the probability of committing a property

[21] Due to their mixed nature, robberies are sometimes defined as violent crimes and sometimes as property crimes. We follow the suggestion in Andresen et al. (2014) that highlight how crime location choice patterns when robberies are considered are more in line with property crimes rather than with violent crimes.

crime in that area by ‘only’ 91 percent. Moreover, doubling the ratio between public transport time and car time reduces the probability of committing a crime by 36 percent for violent crimes, 18 percent for property crimes, and 32 percent for other crimes.

This is in line with the criminology literature on short journeys to crime but our results control for unrestricted origin and destination fixed effects which is not done in other studies and allow us to rule out the possibility that crimes tend to be local because criminals and criminal opportunities are located close together. In Section 5.3 we will provide some results that directly replicate in our context the estimations illustrated in the main criminology papers on distance to crime.

Panel B shows the results for models that include selection controls as illustrated by Equation (10). In those models we control for an interaction between one minus the predicted probability of matching a crime with an offender, and the residualised version of distance. The logarithm of the estimated probability of matching a crime with an offender is included in the model as an offset parameter. Controlling for selection gives results that are similar to the basic results of Panel A, though reducing the influence of distance for all crime types. This suggest that the selection bias is going in the direction of overestimating the importance of distance, this may be due, for instance, to more local crimes being more easily solved. Controlling for selection we find that increasing car time distance by 10 minutes – fixing the public transport distance ratio - reduces the probability of committing a crime in a given place by 92 percent for violent crimes, 83 percent for property crimes, and 93 percent for other crimes. Marginal effects the ratio between public transport time and car time is quite similar to what we find without selection controls. Doubling the ratio reduces the probability of committing a crime by 36 percent for violent crimes, 16 percent for property crimes, and 24 percent for other crimes[22].

We also estimate the model for narrower crime categories. Table A3 shows the estimated results. Within property crimes, burglaries and robberies have a lower cost of distance. Within violent crimes, sexual offences are the more ‘local’ crime category, while looking at other crimes, criminal damage and arson offences are the ones that have a higher cost of distance and are therefore more likely to be perpetrated by a local offender.

[22] To compare the effects of different distance measures, in Table A2 we estimate a double degree polynomial in each of the distance measures available to us. All models in Table A2 control for selection. For all crime types, the impact of distance is much lower when estimated with public transport time, while it’s bigger when estimated with Euclidean distance. Results obtained with physical car and public transport distance are instead very similar to results with car time. Those models are not directly comparable with our main model, though they provide an interesting comparison among different measures, and some more basis to use a mix of car and public transport time in our analysis, given the different results obtained when using the two separately.

Overall, our results suggest that that controlling for selection is important and tends to reduce the extent to which crime is local and alters the perspective on how close to the offenders' locations different types of crimes are. However, crime does remain very local, with violent and other crimes even more local than property crimes, in line with results obtained in the literature using victimisation data for France (Hémet, 2020).

In the Appendix we present some robustness checks on our results. Table A4 restricts the sample to crimes that are concluded, Table A5 restrict the analysis to crimes that have been charged or summonsed, Table A6 includes only to crimes with Immediate or Prompt response grades. In all cases, results are very similar to the corresponding Panels A and B of Table 7. Table A7 restricts the sample to a period where the selection should be relatively lower, as the crime-offender matching rates were higher, that is to say until December 2013. Also, in this case results are similar to Panels A and B of Table 7.

4.4 Local level characteristics influencing the crime and offenders' location

The results reported so far contain origin and destination area fixed effects. The origin area fixed effects contain information on which areas have more offenders while the destination area fixed effects contain information on which areas are more attractive as a location for crime. This section relates these estimated fixed effects to characteristics of the areas. This is useful because it allows us to disentangle the way local conditions influence the number of offenders in an area from the way they affect the crime incidence in the areas. In doing this, we draw on the large body of research that tries to explain the economic drivers of crime.

We estimate the following model:

$$\phi_a^{c,o} = \gamma X_a^{c,o} + u_a^{c,o} \tag{11}$$

We estimate two versions of (11), one for the origin and one for the destination fixed effects derived from our estimates of Equation (10) illustrated in Table 7, panel B. $X_a^{c,o}$ are crime location and offenders' location characteristics. $u_a^{j,i}$ is the idiosyncratic error term.

In both cases, the location characteristics set includes census information as the age distribution of the population, total population, share of married couples, share of foreigners, and share of people with a higher education degree, unemployment rate and share of student. We also include information from the Business Register and Employment Survey, to control for the industrial distribution of the employment in the area, and controls for the occupation composition of the area.

Table 8 shows the results for the model described by Equation (11) when estimated for the offenders' location fixed effects. Though it is well known that offenders tend to be young, the age distribution of people in the area is not particularly significant, only the coefficient for population above 65 is negative and significant for all crime types. For all crime types, offenders are less frequent where more couples live and where businesses are denser, and population density is higher. Unemployment has a positive relation with the incidence of known offenders, as it can be expected given that areas with high unemployment have fewer opportunities for work in the labour market, though the coefficient is significant only for other crimes. Areas with more university graduates have fewer known offenders in their population, with a bigger impact on property crimes. Education is generally found as a factor that reduces the probability of becoming a convicted offender (Lochner and Moretti, 2004; Machin et al., 2011; Fella and Gallipoli, 2014; Lochner, 2020), it is therefore not surprising to find a negative relation between education levels and crime. Also, the occupation composition of the area has a role in explaining the distribution of offenders, while the industrial composition is less relevant.

In Table 9 we replicate the estimates with the destination fixed effects as dependent variables. These estimates can be interpreted as investigating the area characteristics that make some locations more attractive to commit crimes. In this case both unemployment rates and university degree rates do not have a crucial role in explaining the crime location. One might expect that low unemployment areas are more attractive locations for crimes, especially property crimes, but it may also be the case that there are greater crime prevention measures by households (Vollaard and Van Ours, 2011). As for the offender fixed effects specifications, the age distribution of the population in the area is not particularly relevant. The business density is quite relevant for crime locations. Population density is negatively related to the crime incidence, while the occupation distribution does not seem relevant on the crime incidence side. Overall the impact of unemployment is weak both on the offenders' and the crime side, in line with other studies (Cantor and Land, 1985; Gould et al., 2002; Freeman, 1999; Bender and Theodossiou, 2016; Hémet, 2020).

Tables A8 and A9 replicate the fixed effects models for narrower crime categories. Table A8 illustrates the results for the offenders' location fixed effects. Results illustrate that the positive effect of unemployment on offenders' rate for violent crimes is driven by violence without injury. Also, the impact of unemployment is not statistically different from zero for most the crimes, with the exception of shoplifting. The negative impact of education is there for all crime types, with a greater negative effect on burglaries and other thefts. Also the impact of the fraction of couples and population density is there for all crime types, though there is some degree of heterogeneity in the relation across crime types. Looking at the narrow crime categories, the business density is negatively related with a higher prevalence of offenders in robberies, burglaries, and shoplifting.

Table A9 illustrates the results for the crime location fixed effects. In this case unemployment is negatively related to other thefts and sexual offences. The presence of married/stable couples is negatively related with all property crime categories, as well as with sexual offences and criminal damage. Population density is negatively related with most of the crime categories, while a positive relation is found for almost all categories with business density and the rate of foreigners in the population. Drug related crimes are less prevalent where the rate of population belonging to ethnic minorities is higher. The analysis on narrow crime categories highlights that the positive relation between property crimes and commercial activities is driven by shoplifting and other personal thefts.

5 Extensions

5.1 Interactions of distance with area characteristics

In Section 4 we analysed how far offenders travel in a commuting-type framework. It is also relevant to understand whether the characteristics of both the area where offenders come from and in the potential crime area affect the commuting to crime patterns.

To do so we modify the model illustrated by Equation (10) to include interactions between distance and area level characteristics:

$$E(\ln(N_{ab})) = \beta_1 x_b + \beta_2 x_{ab} + \delta_1 x_{ab} x_b + \delta_2 x_{ab} x_a + \ln\big(F(\sigma_1 \hat{c}_{ab})\big) + [1 - F(\sigma_1 \hat{c}_{ab})]\gamma_2 v_{ab} \quad (11)$$

We focus on how commuting for crime changes with respect to local unemployment and the average level of education in the area, two variables that are relevant in explaining the incidence of both crime and offenders in an area according to our fixed effects models. Table 10 shows the results we obtain. Higher unemployment in the area where a potential offender lives makes the travel to offend shorter both for violent and other crimes. The same applies for areas with a higher incidence of people with university degree. Higher unemployment at the offender's location does not seem to have much effect on heterogeneities.

5.2 Heterogeneities with respect to offenders' characteristics

To understand whether offenders with different characteristics have different commuting for crime patterns we re-estimate the model illustrated by Equation (10) on different subsamples of the offenders' population. Table 11 compares the results on the different subsamples by type of crime.

Age is a characteristic that has been showed to be relevant for distance to crime and our data shows similar age-distance patterns to what previous literature finds (Andresen et al., 2014; Ackerman and Rossmo, 2015), distance increases steeply with age up until the early 20s, while it decreases since the late 20s onwards (Figure 12). We divide the sample in three categories, offenders younger than 25, between 25 and 34 and older than 35, and we replicate our distance cost function in the different subgroups. Columns 1-3 of Table 11 shows the results we obtain. For all crime types older offenders tend to be more local, while offenders in the youngest category seem to be willing to travel slightly further to commit a crime. The gradient of the effect across the age groups is increasing for violent and property crimes, while for other crimes the relation looks a bit more U shaped, though also in this case the older category is the least mobile one.

The other aspect that we compare are gender differences (Columns 4 and 5 of Table 11). For all crime types women are less mobile than men, so more sensitive to distance.

The third aspect that we analyse are differences in terms of nationality of the offender (Columns 6 and 7 of Table 11). For all crimes offenders of British nationality are willing to travel less than foreigners.

The last aspect we analyse is ethnic identity (Columns 8 and 9 of Table 11). For all crime types, white offenders tend to be more sensitive to distance than non-white offenders.

5.3 'Traditional' distance function

Papers in the criminology literature have estimated the impact of distance on crime using different methodologies from that used in this paper. In what follows we estimate a model closer to the standard of that literature, in order to compare our data and results. In this, we follow the model proposed in Ackerman and Rossmo (2015) and we estimate the following equation:

$$d_{oct} = \beta_1 X_{ot} + \beta_2 A_{ot} + \beta_3 X_{ct} + \theta_t + u_{oct} \qquad (12)$$

where d_{oct} is the distance covered by the offender o to commit crime c at time t. X_{ot} are characteristics of the offender, A_{ot} are characteristics of the area where the offender lives, and X_{ct} are crime characteristics, θ_t are time fixed effects[23], and u_{oct} is the idiosyncratic error term.

Compared to our approach, there are two disadvantages of these regressions. First, while these models tell us about the average distance to crime, they cannot tell us about the number of crimes and how this is affected by distance. In contrast, our approach uses the number of crimes as the dependent variable. Second, there is no simple way to control for the attractiveness of destination areas as targets for crime; typically, the regressors are individual characteristics and origin area characteristics. As emphasized in the introduction, this means that one cannot distinguish between two hypotheses for why most crime is local (the cost of distance is high, or offenders live close to attractive targets). In contrast our approach is designed to be able to separately estimate a cost of distance and the attractiveness of different areas as targets for crime. There is, however, one advantage to the traditional approach: it is somewhat easier to allow the cost of distance to vary by individual characteristics although this is possible within our framework as well as shown by the results in the previous section. With these considerations in mind, Table 12 shows the estimated results for Equation (12). In the first column we only include the type of crime indicators and time fixed effects. In line with what we find in our main analysis, also in these specifications we find that violent crimes tend to be more local than property crimes, and there is quite a bit of heterogeneity between crime types, even within broad categories. In column (2) we also include offenders' demographics. As in Ackerman and Rossmo (2015), we include a third-degree polynomial of age, finding similar results, though in the UK the relation between age and distance appears to be stronger than what Ackerman and Rossmo (2015) find for Texas. The coefficients of other variables are though different to what they find for Texas. For instance, women in our context tend to travel less than men, while black and other ethnic minority groups tend to travel more.

In Column (3) we also include some census variables at the area of origin, i.e. offenders' residence, level. We find offenders from high unemployment areas tend to travel less. Offenders from areas with higher unemployment, more couples, with a higher population and business density, and with a higher incidence of ethnic minorities tend to travel less, while offenders from areas with a higher incidence of people born abroad tend to travel further away. The coefficients of crime types and offenders' characteristics do not change much with the inclusion of area level controls.

[23] We include fixed effects for year, month, day of the month, day of the week, hour of the day, day of the week interacted with month, and hour interacted with day of the week.

As all the controls included do not allow to control for every characteristic at the area of origin level that might affect the distance covered, so in Column (4) we include area of origin fixed effects. As the area level controls were measured just by one single Census during the observation period, area level controls are mechanically absorbed by fixed effects. Results are quite similar to the ones in Column (2) and (3). To control also for other factors that may influence the distance at which offenders travel to commit a crime, in Column (5) we also include destination fixed effects, i.e. crime location. Results are similar to the previous specifications.

5. Conclusion

In this paper we analyse the commuting to crime patterns of offenders in one of the biggest UK urban areas. We use a unique administrative dataset of the Greater Manchester Police Force that collects detailed information on the location of crimes as well as the location of offenders. From this analysis we exclude domestic abuse, as it tends not to involve commuting, cyber-crimes, for which offenders do not have to be physically present at the location of the offence, and crimes committed by people with no fixed abode.

We model the number of crimes committed in every neighbourhood by residents of every neighbourhood as a function of the distance between them, offence and offender location fixed effects. We then model the crime and offender's area fixed effects obtained from the distance model as separate functions of the characteristics of these areas such as the age composition, industrial structure, and deprivation. With this setting, we can distinguish between the role of commuting costs and the role of local characteristics in explaining the commuting for crime patterns.

We find that crimes tend in general to be very close to the offenders' location, with violent crimes more so than property crimes. We find it is important to control for the potential selection bias caused by the fact that one only observes the location of offenders when they are caught. After controlling for selection, increasing car time distance by 10 minutes reduces the probability of committing a crime in a given place by 92 percent for violent crimes, 83 percent for property crimes, and 93 percent for other crimes. Sensitivity to distance is heterogeneous across individuals' characteristics. For instance, younger offenders and men tend to travel more to commit a crime, across all crime types.

We then study how local socio-economic conditions affect offenders' fixed effects and crime location fixed effects. We find that area level characteristics affect crime location and offenders' location in different ways. Unemployment is positively related with both the probability of observing an offender and of observing a crime, though the relation is not very robust across specifications. The level of education is negatively related with offenders' incidence across all crime types, while it has no significant relation with crime incidence.

Overall our findings suggest that the cost of distance is a big driver of the crime location, crimes appear to be very local due to this high commuting cost, rather than to the appeal of the areas surrounding the offender's location. In this paper we describe commuting for crimes patterns rather than the effectiveness of the police response, though the local dimension of crime may point to the fact that also the police response should be local. To have a definite answer to what is the optimal police reaction though, more study in this respect is required and left for future research.

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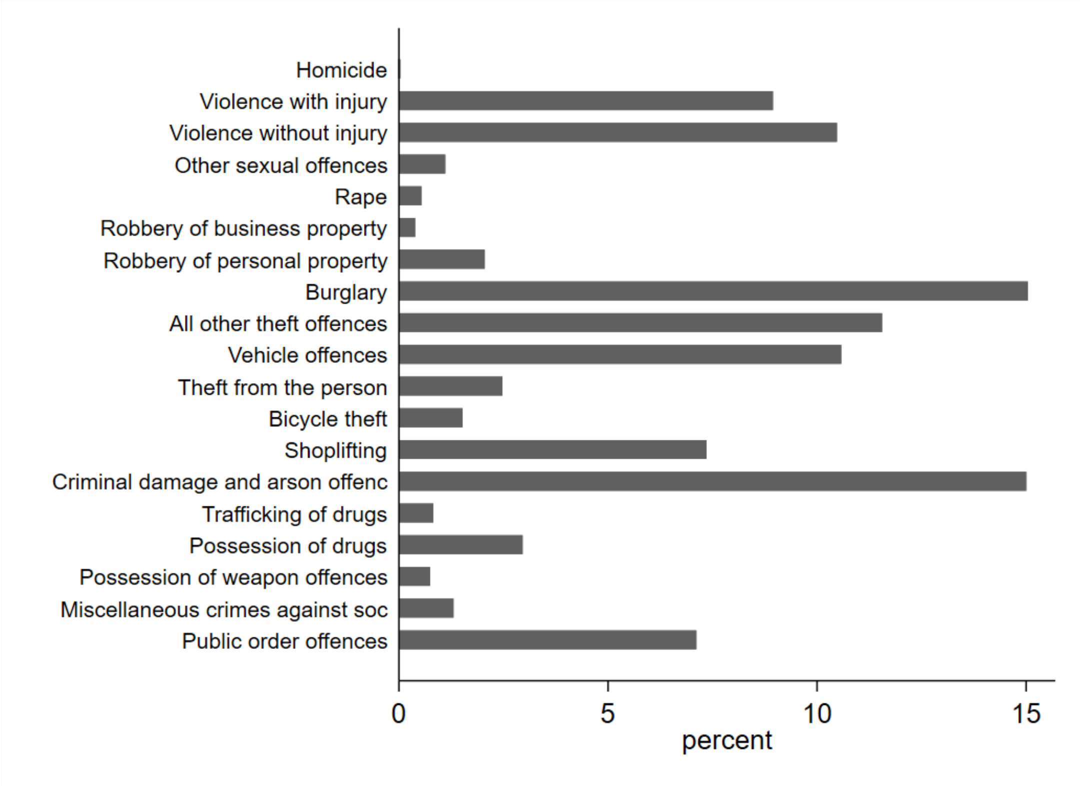
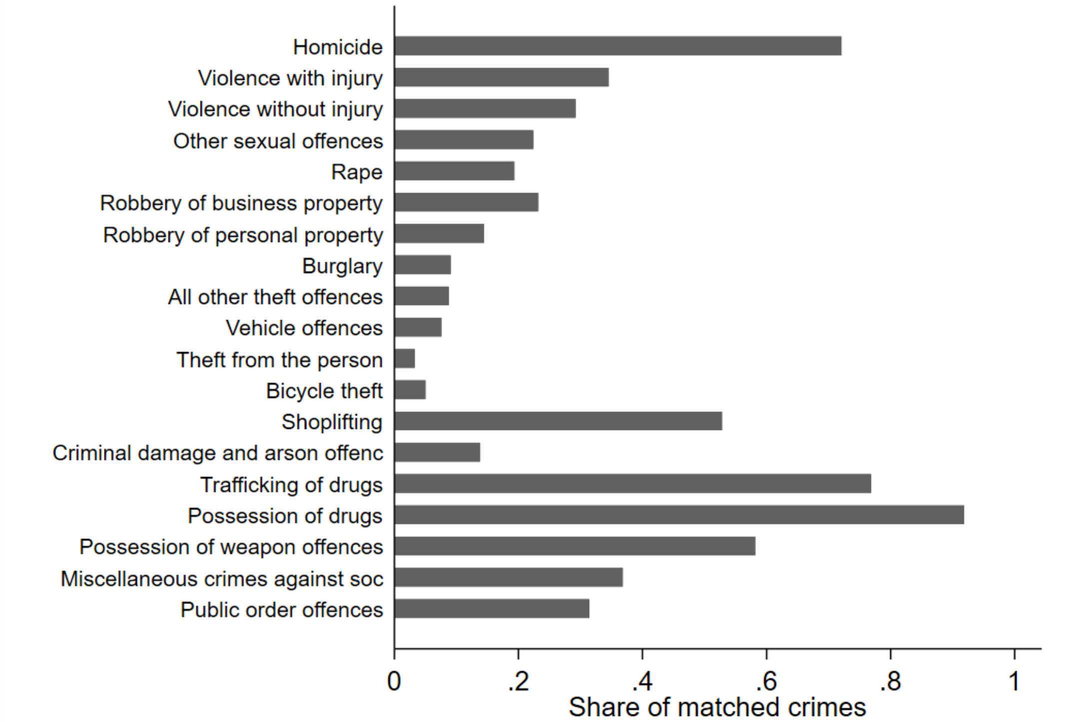
Figures

Figure 1. Distribution of crime types



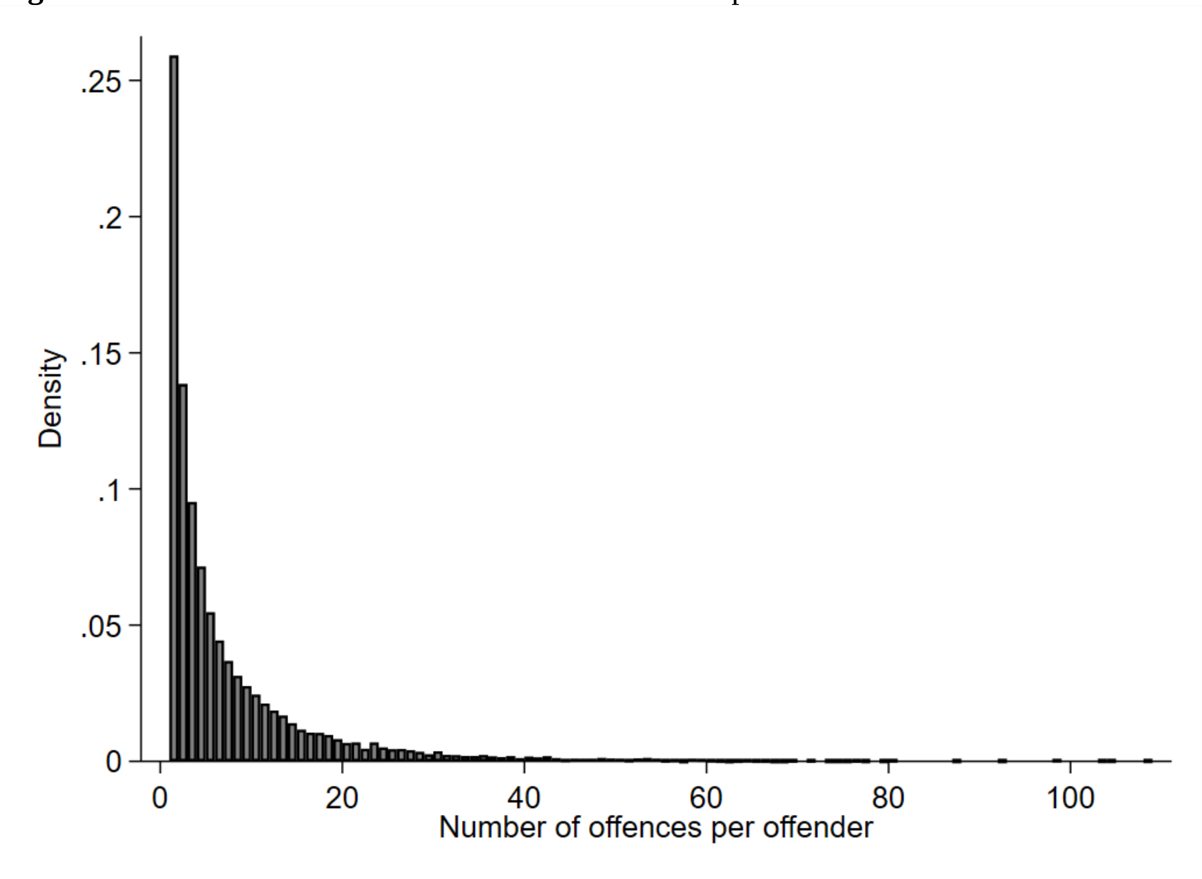
Source: Authors' elaboration of GMP police force data. The crime categorisation follows the Crime Tree Level 3 illustrated in Figure A2 of the Appendix.

Figure 2. Distribution of matched crimes by crime types



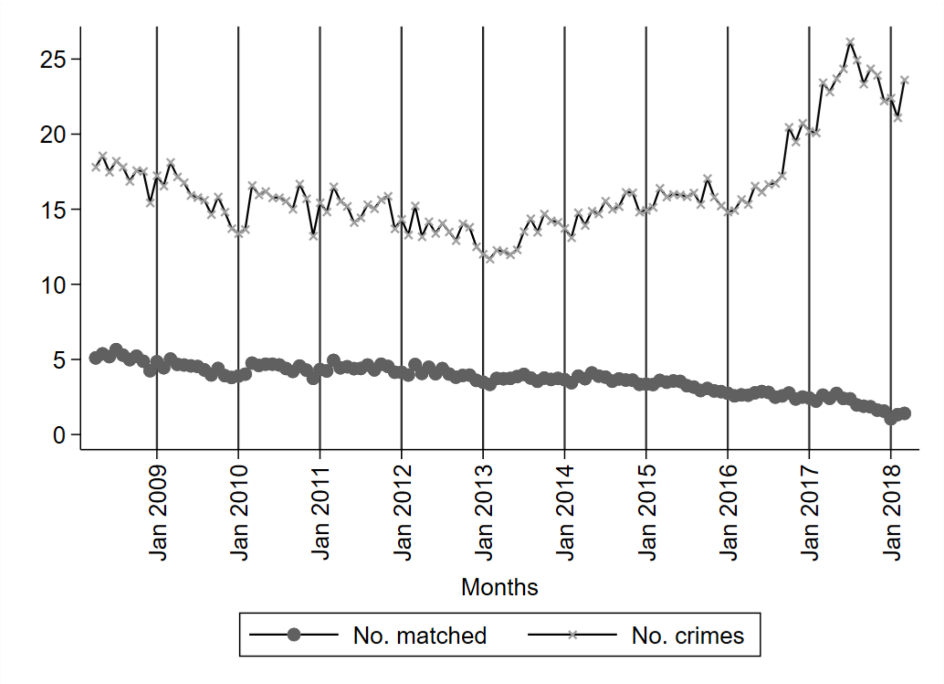
Source: Authors' elaboration of GMP police force data. The crime categorisation follows the Crime Tree Level 3 illustrated in Figure A2 of the Appendix.

Figure 3. Distribution of the number of crimes observed per individual offender



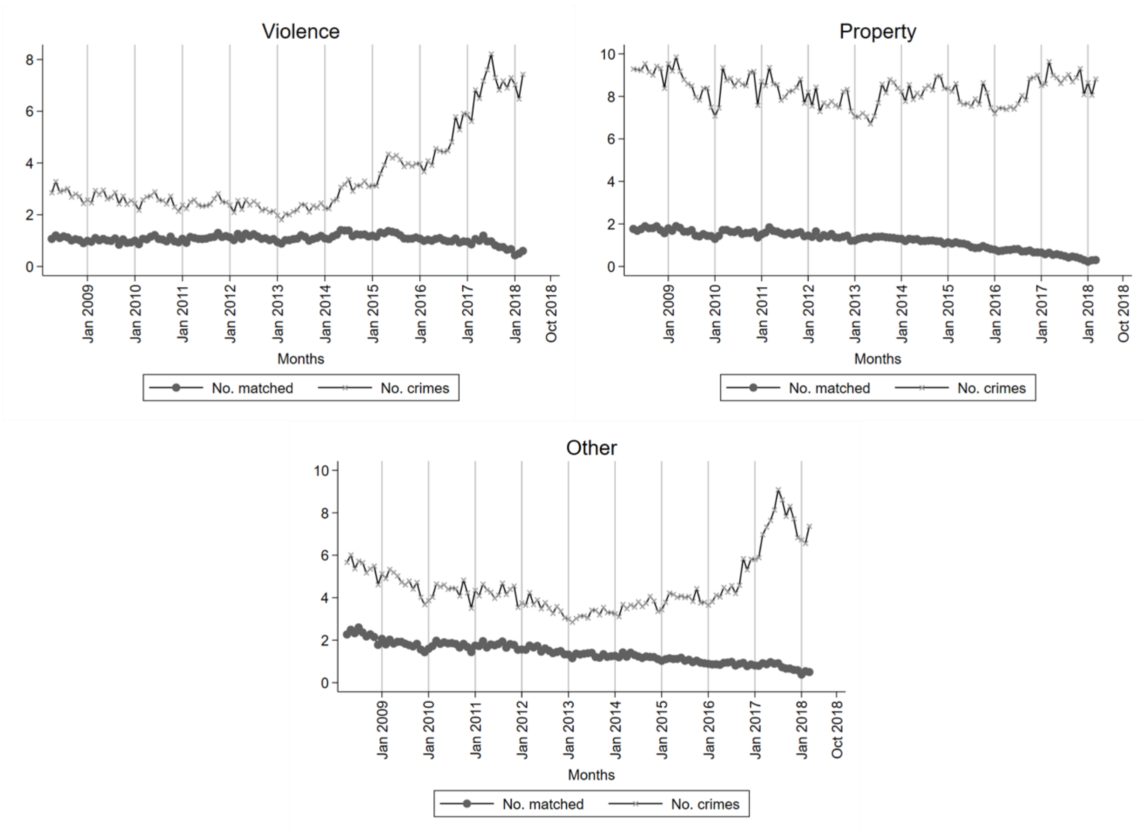
Source: Authors' elaboration of GMP police force data.

Figure 4. Crimes registered and number of crimes matched to at least one offender. Monthly series



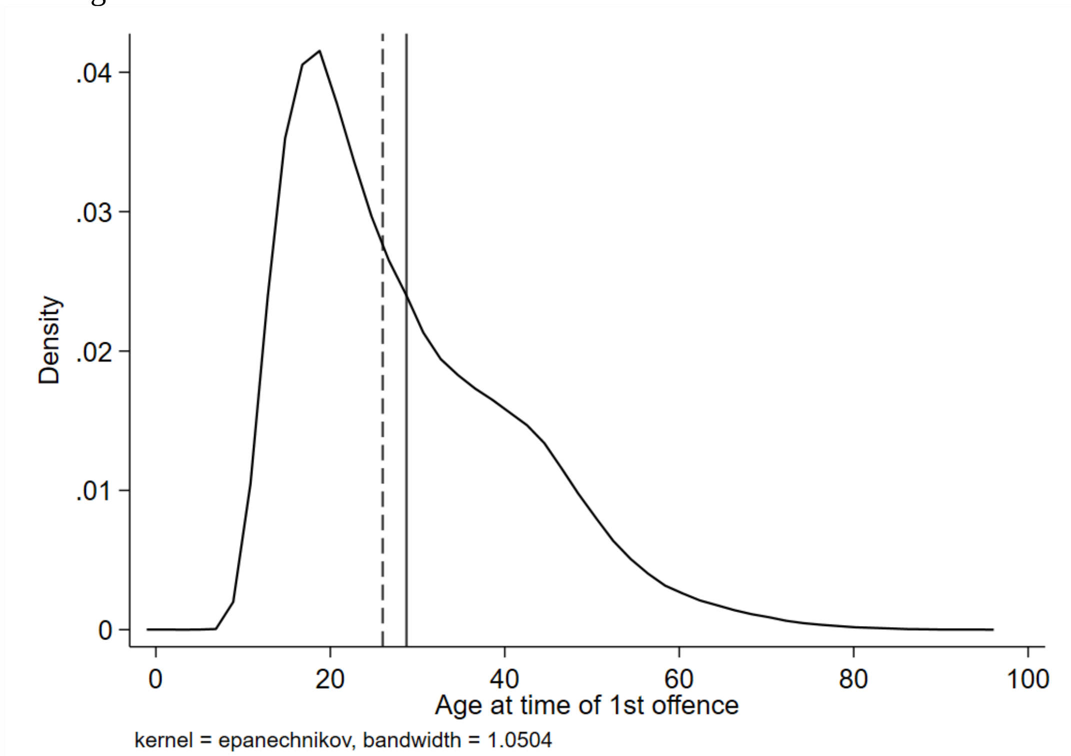
Source: Authors' elaboration of GMP police force data.

Figure 5. Number of crimes registered compared to the number of crimes matched to at least one offender. Monthly series by crime type



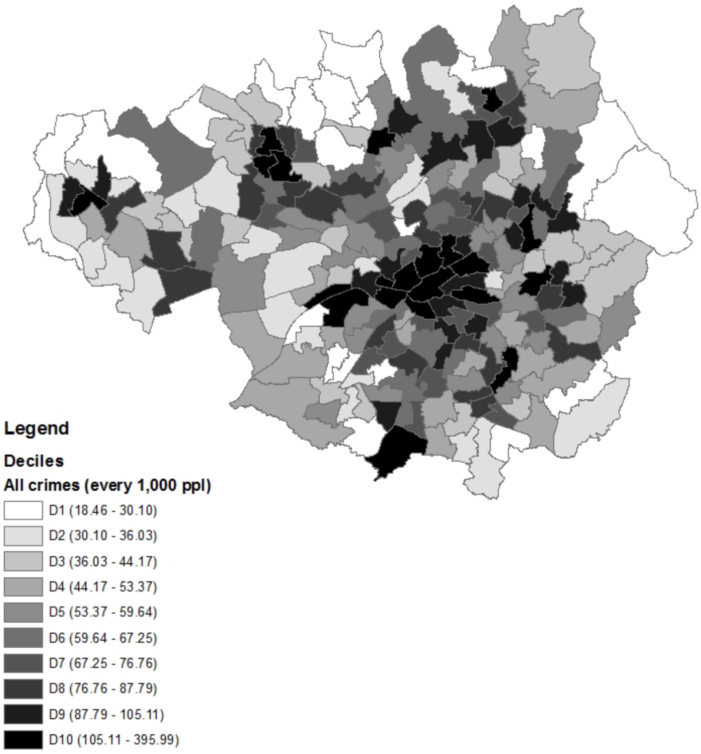
Source: Authors' elaboration of GMP police force data.

Figure 6. Age distribution of the offenders at their first observed offence



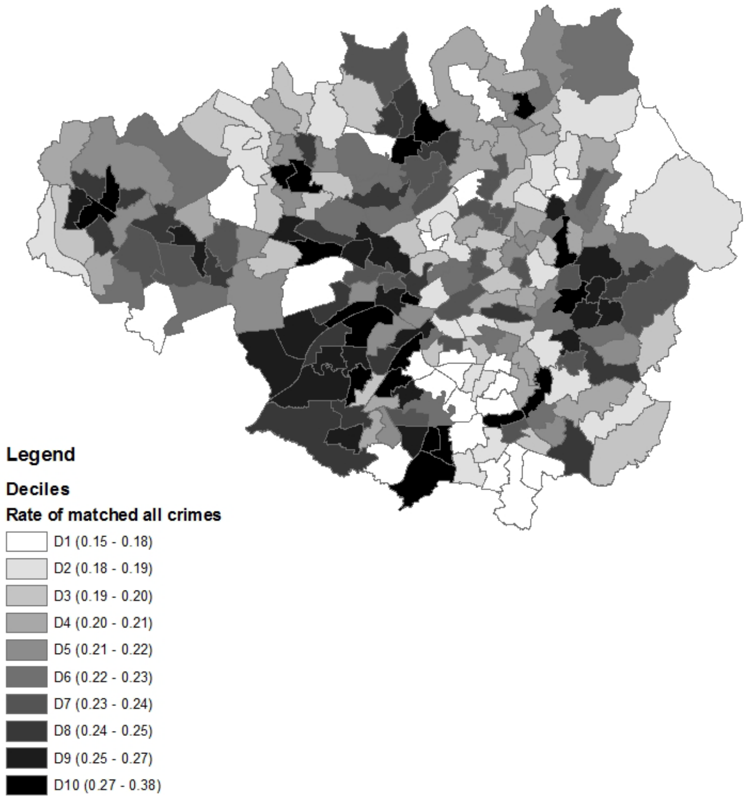
Source: Authors' elaboration of GMP police force data.

Figure 7. Geographical distribution of crimes



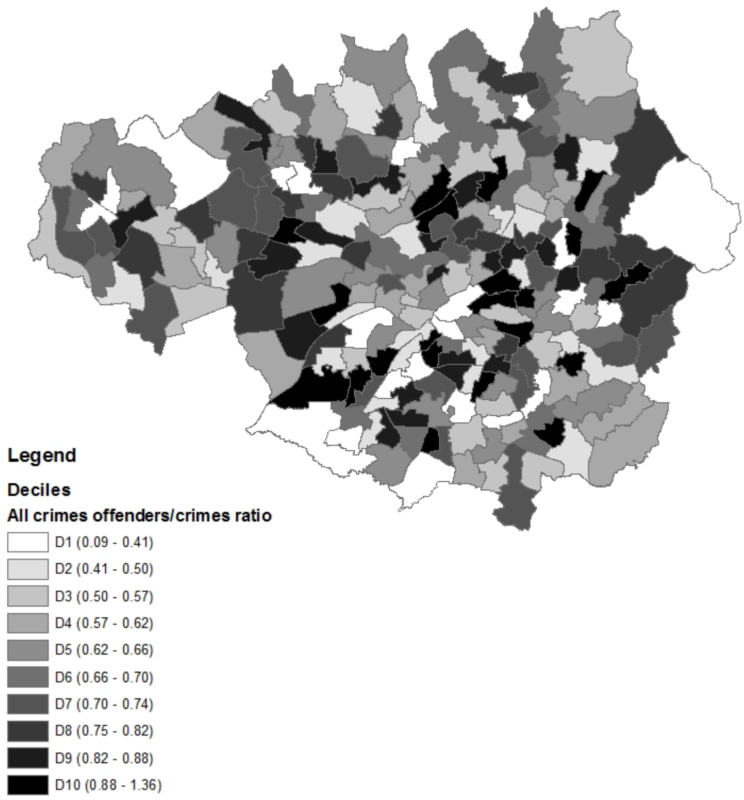
Source: Authors' elaboration of GMP police force data.

Figure 8. Geographical distribution of the rate of matched crimes



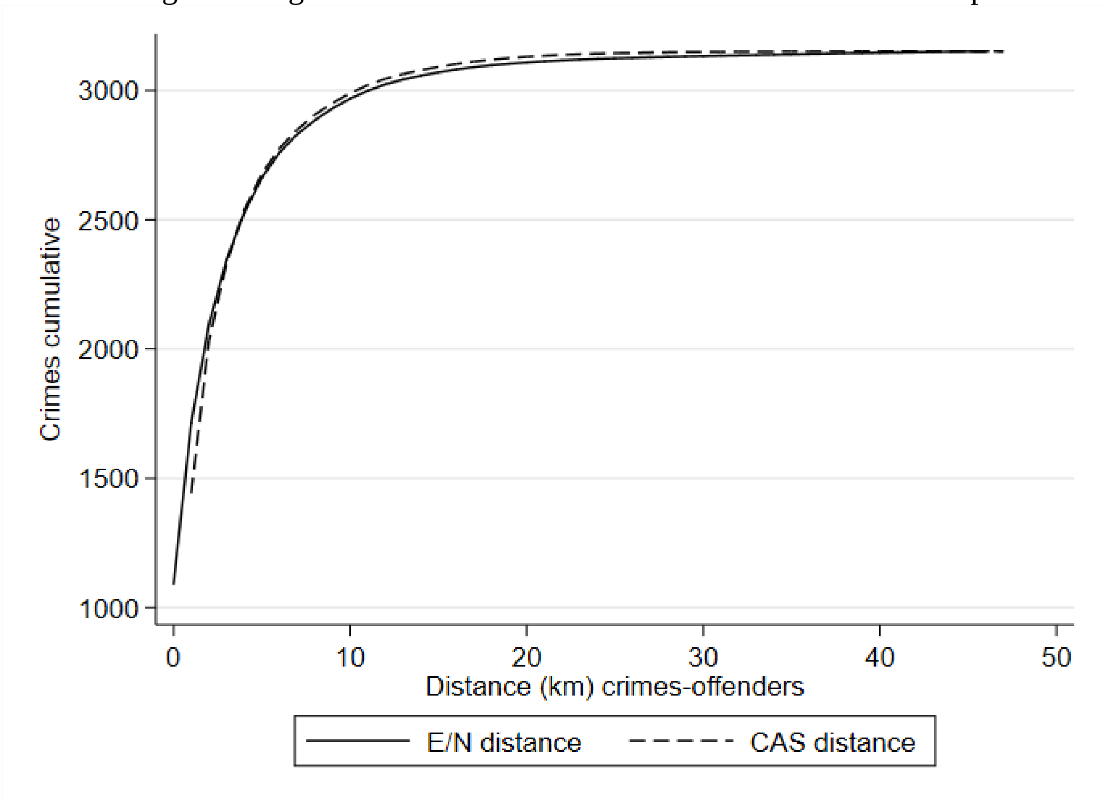
Source: Authors' elaboration of GMP police force data.

Figure 9. Geographical distribution of number of offenders to number of crimes ratio



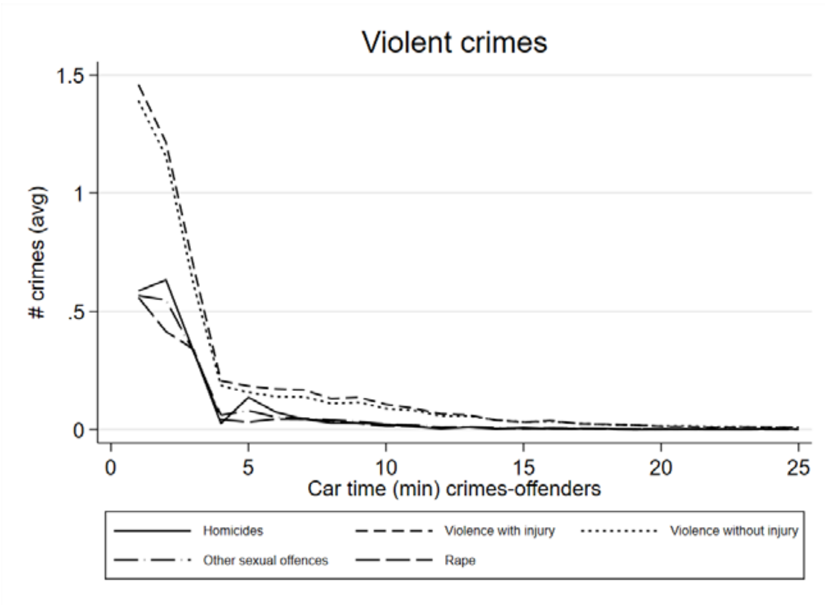
Source: Authors' elaboration of GMP police force data.

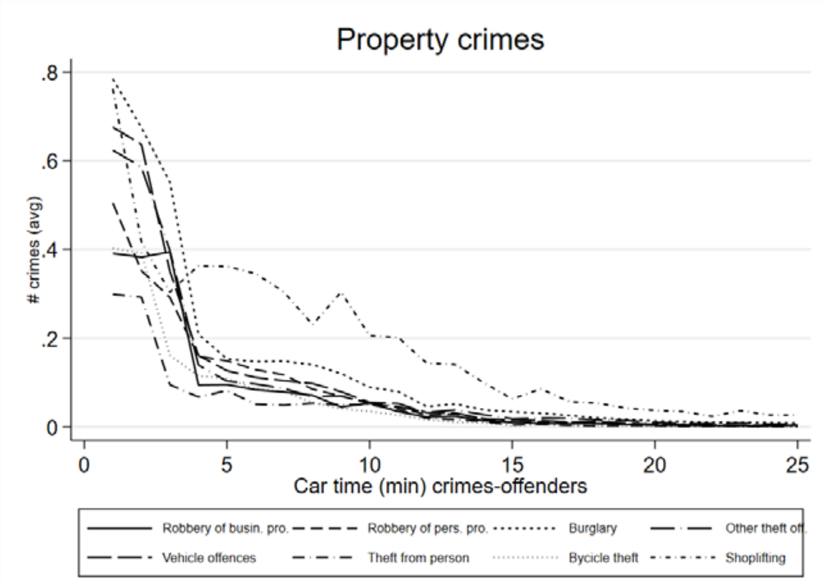
Figure 10. Cumulative distribution of crime-offender location distance. Precise location distance - Easting-Northing coordinates - and CAS Ward centroid distance compared

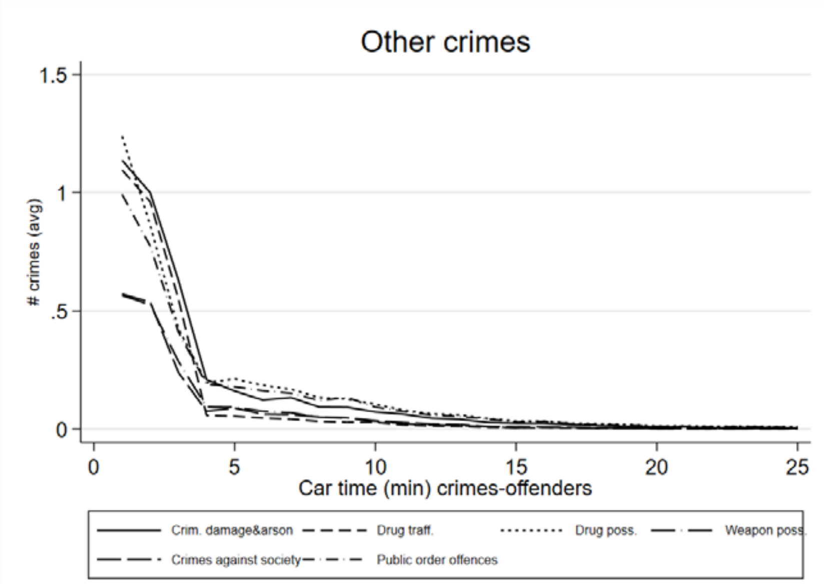


Source: Authors' elaboration of GMP police force data.

Figure 11. Average monthly number of crimes by car time (in minutes) and by crime type

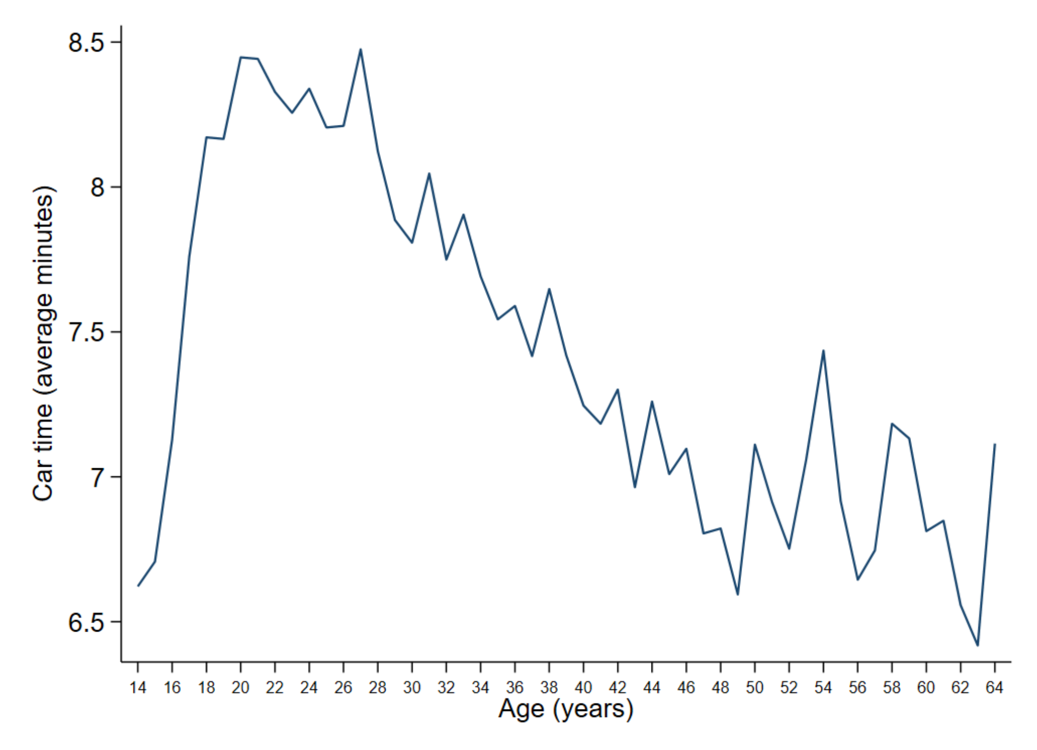






Source: Authors' elaboration of GMP police force data.

Figure 12. Distance by age of the offender



Notes: For illustration purposes age is trimmed to the interval 14-65

Tables

Table 1. Demographic composition of the offenders-crimes dataset

	Mean	SD
A. All matched crimes-offenders		
Age at the time of the offence	27.847	11.808
% Women	18.670	38.967
% Chinese, Japanese, or other South East Asian	0.164	4.044
% Other Asian	5.618	23.028
% Black	5.915	23.590
% Middle Eastern	0.411	6.397
% White – Northern European	72.710	44.545
% White – Southern European	1.007	9.983
% Unknown ethnicity	14.175	34.880
% UK national	74.622	43.518
N	401,770	
B. Offenders at their first offence		
Age at the time of the offence	28.730	12.969
% Women	24.052	42.740
% Chinese, Japanese, or other South East Asian	0.294	5.416
% Other Asian	6.328	24.346
% Black	5.050	21.897
% Middle Eastern	0.502	7.071
% White – Northern European	64.107	47.969
% White – Southern European	1.050	10.194
% Unknown ethnicity	22.669	41.869
% UK national	62.326	48.457
N	169,964	

Notes: Panel A: Descriptive statistics are on the full sample of matched crimes to offender with non-missing location information. Each observation unit is a crime-offender matched pair. Panel B: Descriptive statistics are on the sample of unique offenders. All variables are measured at the time of the offenders' first offence.

Table 2. Census characteristics of GMP, compared to the England and Wales

	Manchester	England and Wales
Total population	6,681,959	56,067,716
% Population below 16 years old	19.909	18.866
% Population between 16 and 64 years old	65.559	64.685
% Population above 65	14.532	16.446
% UK born	87.960	86.620
% University degree	24.282	27.217
% Women	50.592	50.829
% White	83.815	85.975
% Asian	10.144	7.513
% Black	2.758	3.324
% Mixed ethnicity	2.262	2.183
% Other ethnicity	1.020	1.005
% Married	42.782	46.824
% Students	7.553	6.775
Unemployment rate	7.765	6.603

Notes: Authors' elaboration of 2011 Census of Population for Greater Manchester Police area and for England and Wales. Source: Nomis.

Table 3. Correlation between different distance functions

	Euclidean distance	Car distance	PT distance	Car time	PT time
Euclidean distance	1				
Car distance	0.9654	1			
PT distance	0.9343	0.9124	1		
Car time	0.9270	0.9336	0.8778	1	
PT time	0.7337	0.7419	0.7926	0.7517	1

Notes: PT = Public Transport. Car and public transport distance (in km) and time (in minutes) between CAS Ward centroids are calculated using average traffic conditions, using HERE software (www.here.com).

Table 4. Crime characteristics

	Mean	SD
A. All crimes		
Grade: Immediate	0.129	0.335
Grade: Priority	0.231	0.422
Grade: Prompt	0.173	0.378
Response Time (not imputed)	277.085	1016.550
Response time: share imputed	0.444	0.497
Suspect named	0.209	0.407
Suspect described	0.193	0.395
Found by police	0.066	0.248
Found while patrolling	0.018	0.135
Reported by the victim	0.625	0.484
Location: House	0.313	0.464
Location: Shop	0.169	0.374
Location: Other closed public/offices	0.082	0.275
Location: Open air public	0.366	0.482
Location: Transportation	0.013	0.111
Location: Other	0.049	0.216
Location: N/A	0.009	0.092
N	1,955,591	
B. Crimes matched to at least one offender		
Grade: Immediate	0.237	0.425
Grade: Priority	0.361	0.480
Grade: Prompt	0.221	0.415
Response Time (not imputed)	141.731	681.290
Response time: imputed flag	0.149	0.356
Suspect named	0.448	0.497
Suspect described	0.127	0.333
Found by police	0.236	0.425
Found while patrolling	0.033	0.178
Reported by the victim	0.390	0.488
Location: Home	0.292	0.455
Location: Shop	0.250	0.433
Location: Other closed public/offices	0.076	0.265
Location: Open air public	0.339	0.473
Location: Transportation	0.009	0.099
Location: Other	0.029	0.167
Location: N/A	0.005	0.073
N	443,731	

Notes: Panel A: Descriptives are on the full sample of matched crimes to offender. Therefore, each observation is a crime-offender matched pair. Panel B: Descriptives are on the sample of unique offenders, all variables are measured at the time of their first offence.

Table 5. Logit models of selection. Dependent variable: indicator for crime matched to at least one offender. Odd ratios displayed.

	(1) Violent		(2) Property		(3) Other crimes	
Response time (log) - Imputed	0.9194***	(0.0028)	0.8825***	(0.0028)	0.8890***	(0.0028)
Response time - dummy for imputed values	0.7137***	(0.0244)	0.2624***	(0.0088)	0.3186***	(0.0097)
Response time (log) * Dummy for imputed	1.0121***	(0.0043)	1.1169***	(0.0047)	1.0900***	(0.0045)
Suspect Named	1.8440***	(0.0149)	6.9216***	(0.0808)	4.3663***	(0.0471)
Suspect Described	0.6129***	(0.0062)	0.6087***	(0.0063)	0.7036***	(0.0095)
Found by the Police	4.0312***	(0.0919)	2.8941***	(0.0724)	3.6263***	(0.0611)
Found while Patrolling	1.2865***	(0.0323)	1.0582**	(0.0246)	1.5194***	(0.0406)
Reported by the victim	0.8538***	(0.0071)	0.6685***	(0.0058)	0.6545***	(0.0067)
Type of crime:						
Homicide	*Omitted*					
Violence with injury	0.1374***	(0.0185)				
Violence without injury	0.1324***	(0.0179)				
Other sexual offences	0.0985***	(0.0134)				
Rape	0.0725***	(0.0100)				
Robbery of business property			*Omitted*			
Robbery of personal property			1.0027	(0.0368)		
Burglary			0.5730***	(0.0195)		
All other theft offences			0.8809***	(0.0304)		
Vehicle offences			0.6699***	(0.0237)		
Theft from the person			0.3718***	(0.0158)		
Bicycle theft			0.6473***	(0.0285)		
Shoplifting			4.6904***	(0.1574)		
Criminal damage and arson offences					*Omitted*	
Trafficking of drugs					3.7442***	(0.1000)
Possession of drugs					9.9851***	(0.2178)
Possession of weapon offences					2.5998***	(0.0636)
Miscellaneous crimes against society					1.8645***	(0.0381)
Public order offences					2.6974***	(0.0314)
Grade:						
Immediate	1.4198***	(0.0297)	2.3848***	(0.0603)	2.4178***	(0.0568)
Priority	1.1570***	(0.0205)	1.8891***	(0.0401)	1.5226***	(0.0320)
Prompt	0.9273***	(0.0172)	1.2135***	(0.0255)	1.0491**	(0.0217)
Location:						
Home	*Omitted*		*Omitted*		*Omitted*	
Shop	1.1918***	(0.0168)	1.1459***	(0.0166)	1.2654***	(0.0209)
Other closed public/offices	1.5810***	(0.0240)	1.0409***	(0.0157)	1.3660***	(0.0240)
Open air public	0.9067***	(0.0086)	0.8944***	(0.0127)	1.0113	(0.0110)
Transportation	1.1839***	(0.0422)	0.9379	(0.0407)	1.1989***	(0.0485)
Other	1.0816***	(0.0303)	0.9055***	(0.0159)	0.8595***	(0.0197)
N/A	0.7786***	(0.0256)	1.0015	(0.0842)	0.8778**	(0.0490)
Observations	412,307		996,692		546,590	

Notes: Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1. Constant not reported. Models include fixed effects for the CAS Ward of the crime, year, month, day of the month, day of the week, hour of the day, day of the week interacted with month, and hour interacted with day of the week. *Response time – dummy for imputed values* is a dummy variable for crimes with missing time of arrival of a police officer on the crime scene, when police arrival time is missing, response time was imputed using the closing time instead.

Table 6. Car time in minutes by crime categories

	Mean	SD	Median	N
A. Violent crimes				
Homicides	9.925	13.158	5.700	342
Violence with injury	8.613	13.027	2.851	54,807
Violence without injury	8.767	13.133	2.462	50,328
Rape	9.920	13.759	5.750	1,643
Other sexual offence	9.807	12.865	5.850	3,899
B. Property crimes				
Robbery of business property	14.329	14.904	10.117	2,419
Robbery of personal property	12.033	14.199	8.458	7,248
Burglary	13.064	15.925	8.583	27,123
All other theft offences	11.795	14.210	8.217	18,260
Vehicle offences	11.494	14.943	7.583	14,843
Theft from the person	13.368	15.120	9.583	1,280
Bicycle theft	9.781	12.142	7.250	1,412
Shoplifting	13.155	13.906	9.567	69,173
C. Other crimes				
Criminal damage and arson	8.794	13.401	3.056	36,388
Trafficking of drugs	5.875	10.493	1.269	12,684
Possession of drugs	9.145	12.739	5.817	45,176
Possession of weapon	10.548	15.403	6.133	7,145
Miscellaneous crimes against society	11.016	14.704	7.083	8,435
Public order offences	11.275	15.580	6.983	39,143

Notes: Full sample of matched crimes to offender.

Table 7. Poisson estimates of the crime-offenders locations distance function. Comparison between car time distance and public transport distance

	(1) Violent crimes	(2) Property crimes	(3) Other crimes
Panel A			
Car time (minutes)	-0.3016***	-0.2431***	-0.2983***
	(0.0055)	(0.0057)	(0.0054)
Public transport time/Car time	-0.4470***	-0.1944***	-0.3785***
	(0.0342)	(0.0201)	(0.0313)
N	5,495,520	5,495,520	5,495,520
Panel B			
Car time (minutes)	-0.2582***	-0.1789***	-0.2663***
	(0.0053)	(0.0069)	(0.0054)
Public transport time/Car time	-0.4461***	-0.1782***	-0.2726***
	(0.0343)	(0.0267)	(0.0267)
(1-Pr(match))*v_{ab}	-0.0782***	-0.1275***	-0.0408***
	(0.0036)	(0.0062)	(0.0013)
N	5,495,520	5,495,520	5,495,520

Notes: Standard errors clustered at the destination area level in parenthesis. ***p<0.01, **p<0.05, *p<0.1. All models include crime location (CAS Ward) fixed effects and offender-crime fixed effects. (1-Pr(match))*v_{ab} corresponds to $[1 - F(\sigma_1 c_{ab})]v_{ab}$

Table 8. Offender location fixed effects models

	(1) Violent	(2) Property	(3) Other
Unemployment rate (%)	0.0254	0.0051	0.0309**
	(0.0190)	(0.0167)	(0.0155)
Population with a degree over 16+ (%)	-0.0460***	-0.0422***	-0.0296***
	(0.0099)	(0.0101)	(0.0107)
Population under 15 (%)	0.0295	0.0355	0.0178
	(0.0235)	(0.0224)	(0.0201)
Population 16-19 (%)	0.0024	0.0131	-0.0374
	(0.0354)	(0.0386)	(0.0327)
Population 20-24 (%)	0.0144	0.0096	-0.0083
	(0.0219)	(0.0238)	(0.0222)
Population 25-29 (%)	-0.0055	-0.0073	0.0079
	(0.0323)	(0.0313)	(0.0293)
Population 45-64 (%)	0.0112	0.0154	0.0103
	(0.0261)	(0.0269)	(0.0246)
Population above 65 (%)	-0.0130	-0.0017	-0.0265*
	(0.0151)	(0.0161)	(0.0137)
Married/Couples over total population (%)	-0.0231***	-0.0388***	-0.0153***
	(0.0076)	(0.0077)	(0.0056)
Students (% of population 16-64)	-0.0080	-0.0152	0.0132
	(0.0198)	(0.0202)	(0.0186)
Population density (standardised)	-0.0810***	-0.0619**	-0.0698**
	(0.0275)	(0.0305)	(0.0275)
Number of business density (standardised)	-0.0952***	-0.0788***	-0.0858***
	(0.0245)	(0.0251)	(0.0318)
People born abroad (% of population)	0.0131	0.0114	-0.0073
	(0.0091)	(0.0084)	(0.0072)
Ethnic minorities (%)	0.0001	0.0071*	0.0054
	(0.0043)	(0.0042)	(0.0036)
Agriculture and manufacturing (%)	-0.0019	-0.0029	0.0008
	(0.0023)	(0.0026)	(0.0026)
Construction/Utilities/Transportation (%)	0.0036	0.0021	-0.0007
	(0.0033)	(0.0032)	(0.0025)
Commerce (%)	-0.0022	-0.0005	-0.0040*
	(0.0025)	(0.0024)	(0.0021)
Hospitality (%)	-0.0042	-0.0031	-0.0021
	(0.0035)	(0.0037)	(0.0028)
Occupation: associate professionals, admin, skilled trade (%)	-0.0122	-0.0068	-0.0039
	(0.0139)	(0.0148)	(0.0145)
Occupation: care, procedural, sales, elementary (%)	-0.0524***	-0.0461***	-0.0290**
	(0.0133)	(0.0132)	(0.0131)
Constant	3.6873*	4.2293**	2.8772
	(2.0198)	(2.1141)	(2.0348)
Observations	214	214	214

Notes: Robust standard errors in round parenthesis. ***p<0.01, **p<0.05, *p<0.1. Models are weighted for population.

Table 9. Crime location fixed effects models

	(1) Violent	(2) Property	(3) Other
Unemployment rate (%)	0.0052	-0.0006	0.0393*
	(0.0185)	(0.0200)	(0.0220)
Population with a degree over 16+ (%)	-0.0148	-0.0326**	-0.0183
	(0.0120)	(0.0157)	(0.0179)
Population under 15 (%)	-0.0278	-0.0227	-0.0732**
	(0.0202)	(0.0289)	(0.0328)
Population 16-19 (%)	-0.0057	-0.0316	-0.0710
	(0.0420)	(0.0443)	(0.0472)
Population 20-24 (%)	-0.0002	-0.0120	-0.0286
	(0.0268)	(0.0285)	(0.0307)
Population 25-29 (%)	-0.0405	-0.0418	-0.0535
	(0.0308)	(0.0386)	(0.0389)
Population 45-64 (%)	-0.0065	-0.0098	-0.0370
	(0.0263)	(0.0356)	(0.0434)
Population above 65 (%)	-0.0190	-0.0103	-0.0483***
	(0.0146)	(0.0186)	(0.0182)
Married/Couples over total population (%)	-0.0160*	-0.0338***	0.0008
	(0.0088)	(0.0113)	(0.0116)
Students (% of population 16-64)	-0.0157	-0.0089	0.0021
	(0.0240)	(0.0229)	(0.0245)
Population density (standardised)	-0.1488***	-0.1143***	-0.1602***
	(0.0337)	(0.0388)	(0.0482)
Number of business density (standardised)	0.2006***	0.1294***	0.1873***
	(0.0202)	(0.0246)	(0.0245)
People born abroad (% of population)	0.0216**	0.0498***	0.0283**
	(0.0103)	(0.0119)	(0.0111)
Ethnic minorities (%)	-0.0036	-0.0118**	-0.0136**
	(0.0053)	(0.0055)	(0.0053)
Agriculture and manufacturing (%)	-0.0011	-0.0051	-0.0004
	(0.0024)	(0.0033)	(0.0034)
Construction/Utilities/Transportation (%)	-0.0049	-0.0017	-0.0044
	(0.0033)	(0.0041)	(0.0054)
Commerce (%)	0.0037	0.0029	0.0061**
	(0.0023)	(0.0028)	(0.0027)
Hospitality (%)	-0.0028	0.0009	-0.0018
	(0.0030)	(0.0053)	(0.0043)
Occupation: associate professionals, admin, skilled trade (%)	-0.0247	-0.0332*	-0.0427**
	(0.0156)	(0.0184)	(0.0187)
Occupation: care, procedural, sales, elementary (%)	-0.0080	-0.0341*	-0.0119
	(0.0146)	(0.0199)	(0.0222)
Constant	2.9611	4.5286	4.3625
	(2.3025)	(2.9830)	(3.5062)
Observations	214	214	214

Notes: Robust standard errors in round parenthesis. ***p<0.01, **p<0.05, *p<0.1. Models are weighted for population.

Table 10. Heterogeneities in the distance function with respect to offenders' and crime area characteristics

	(1) Violent crimes	(2) Property crimes	(3) Other crimes
Car time (minutes)	-0.2493***	-0.1591***	-0.2586***
	(0.0202)	(0.0194)	(0.0204)
Public transport time/Car time	-0.2741*	-0.2785**	-0.02868*
	(0.1601)	(0.1380)	(0.1525)
Car time (minutes)*Unemployment O	-0.0027**	0.0004	-0.0035***
	(0.0012)	(0.0010)	(0.0012)
Public transport time/Car time*Unemployment O	0.0104	0.0165**	0.0020
	(0.0097)	(0.0080)	(0.0083)
Car time (minutes)*Unemployment C	-0.0009	-0.0048*	0.0013
	(0.0014)	(0.0013)	(0.0014)
Public transport time/Car time*Unemployment C	-0.0039	0.0021	0.0029
	(0.0089)	(0.0061)	(0.0078)
Car time (minutes)*% with univ. degree O	-0.0024**	0.0002	-0.0014*
	(0.0012)	(0.0004)	(0.0008)
Public transport time/Car time*% with univ. degree O	-0.0075**	-0.0007	-0.0069*
	(0.0038)	(0.0033)	(0.0039)
Car time (minutes)*% with univ. degree C	0.0019	0.0006	0.0023*
	(0.0012)	(0.0007)	(0.0012)
Public transport time/Car time*% with univ. degree C	-0.0022	-0.0020	0.0015
	(0.0028)	(0.0020)	(0.0024)
(1-Pr(match))*v_{ab}	-0.0779***	-0.1288***	-0.0762***
	(0.0036)	(0.0060)	(0.0036)
Constant	1.9089***	0.8923***	2.1375***
	(0.0803)	(0.1018)	(0.0794)
N	5,495,520	5,495,520	5,495,520

Notes: Standard errors clustered at the destination area level in parenthesis. ***p<0.01, **p<0.05, *p<0.1. All models include crime location (CAS Ward) fixed effects and offender-crime fixed effects. (1-Pr(match))*v_{ab} corresponds to $[1 - F(\sigma_1 c_{ab})]v_{ab}$. O refers to variables measured at the offenders' location, while C refers to variables measured at the crime location level

Table 11. Heterogeneities with respect to offenders' characteristics

	(1) Younger than 24	(2) 25-34	(3) Older than 35	(4) Men	(5) Women	(6) British nationals	(7) Foreigners	(8) Whites	(9) Non-whites
					Violent crimes				
Car time (minutes)	-0.2519***	-0.2537***	-0.2740***	-0.2517***	-0.2867***	-0.2610***	-0.2425***	-0.2634***	-0.2240***
	(0.0058)	(0.0057)	(0.0049)	(0.0051)	(0.0067)	(0.0053)	(0.0081)	(0.0055)	(0.0062)
Public transport time/Car time	-0.3658***	-0.4817***	-0.5422***	-0.4437***	-0.4503***	-0.4212***	-0.5736***	-0.4243***	-0.4964***
	(0.0351)	(0.0359)	(0.0365)	(0.0334)	(0.0425)	(0.0330)	(0.0595)	(0.0344)	(0.0355)
(1-Pr(match))*v_{ab}	-0.0876***	-0.0590***	-0.0808***	-0.0802***	-0.0676***	-0.0666***	-0.0997***	-0.0683***	-0.0928***
	(0.0042)	(0.0049)	(0.0036)	(0.0037)	(0.0052)	(0.0032)	(0.0099)	(0.0033)	(0.0068)
					Property crimes				
Car time (minutes)	-0.1680***	-0.1752***	-0.2002***	-0.1699***	-0.2122***	-0.1776***	-0.1572***	-0.1807***	-0.1344***
	(0.0084)	(0.0055)	(0.0060)	(0.0059)	(0.0100)	(0.0066)	(0.0090)	(0.0061)	(0.0125)
Public transport time/Car time	-0.1972***	-0.1707***	-0.1521***	-0.1865***	-0.1608***	-0.1802***	-0.1578***	-0.1711***	-0.2053***
	(0.0296)	(0.0253)	(0.0274)	(0.0243)	(0.0374)	(0.0268)	(0.0406)	(0.0262)	(0.0364)
(1-Pr(match))*v_{ab}	-0.1536***	-0.1133***	-0.0930***	-0.1441***	-0.0710***	-0.1317***	-0.1061***	-0.1264***	-0.1663***
	(0.0076)	(0.0054)	(0.0051)	(0.0063)	(0.0056)	(0.0061)	(0.0093)	(0.0056)	(0.0118)
					Other crimes				
Car time (minutes)	-0.2265***	-0.2154***	-0.2448***	-0.2245***	-0.2473***	-0.2283***	-0.1839***	-0.2320***	-0.1784***
	(0.0065)	(0.0062)	(0.0056)	(0.0061)	(0.0065)	(0.0060)	(0.0095)	(0.0058)	(0.0080)
Public transport time/Car time	-0.3141***	-0.4053***	-0.4503***	-0.3474***	-0.4886***	-0.3613***	-0.3392***	-0.3576***	-0.3609***
	(0.0283)	(0.0314)	(0.0361)	(0.0291)	(0.0360)	(0.0296)	(0.0512)	(0.0308)	(0.0273)
(1-Pr(match))*v_{ab}	-0.1300***	-0.1262***	-0.1308***	-0.1291***	-0.1283***	-0.1264***	-0.1490***	-0.1246***	-0.1557***
	(0.0053)	(0.0051)	(0.0048)	(0.0050)	(0.0055)	(0.0049)	(0.0088)	(0.0048)	(0.0066)

Notes: Standard errors clustered at the destination area level in parenthesis. ***p<0.01, **p<0.05, *p<0.1. All models include crime location (CASWard) fixed effects and offender-crime fixed effects. (1-Pr(match))*v_{ab} corresponds to $[1 - F(\sigma_1 c_{ab})]v_{ab}$. Number of observations 5,495,520.

Table 12 (continues in the next page). Distance models, dependent variable: car time in minutes between the offender's and the crime location

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
Omitted category: Burglary in dwelling					
Homicide and Violence with injury	-3.1737***	-3.0224***	-3.1247***	-2.9041***	-2.9155***
	(0.0735)	(0.0737)	(0.0734)	(0.0700)	(0.0678)
Violence w/o injury	-2.8787***	-2.6977***	-2.7971***	-2.5875***	-2.5315***
	(0.0751)	(0.0754)	(0.0751)	(0.0719)	(0.0697)
Sexual off/rape	-1.5703***	-1.4269***	-1.5246***	-1.3654***	-1.3008***
	(0.1332)	(0.1343)	(0.1333)	(0.1304)	(0.1286)
Burglary other	-0.5199***	-0.4048***	-0.2752***	-0.1471	-0.7952***
	(0.1055)	(0.1050)	(0.1044)	(0.1004)	(0.0974)
Robbery	0.2239**	0.1664	0.1843*	0.3039***	0.0872
	(0.1072)	(0.1066)	(0.1058)	(0.1016)	(0.0989)
Other theft	-0.3295***	-0.2433***	-0.2789***	-0.0907	-0.6364***
	(0.0888)	(0.0886)	(0.0880)	(0.0850)	(0.0816)
Vehicle theft	-1.2941***	-1.2695***	-1.2394***	-1.1064***	-1.1358***
	(0.0938)	(0.0934)	(0.0932)	(0.0890)	(0.0863)
Shoplifting	0.9400***	1.1258***	1.1841***	1.4297***	-0.0518
	(0.0738)	(0.0748)	(0.0742)	(0.0708)	(0.0693)
Criminal Damage and Arson Offences	-3.2212***	-3.0036***	-3.1039***	-2.8722***	-2.8021***
	(0.0764)	(0.0763)	(0.0759)	(0.0726)	(0.0704)
Drugs	-2.7961***	-2.9782***	-3.0781***	-2.8705***	-2.8549***
	(0.0735)	(0.0735)	(0.0731)	(0.0698)	(0.0674)
Other	-1.9846***	-1.8642***	-1.9075***	-1.6893***	-1.9692***
	(0.0746)	(0.0745)	(0.0740)	(0.0707)	(0.0683)
Age		0.6334***	0.6708***	0.6665***	0.5728***
		(0.0141)	(0.0140)	(0.0139)	(0.0131)
Age^2		-0.0169***	-0.0177***	-0.0176***	-0.0150***
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Age^3		0.0001***	0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Woman		-0.4168***	-0.4323***	-0.4151***	-0.5272***
		(0.0312)	(0.0309)	(0.0307)	(0.0289)
Black		1.1329***	1.3380***	1.2408***	0.9346***
		(0.0523)	(0.0546)	(0.0550)	(0.0532)
Other ethnic groups		0.4323***	0.9834***	0.9913***	0.7234***
		(0.0525)	(0.0550)	(0.0551)	(0.0522)
Unknown ethnicity		0.1651***	0.2130***	0.1872***	-0.0528
		(0.0388)	(0.0386)	(0.0384)	(0.0362)
N	380,013	373,215	373,215	373,215	373,215
Offender area FE				Yes	Yes
Crime area FE					Yes

Notes: Standard errors clustered at the destination area level in parenthesis. ***p<0.01, **p<0.05, *p<0.1. All models include year, month, day of the month and hour of the day fixed effects. Age is rescaled to be centred at 16.

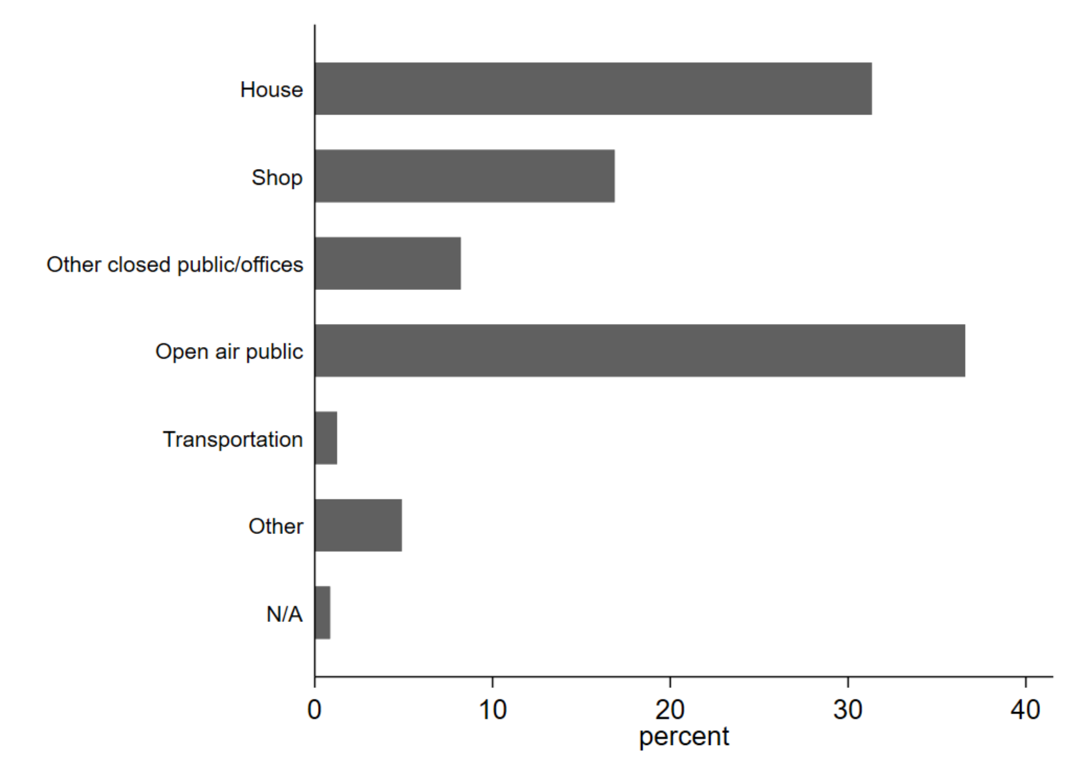
Table 12 (cont'ed). Distance models, dependent variable: car time in minutes between the offender's and the crime location

	(1)	(2)	(3)	(4)	(5)
Unemployed over workers+unemployed (%)			-0.1405***		
			(0.0103)		
Population with a degree over 16+ (%)			0.0098		
			(0.0082)		
% population under 15			0.2127***		
			(0.0147)		
% population under 16 to 19			-0.1019***		
			(0.0259)		
% population under 20 to 24			-0.0424**		
			(0.0173)		
% population under 25 to 29			0.1394***		
			(0.0211)		
% population under 45 to 64			0.2145***		
			(0.0176)		
% population above 65			0.0567***		
			(0.0114)		
Married/Couples over total population (%)			-0.0457***		
			(0.0044)		
Students (% of population 16-64)			0.1382***		
			(0.0136)		
Population density (standardised)			-0.4444***		
			(0.0189)		
Business density (standardised)			-0.3480***		
			(0.0153)		
People born abroad (% of population)			0.0486***		
			(0.0065)		
Ethnic minorities (%)			-0.0081***		
			(0.0030)		
Agriculture and manufacturing (%)			-0.0054***		
			(0.0016)		
Construction/Utilities/Transportation (%)			0.0165***		
			(0.0018)		
Commerce (%)			0.0011		
			(0.0015)		
Hospitality (%)			0.0313***		
			(0.0027)		
Occupation: associate professionals, admin, skilled trade (%)			0.0864***		
			(0.0103)		
Occupation: care, procedural, sales, elementary (%)			-0.0145		
			(0.0094)		
N	380,013	373,215	373,215	373,215	373,215
Offender area FE				Yes	Yes
Crime area FE					Yes

Notes: Standard errors clustered at the destination area level in parenthesis. ***p<0.01, **p<0.05, *p<0.1. All models include year, month, day of the month and hour of the day fixed effects. Age is rescaled to be centred at 16.

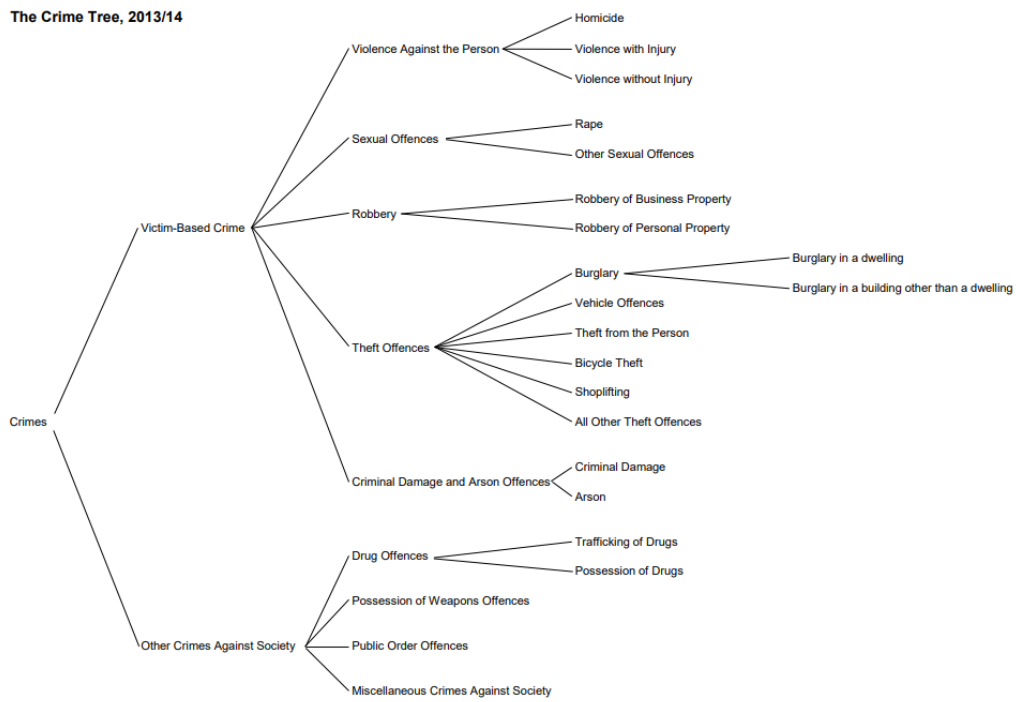
Appendix A
Tables and figures

Figure A1. Distribution of crimes by location category



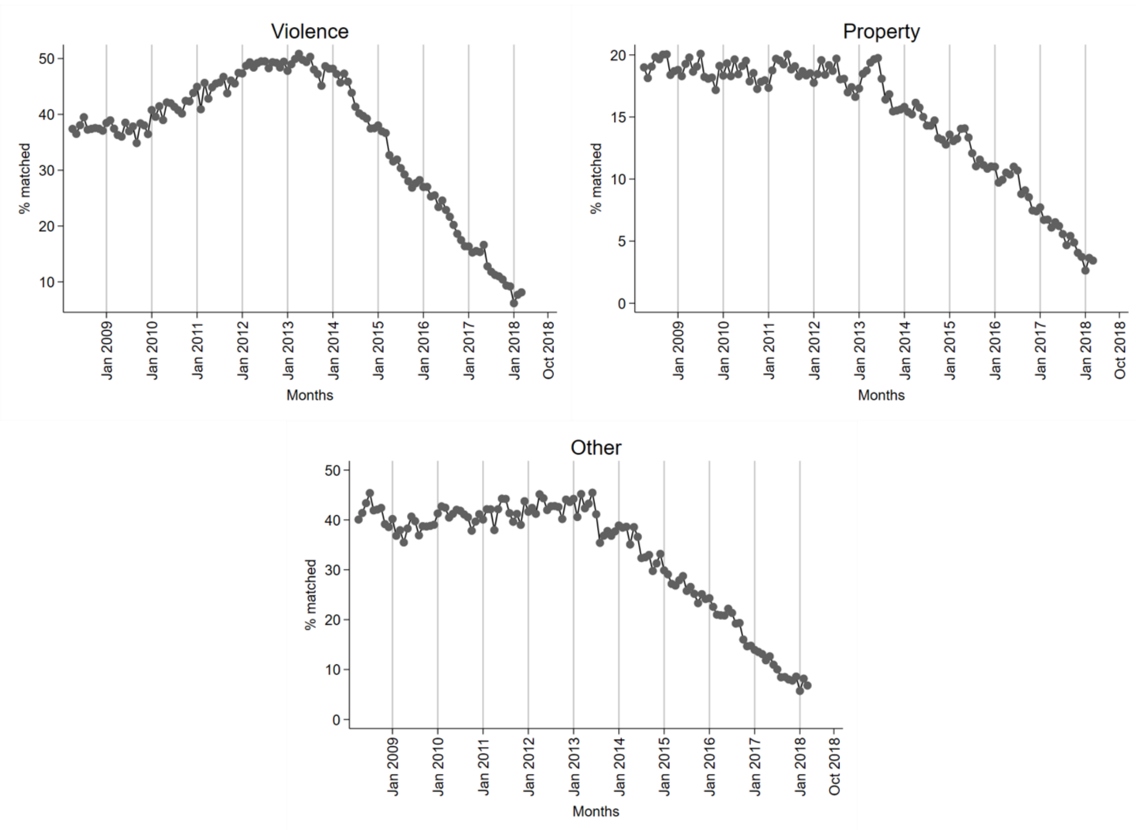
Source: Authors' elaboration of GMP police force data.

Figure A2. Crime Tree



Notes: Source https://www.justiceinspectorates.gov.uk/hmicfrs/media/crime-tree.pdf

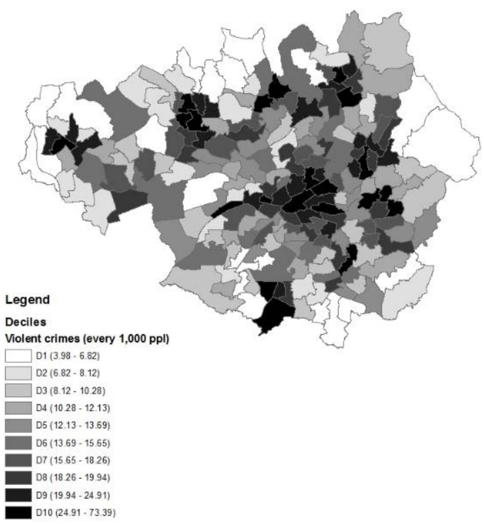
Figure A3. Crimes matched to at least one offender. Monthly trends



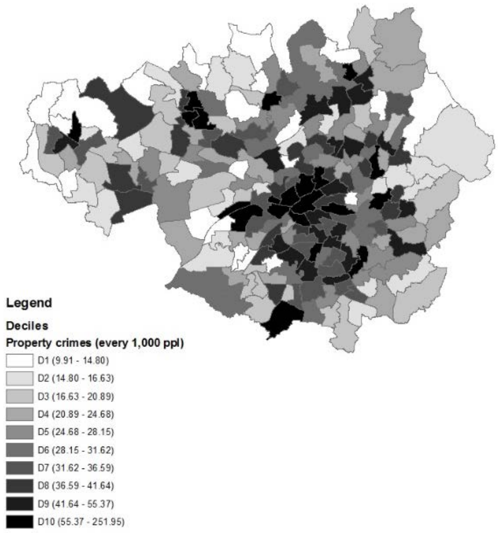
Source: Authors' elaboration of GMP police force data.

Figure A4. Distribution of crimes across GMP, by crime type

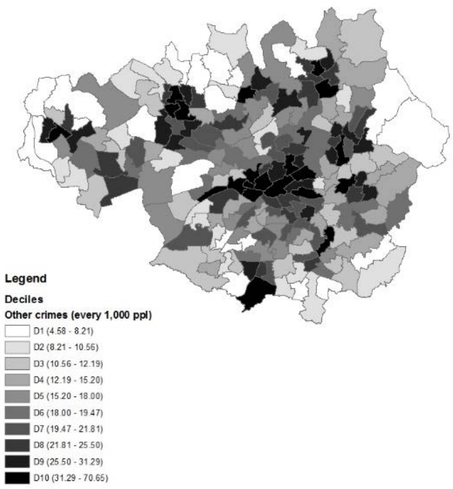
B. Violent crimes



A. Property crimes



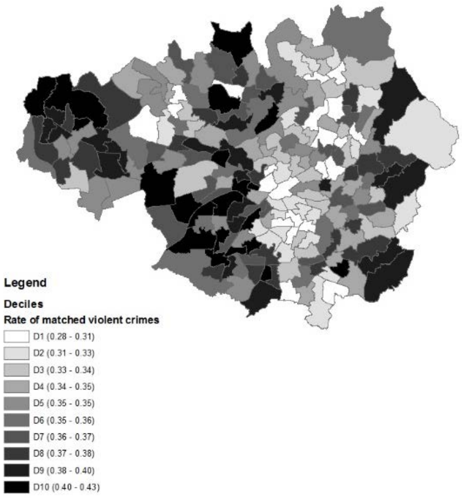
C. Other crimes



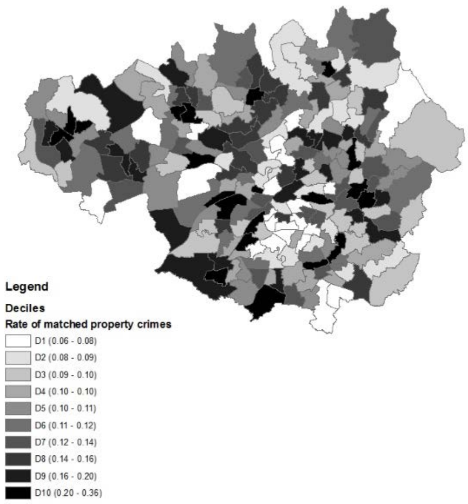
Source: Authors' elaboration of GMP police force data.

Figure A5. Distribution of matched crimes across GMP, by crime type

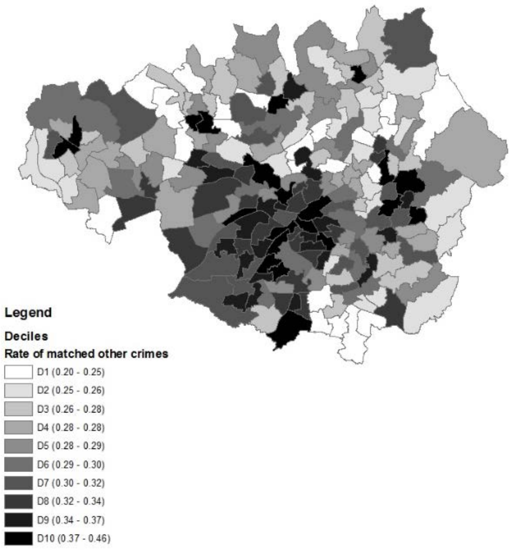
A. Violent crimes



B. Property crimes



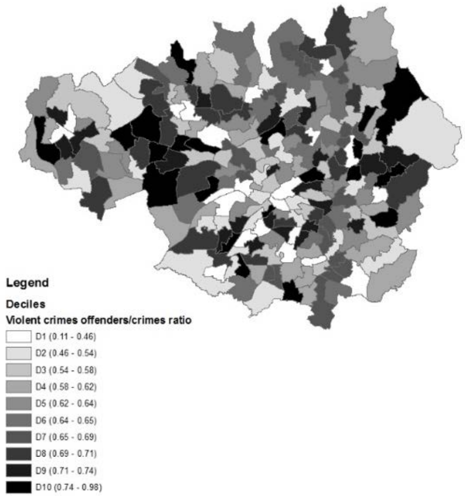
C. Other crimes



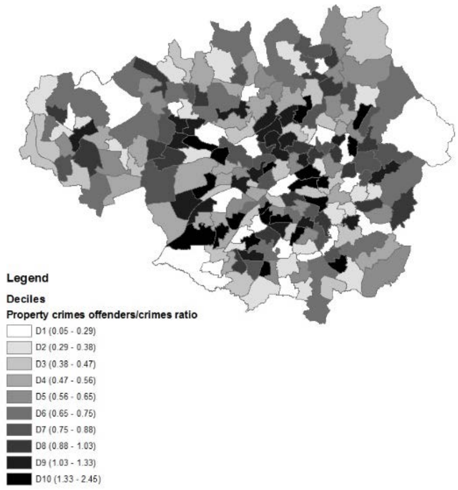
Source: Authors' elaboration of GMP police force data.

Figure A6. Distribution of number of offenders to crimes ratios across GMP, by crime type

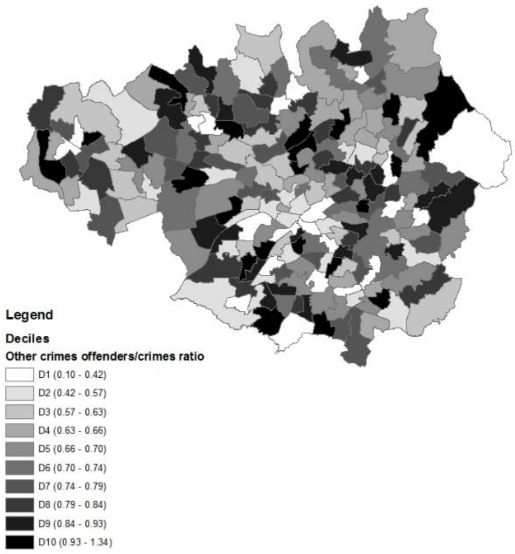
A. Violent crimes



B. Property crimes

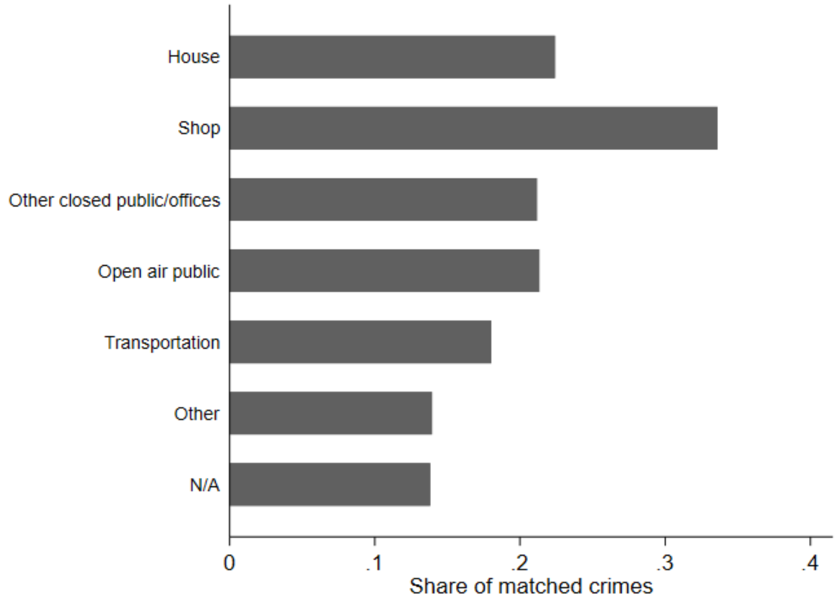


C. Other crimes



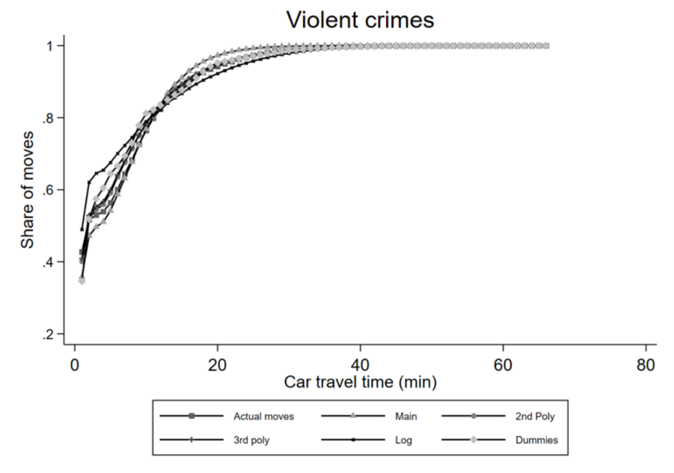
Source: Authors' elaboration of GMP police force data.

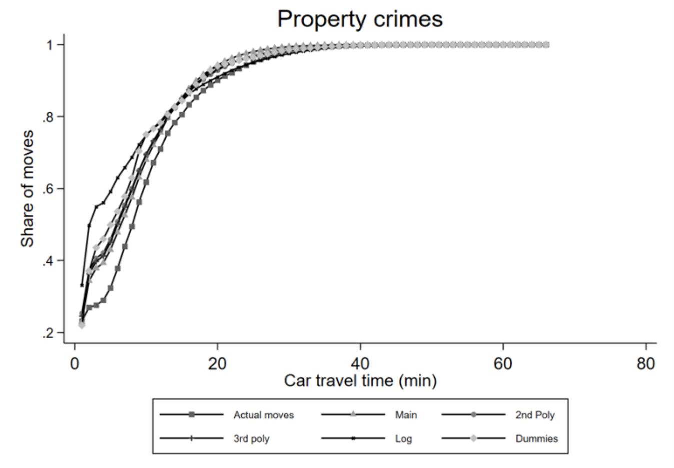
Figure A7. Share of crimes matched to at least one offender, by type of crime location

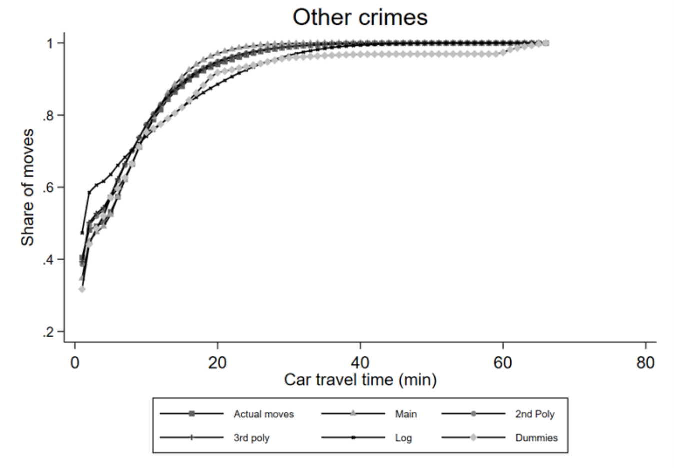


Source: Authors' elaboration of GMP police force data.

Figure A8. Comparison of different functional forms







Source: Authors' elaboration of GMP police force data.

Table A1. Offenders' descriptive statistics by type of crime

	(1)	(2)	(3)	(4)	(5)
	Age	Women	UK national	Share that is a first offence	N
Panel A: Violent crimes					
Homicides	29.105	0.111	0.763	0.427	342
	(10.964)	(0.315)	(0.426)	(0.495)	
Violence with injury	28.117	0.201	0.729	0.495	54,807
	(12.118)	(0.401)	(0.445)	(0.500)	
Violence without injury	29.687	0.235	0.686	0.422	50,328
	(12.753)	(0.424)	(0.464)	(0.494)	
Other sexual offences	33.108	0.022	0.567	0.596	3,899
	(15.677)	(0.148)	(0.496)	(0.491)	
Rape	29.112	0.004	0.603	0.600	1,643
	(12.177)	(0.061)	(0.489)	(0.490)	
Panel B: Property crimes					
Robbery of business property	25.454	0.059	0.899	0.172	2,419
	(7.986)	(0.235)	(0.303)	(0.377)	
Robbery of personal property	20.988	0.089	0.793	0.212	7,248
	(7.816)	(0.285)	(0.405)	(0.409)	
Burglary	25.041	0.046	0.891	0.185	27,123
	(9.793)	(0.209)	(0.312)	(0.388)	
All other theft offences	27.694	0.210	0.727	0.441	18,260
	(11.444)	(0.407)	(0.446)	(0.497)	
Vehicle offences	24.178	0.041	0.859	0.232	14,843
	(8.994)	(0.198)	(0.348)	(0.422)	
Theft from the person	24.733	0.197	0.611	0.265	1,280
	(10.198)	(0.396)	(0.488)	(0.441)	
Bicycle theft	21.119	0.032	0.761	0.269	1,412
	(9.670)	(0.177)	(0.426)	(0.444)	
Shoplifting	31.084	0.374	0.705	0.412	69,173
	(12.620)	(0.484)	(0.456)	(0.492)	
Panel C: Other crimes					
Criminal damage and arson	24.335	0.138	0.733	0.429	36,388
	(11.199)	(0.345)	(0.443)	(0.495)	
Trafficking of drugs	30.432	0.110	0.785	0.467	12,684
	(10.595)	(0.313)	(0.411)	(0.499)	
Possession of drugs	26.001	0.098	0.760	0.536	45,176
	(9.081)	(0.298)	(0.427)	(0.499)	
Possession of weapon offences	27.672	0.081	0.762	0.415	7,145
	(11.577)	(0.273)	(0.426)	(0.493)	
Miscellaneous crimes against society	28.918	0.128	0.747	0.378	8,435
	(11.467)	(0.334)	(0.435)	(0.485)	
Public order offences	28.322	0.181	0.777	0.472	39,143
	(12.513)	(0.385)	(0.416)	(0.499)	

Notes: Standard errors in parenthesis. All descriptives refer to the full sample of offenders. *Share at first offence* is the share of crimes in the category that has an offender at his/her first offence

Table A2. Poisson estimates of the crime-offenders locations distance function. Comparison between alternative distance measures– quadratic polynomial

	(1) Violent crimes	(2) Property crimes	(3) Other crimes
Panel A			
Car time (min)	-0.3949***	-0.2472***	-0.3738***
	(0.0047)	(0.0058)	(0.0051)
Car time^2 (/100)	0.5340***	0.2496***	0.4494***
	(0.0145)	(0.0210)	(0.0169)
(1-Pr(match))*v_{ab}	-0.0757***	-0.1233***	-0.0431***
	(0.0035)	(0.0060)	(0.0013)
Panel B			
Public transport time (min)	-0.1243***	-0.0641***	-0.1346***
	(0.0031)	(0.0037)	(0.0035)
Public transport time^2 (/100) (min)	0.0607***	0.0014	0.0514***
	(0.0038)	(0.0053)	(0.0051)
(1-Pr(match))*v_{ab}	-0.1331***	-0.1617***	-0.0376***
	(0.0059)	(0.0075)	(0.0012)
Panel C			
Car distance (km)	-0.4349***	-0.3054***	-0.4958***
	(0.0171)	(0.0166)	(0.0158)
Car distance^2 (/100) (km)	0.6136***	0.4228***	0.6445***
	(0.0225)	(0.0376)	(0.0222)
(1-Pr(match))*v_{ab}	-0.1673***	-0.1556***	-0.0591***
	(0.0088)	(0.0080)	(0.0023)
Panel D			
Public transport distance (km)	-0.4317***	-0.2924***	-0.4657***
	(0.0124)	(0.0113)	(0.0120)
Public transport distance^2 (/100) (km)	0.6409***	0.3966***	0.6516***
	(0.0185)	(0.0177)	(0.0189)
(1-Pr(match))*v_{ab}	-0.1673***	-0.1457***	-0.0522***
	(0.0067)	(0.0069)	(0.0020)
Panel E			
Euclidean distance (km)	-0.6381***	-0.4738***	-0.7365***
	(0.0275)	(0.0210)	(0.0259)
Euclidean distance^2 (/100)	1.4483***	1.035***	1.5005***
	(0.0544)	(0.0479)	(0.0543)
(1-Pr(match))*v_{ab}	-0.1906***	-0.1557***	-0.0664***
	(0.0087)	(0.0076)	(0.0023)

Notes: Standard errors clustered at the destination area level in parenthesis. ***p<0.01, **p<0.05, *p<0.1. All models include crime location (CASWard) fixed effects and offender-crime fixed effects. (1-Pr(match))*v_{ab} corresponds to $[1 - F(\sigma_1 c_{ab})]v_{ab}$. N = 5,495,520

Table A3. Poisson estimates of the crime-offenders locations distance function. Narrow definition of crime types

	Independent variables		
	Car time	Public transport time/Car time	Selection parameter
Crime types:			
Homicide & Violence with injury	-0.2503***	-0.4217***	-0.1064***
	(0.0064)	(0.0373)	(0.0051)
Violence without injury	-0.2562***	-0.4785***	-0.0800***
	(0.0048)	(0.0336)	(0.0034)
Sexual offence and rape	-0.1733***	-0.4051***	-0.1456***
	(0.0125)	(0.0524)	(0.0167)
Robbery	-0.1328***	-0.1673***	-0.1618***
	(0.0135)	(0.0296)	(0.0169)
Burglary	-0.1310***	-0.2571***	-0.1637***
	(0.0063)	(0.0303)	(0.0072)
Other theft offences	-0.1613***	-0.3491***	-0.1379***
	(0.0076)	(0.0407)	(0.0080)
Vehicle, bicycle theft & theft from the person	-0.1665***	-0.2324***	-0.1511***
	(0.0068)	(0.0256)	(0.0076)
Shoplifting	-0.2151***	-0.1207***	-0.0868***
	(0.0078)	(0.0328)	(0.0059)
Criminal damage and arson	-0.2296***	-0.3671***	-0.1388***
	(0.0060)	(0.0351)	(0.0055)
Trafficking and possession of drugs	-0.2972***	-0.4121***	-0.1010***
	(0.0051)	(0.0314)	(0.0059)
Other crimes miscellaneous	-0.2504***	-0.3316***	-0.0958***
	(0.0064)	(0.0315)	(0.0062)

Notes: Standard errors clustered at the destination area level in parenthesis. ***p<0.01, **p<0.05, *p<0.1. All models include crime location (CAS Ward) fixed effects, offender-crime fixed effects, and time fixed effects. N = 5,495,520

Table A4. Poisson estimates of the crime-offenders locations distance function. Crimes concluded

	(1) Violent crimes	(2) Property crimes	(3) Poisson
Car time (min)	-0.3016***	-0.2431***	-0.2981***
	(0.0055)	(0.0057)	(0.0055)
Public transport time/car time	-0.4470***	-0.1944***	-0.3764***
	(0.0342)	(0.0293)	(0.0314)
N	5,495,520	5,495,520	5,495,520
Car time (min)	-0.2626***	-0.1812***	-0.2703***
	(0.0053)	(0.0069)	(0.0055)
Public transport time/car time	-0.4464***	-0.1801***	-0.3731***
	(0.0342)	(0.0270)	(0.0311)
(1-Pr(match))*v_{ab}	-0.0703***	-0.1220***	-0.0869***
	(0.0034)	(0.0059)	(0.0030)
N	5,495,520	5,495,520	5,495,520

Notes: Standard errors clustered at the destination area level in parenthesis. ***p<0.01, **p<0.05, *p<0.1. All models include crime location (CAS Ward) fixed effects and offender-crime fixed effects. (1-Pr(match))*v_{ab} corresponds to $[1 - F(\sigma_1 c_{ab})]v_{ab}$

Table A5. Poisson estimates of the crime-offenders locations distance function. Offenders who are charged or summonsed

	(1) Violent crimes	(2) Property crimes	(3) Poisson
Car time (min)	-0.2906***	-0.2397***	-0.2966***
	(0.0052)	(0.0047)	(0.0051)
Public transport time/car time	-0.4508***	-0.1935***	-0.3892***
	(0.0337)	(0.0286)	(0.0314)
N	5,495,520	5,495,520	5,495,520
Car time (min)	-0.2175***	-0.0991***	-0.2217***
	(0.0052)	(0.0088)	(0.0057)
Public transport time/car time	-0.4498***	-0.1852***	-0.3847***
	(0.0337)	(0.0276)	(0.0309)
(1-Pr(match))*v_{ab}	-0.1101***	-0.1934***	-0.1251***
	(0.0045)	(0.0092)	(0.0046)
N	5,495,520	5,495,520	5,495,520

Notes: Standard errors clustered at the destination area level in parenthesis. ***p<0.01, **p<0.05, *p<0.1. All models include crime location (CAS Ward) fixed effects and offender-crime fixed effects. (1-Pr(match))*v_{ab} corresponds to $[1 - F(\sigma_1 c_{ab})]v_{ab}$

Table A6. Poisson estimates of the crime-offenders locations distance function. Only crimes with Immediate or Prompt priority grade

	(1) Violent crimes	(2) Property crimes	(3) Other crimes
Car time (min)	-0.3054***	-0.2399***	-0.2946***
	(0.0056)	(0.0064)	(0.0057)
Public transport time/car time	-0.4962***	-0.1753***	-0.3552***
	(0.0361)	(0.0297)	(0.0330)
N	5,495,520	5,495,520	5,495,520
Car time (min)	-0.2685***	-0.1986***	-0.2665***
	(0.0058)	(0.0073)	(0.0059)
Public transport time/car time	-0.4951***	-0.1588***	-0.3516***
	(0.0360)	(0.0268)	(0.0324)
(1-Pr(match))*v_{ab}	-0.0713***	-0.1051***	-0.0824***
	(0.0034)	(0.0057)	(0.0036)
N	5,495,520	5,495,520	5,495,520

Notes: Standard errors clustered at the destination area level in parenthesis. ***p<0.01, **p<0.05, *p<0.1. All models include crime location (CAS Ward) fixed effects and offender-crime fixed effects. (1-Pr(match))*v_{ab} corresponds to $[1-F(\sigma_1 c_{ab})]v_{ab}$

Table A7. Poisson estimates of the crime-offenders locations distance function. Years until 2013

	(1) Violent crimes	(2) Property crimes	(3) Other crimes
Car time (min)	-0.3049***	-0.2451***	-0.2983***
	(0.0057)	(0.0057)	(0.0056)
Public transport time/car time	-0.4201***	-0.1924***	-0.3598***
	(0.0352)	(0.0300)	(0.0316)
N	3,159,924	3,159,924	3,159,924
Car time (min)	-0.2745***	-0.1871***	-0.2744***
	(0.0056)	(0.0071)	(0.0058)
Public transport time/car time	-0.4200***	-0.1776***	-0.2829***
	(0.0353)	(0.0274)	(0.0277)
(1-Pr(match))*v_{ab}	-0.0601***	-0.1167***	-0.0347***
	(0.0037)	(0.0057)	(0.0015)
N	3,159,924	3,159,924	3,159,924

Notes: Standard errors clustered at the destination area level in parenthesis. ***p<0.01, **p<0.05, *p<0.1. All models include crime location (CAS Ward) fixed effects and offender-crime fixed effects. (1-Pr(match))*v_{ab} corresponds to $[1-F(\sigma_1 c_{ab})]v_{ab}$

Table A8. Offenders' location fixed effects models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Violent with injury	Violent without injury	Sexual offences	Robbery	Burglaries	Other Personal thefts	Shoplifting	Other thefts	Criminal damage and arson	Drug	Other crimes
Unemployment rate (%)	0.0094	0.0348*	0.0029	-0.0309	0.0138	0.0254	0.0699***	0.0060	-0.0248	0.0242	0.0422**
	(0.0203)	(0.0204)	(0.0209)	(0.0407)	(0.0414)	(0.0268)	(0.0208)	(0.0291)	(0.0212)	(0.0191)	(0.0177)
Population with a degree over 16+ (%)	-0.0391***	-0.0529***	-0.0554***	-0.0738*	-0.1634**	-0.0810***	-0.0303*	-0.1163***	-0.0465***	-0.0190	-0.0395***
	(0.0112)	(0.0106)	(0.0179)	(0.0408)	(0.0820)	(0.0135)	(0.0178)	(0.0405)	(0.0106)	(0.0128)	(0.0122)
Population under 15 (%)	0.0392	0.0361	0.0052	0.0591	-0.0265	0.0550*	0.0169	0.0099	0.0390	0.0411	0.0312
	(0.0257)	(0.0250)	(0.0306)	(0.0471)	(0.0754)	(0.0324)	(0.0309)	(0.0432)	(0.0243)	(0.0251)	(0.0242)
Population 16-19 (%)	0.0234	-0.0012	-0.0212	0.0128	-0.1386	-0.0582	0.0083	-0.0770	0.0183	0.0109	-0.0162
	(0.0411)	(0.0358)	(0.0549)	(0.0836)	(0.1274)	(0.0491)	(0.0514)	(0.0691)	(0.0391)	(0.0411)	(0.0392)
Population 20-24 (%)	0.0301	0.0107	-0.0224	0.0377	-0.0566	-0.0418	0.0341	-0.0244	0.0107	0.0254	-0.0030
	(0.0256)	(0.0232)	(0.0342)	(0.0510)	(0.0640)	(0.0346)	(0.0363)	(0.0405)	(0.0248)	(0.0275)	(0.0271)
Population 25-29 (%)	-0.0326	0.0290	-0.0279	0.0153	0.0098	0.0828*	-0.0052	0.0333	-0.0285	0.0142	0.0149
	(0.0359)	(0.0333)	(0.0419)	(0.0569)	(0.0650)	(0.0445)	(0.0476)	(0.0482)	(0.0350)	(0.0346)	(0.0340)
Population 45-64 (%)	0.0010	0.0359	-0.0089	0.0735	0.0304	0.0566	0.0373	0.0231	-0.0083	0.0374	0.0108
	(0.0301)	(0.0260)	(0.0342)	(0.0453)	(0.0566)	(0.0363)	(0.0377)	(0.0388)	(0.0307)	(0.0305)	(0.0272)
Population above 65 (%)	-0.0016	-0.0118	-0.0096	0.0004	-0.0490	-0.0201	-0.0327	-0.0149	0.0062	-0.0158	-0.0134
	(0.0175)	(0.0173)	(0.0187)	(0.0353)	(0.0568)	(0.0202)	(0.0348)	(0.0319)	(0.0160)	(0.0173)	(0.0200)
Married/Couples over total population (%)	-0.0358***	-0.0190**	-0.0300***	-0.0934***	-0.0974***	-0.0269***	-0.0161**	-0.0617***	-0.0480***	-0.0166**	-0.0192**
	(0.0086)	(0.0078)	(0.0096)	(0.0149)	(0.0166)	(0.0101)	(0.0080)	(0.0127)	(0.0082)	(0.0072)	(0.0077)
Students (% of population 16-64)	-0.0245	0.0023	-0.0037	-0.0352	0.0077	0.0416	-0.0195	0.0005	-0.0219	-0.0059	0.0083
	(0.0219)	(0.0208)	(0.0290)	(0.0355)	(0.0481)	(0.0318)	(0.0277)	(0.0305)	(0.0215)	(0.0226)	(0.0224)
Population density (standardised)	-0.0738**	-0.0791***	-0.1167***	-0.1181**	-0.1390*	-0.0394	-0.1032***	-0.0602	-0.0520	-0.1050***	-0.1010***
	(0.0301)	(0.0302)	(0.0410)	(0.0535)	(0.0816)	(0.0426)	(0.0400)	(0.0484)	(0.0340)	(0.0354)	(0.0341)
Number of business density (standardised)	-0.1123***	-0.0845***	-0.0260	-0.1474***	-0.0810	-0.0494	-0.0680	-0.0792	-0.0952***	-0.0969***	-0.1074***
	(0.0270)	(0.0238)	(0.0378)	(0.0433)	(0.0895)	(0.0344)	(0.0427)	(0.0498)	(0.0286)	(0.0301)	(0.0373)
People born abroad (% of population)	0.0149	0.0154	0.0306**	0.0634***	0.0647***	0.0204*	0.0142	0.0614***	0.0163*	-0.0148*	0.0041
	(0.0100)	(0.0103)	(0.0142)	(0.0153)	(0.0245)	(0.0124)	(0.0127)	(0.0156)	(0.0096)	(0.0090)	(0.0089)
Ethnic minorities (%)	0.0023	-0.0014	0.0015	0.0088	0.0029	-0.0046	-0.0026	-0.0086	0.0036	0.0154***	-0.0005
	(0.0049)	(0.0046)	(0.0057)	(0.0072)	(0.0091)	(0.0061)	(0.0059)	(0.0062)	(0.0045)	(0.0048)	(0.0044)
Agriculture and manufacturing (%)	-0.0036	-0.0010	-0.0047	-0.0116**	-0.0064	-0.0016	0.0021	-0.0103**	-0.0025	-0.0005	0.0013
	(0.0026)	(0.0026)	(0.0030)	(0.0050)	(0.0074)	(0.0027)	(0.0033)	(0.0046)	(0.0026)	(0.0029)	(0.0030)
Construction/Utilities/Transportation (%)	0.0060	0.0014	0.0063	-0.0002	-0.0076	0.0004	0.0035	-0.0040	0.0015	0.0008	0.0015
	(0.0037)	(0.0037)	(0.0043)	(0.0056)	(0.0072)	(0.0045)	(0.0046)	(0.0052)	(0.0036)	(0.0027)	(0.0032)
Commerce (%)	-0.0025	-0.0017	0.0023	0.0127	0.0177	-0.0017	-0.0125***	0.0041	-0.0034	-0.0046*	-0.0045*
	(0.0027)	(0.0026)	(0.0050)	(0.0081)	(0.0137)	(0.0031)	(0.0034)	(0.0087)	(0.0027)	(0.0026)	(0.0027)
Hospitality (%)	-0.0049	-0.0038	0.0023	0.0117	0.0302**	0.0029	-0.0051	0.0097	-0.0039	-0.0033	-0.0021
	(0.0040)	(0.0034)	(0.0073)	(0.0119)	(0.0146)	(0.0050)	(0.0050)	(0.0117)	(0.0041)	(0.0032)	(0.0036)
Occupation: associate professionals, admin, skilled trade (%)	0.0046	-0.0242	-0.0273	-0.0102	-0.0378	-0.0435**	-0.0260	-0.0474**	-0.0159	0.0079	-0.0106
	(0.0151)	(0.0149)	(0.0191)	(0.0272)	(0.0418)	(0.0198)	(0.0215)	(0.0223)	(0.0165)	(0.0167)	(0.0163)
Occupation: care, procedural, sales, elementary (%)	-0.0469***	-0.0602***	-0.0557**	-0.0773*	-0.1473*	-0.0775***	-0.0387**	-0.1066**	-0.0498***	-0.0227	-0.0457***
	(0.0146)	(0.0143)	(0.0223)	(0.0424)	(0.0826)	(0.0170)	(0.0192)	(0.0421)	(0.0148)	(0.0152)	(0.0143)
Constant	3.5839	3.1341	6.2762**	5.9014	15.7558	4.3327	2.2128	9.6117*	5.7473**	1.3877	2.8499
	(2.3291)	(2.0906)	(2.9890)	(5.6041)	(9.8391)	(2.7165)	(3.5794)	(5.0507)	(2.3674)	(2.3462)	(2.4771)
Observations	214	214	214	214	214	214	214	214	214	214	214

Notes: Robust standard errors in round parenthesis. ***p<0.01, **p<0.05, *p<0.1. Models are weighted for population. *Violent crimes with injury* also include homicides; *Sexual offences* also include rape; Drug contains drug possession and drug trafficking; *Other personal thefts* include vehicle thefts, bicycle thefts, and other personal thefts; *Other crimes* includes weapon possession, miscellaneous crimes against society, and public order offences.

Table A9. Crime location fixed effects models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Violent with injury	Violent without injury	Sexual offences	Robbery	Burglaries	Other, Personal thefts	Shoplifting	Other thefts	Criminal damage and arson	Drug	Other crimes
Unemployment rate (%)	0.0153	-0.0160	-0.0372*	0.0040	0.0052	-0.0578	0.0587	-0.0410*	0.0127	0.0366	0.0173
	(0.0185)	(0.0220)	(0.0194)	(0.0306)	(0.0218)	(0.0422)	(0.0846)	(0.0248)	(0.0212)	(0.0287)	(0.0266)
Population with a degree over 16+ (%)	-0.0226	-0.0061	-0.0335**	-0.0069	0.0110	-0.0159	0.0109	-0.0333*	-0.0342***	-0.0137	-0.0213
	(0.0138)	(0.0124)	(0.0137)	(0.0176)	(0.0145)	(0.0228)	(0.0532)	(0.0192)	(0.0125)	(0.0224)	(0.0249)
Population under 15 (%)	-0.0212	-0.0283	0.0187	-0.0314	0.0012	-0.0504	-0.4805***	-0.0370	-0.0199	-0.0094	-0.1013**
	(0.0246)	(0.0212)	(0.0249)	(0.0353)	(0.0274)	(0.0509)	(0.1429)	(0.0460)	(0.0260)	(0.0433)	(0.0426)
Population 16-19 (%)	-0.0009	-0.0072	0.0354	0.0402	-0.0004	-0.0098	-0.2463	-0.0206	-0.0220	-0.0015	-0.0281
	(0.0505)	(0.0413)	(0.0440)	(0.0520)	(0.0535)	(0.1012)	(0.2634)	(0.0835)	(0.0446)	(0.0502)	(0.0786)
Population 20-24 (%)	0.0084	-0.0036	0.0139	0.0105	0.0403	-0.0069	-0.1906	-0.0101	-0.0078	0.0143	-0.0182
	(0.0308)	(0.0284)	(0.0333)	(0.0374)	(0.0347)	(0.0657)	(0.1261)	(0.0549)	(0.0305)	(0.0322)	(0.0469)
Population 25-29 (%)	-0.0250	-0.0661**	-0.0353	-0.1589***	-0.0693*	-0.1591***	-0.4783***	-0.0622	-0.0381	-0.0142	-0.1069**
	(0.0375)	(0.0315)	(0.0374)	(0.0550)	(0.0379)	(0.0518)	(0.1343)	(0.0486)	(0.0392)	(0.0564)	(0.0484)
Population 45-64 (%)	0.0208	-0.0345	0.0191	-0.0890*	-0.0202	-0.0692	-0.3266**	-0.0289	0.0110	-0.0027	-0.0637
	(0.0340)	(0.0255)	(0.0295)	(0.0494)	(0.0311)	(0.0593)	(0.1314)	(0.0553)	(0.0371)	(0.0590)	(0.0508)
Population above 65 (%)	-0.0241	-0.0070	0.0113	0.0073	0.0516*	-0.0251	-0.2846***	-0.0235	0.0012	-0.0235	-0.0572**
	(0.0178)	(0.0168)	(0.0208)	(0.0270)	(0.0267)	(0.0310)	(0.0723)	(0.0262)	(0.0206)	(0.0236)	(0.0273)
Married/Couples over total population (%)	-0.0155	-0.0220**	-0.0568***	-0.0332***	-0.0260***	-0.0463***	0.0544*	-0.0203**	-0.0338***	-0.0015	-0.0086
	(0.0095)	(0.0087)	(0.0090)	(0.0126)	(0.0080)	(0.0135)	(0.0303)	(0.0103)	(0.0088)	(0.0128)	(0.0161)
Students (% of population 16-64)	-0.0155	-0.0223	-0.0248	-0.0475	-0.0263	-0.0424	-0.0438	-0.0124	-0.0097	-0.0078	-0.0362
	(0.0281)	(0.0233)	(0.0265)	(0.0300)	(0.0289)	(0.0449)	(0.0873)	(0.0353)	(0.0262)	(0.0289)	(0.0363)
Population density (standardised)	-0.1707***	-0.1438***	-0.0983**	-0.0865*	-0.1429***	-0.3196***	-0.4425*	-0.2706***	-0.1556***	-0.1494***	-0.2232***
	(0.0375)	(0.0347)	(0.0403)	(0.0494)	(0.0422)	(0.0864)	(0.2515)	(0.0749)	(0.0388)	(0.0471)	(0.0701)
Number of business density (standardised)	0.2327***	0.1703***	0.1170***	0.1479***	0.1055***	0.1922***	0.4065***	0.1331***	0.1422***	0.1353***	0.2219***
	(0.0235)	(0.0184)	(0.0193)	(0.0240)	(0.0246)	(0.0298)	(0.1112)	(0.0229)	(0.0212)	(0.0288)	(0.0336)
People born abroad (% of population)	0.0289**	0.0210**	0.0462***	0.0351**	0.0156	0.0392*	0.0056	0.0427***	0.0311***	0.0678***	0.0309**
	(0.0120)	(0.0107)	(0.0130)	(0.0158)	(0.0137)	(0.0208)	(0.0448)	(0.0153)	(0.0119)	(0.0170)	(0.0157)
Ethnic minorities (%)	-0.0052	-0.0023	-0.0026	0.0014	0.0051	0.0028	0.0052	-0.0032	-0.0017	-0.0361***	-0.0060
	(0.0059)	(0.0053)	(0.0060)	(0.0079)	(0.0056)	(0.0090)	(0.0259)	(0.0078)	(0.0055)	(0.0084)	(0.0072)
Agriculture and manufacturing (%)	-0.0006	-0.0021	-0.0031	-0.0028	0.0045	-0.0020	-0.0027	0.0014	-0.0009	0.0018	-0.0041
	(0.0028)	(0.0025)	(0.0035)	(0.0039)	(0.0035)	(0.0048)	(0.0102)	(0.0035)	(0.0031)	(0.0040)	(0.0043)
Construction/Utilities/Transportation (%)	-0.0062*	-0.0033	-0.0021	0.0014	0.0029	0.0095	-0.0335**	0.0084*	-0.0012	-0.0045	-0.0040
	(0.0037)	(0.0038)	(0.0041)	(0.0058)	(0.0041)	(0.0084)	(0.0155)	(0.0043)	(0.0038)	(0.0046)	(0.0079)
Commerce (%)	0.0056**	0.0021	0.0046	0.0088**	0.0044	0.0143**	0.0606***	0.0087**	0.0062**	0.0068**	0.0056
	(0.0026)	(0.0025)	(0.0028)	(0.0045)	(0.0034)	(0.0065)	(0.0109)	(0.0036)	(0.0030)	(0.0033)	(0.0035)
Hospitality (%)	-0.0020	-0.0041	-0.0012	-0.0076	-0.0043	-0.0062	-0.0408**	-0.0049	-0.0002	-0.0001	-0.0078
	(0.0032)	(0.0039)	(0.0040)	(0.0054)	(0.0049)	(0.0074)	(0.0176)	(0.0064)	(0.0052)	(0.0055)	(0.0061)
Occupation: associate professionals, admin, skilled trade (%)	-0.0335**	-0.0112	-0.0136	-0.0148	-0.0075	-0.0285	-0.0361	-0.0520**	-0.0339**	-0.0383	-0.0583**
	(0.0169)	(0.0170)	(0.0194)	(0.0225)	(0.0195)	(0.0302)	(0.0718)	(0.0263)	(0.0167)	(0.0244)	(0.0270)
Occupation: care, procedural, sales, elementary (%)	-0.0186	0.0036	-0.0357**	-0.0339*	-0.0217	-0.0276	0.0403	-0.0528**	-0.0416***	-0.0204	-0.0127
	(0.0159)	(0.0154)	(0.0171)	(0.0204)	(0.0173)	(0.0283)	(0.0683)	(0.0223)	(0.0147)	(0.0281)	(0.0310)
Constant	2.5673	3.2221	3.7500	6.8281*	2.1976	9.0203	23.6304	7.4353	5.0680*	-1.1978	7.9408
	(2.6223)	(2.5150)	(2.6609)	(3.4839)	(2.9288)	(5.7720)	(14.5120)	(4.8051)	(2.6365)	(3.8131)	(5.0306)
Observations	214	214	214	214	214	214	214	214	214	214	214

Notes: Robust standard errors in round parenthesis. ***p<0.01, **p<0.05, *p<0.1. Models are weighted for population. *Violent crimes with injury* also include homicides; *Sexual offences* also include rape; Drug contains drug possession and drug trafficking; *Other personal thefts* include vehicle thefts, bicycle thefts, and other personal thefts; *Other crimes* includes weapon possession, miscellaneous crimes against society, and public order offences.

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