Exposure to crime and pupils' outcomes: evidence from London*

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This Version: September 2, 2021

First Version: September 2018

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Abstract

Estimation of unintended costs of crime is scarce, although essential. This paper investigates a prominent indirect cost of crime, i.e. the effect of exposure to crime on achievement of pupils enrolled in primary school. I employ novel geo-referenced data on the universe of crimes from police records in London. The analysis takes advantage of the very fine spatial variation in crimes and in pupils' residences, precisely measuring the exposure to crime in the surroundings of pupils' homes. By exploiting the within-school variation in crime, I find that crime occurring where pupils live lowers impact on pupils' achievement at final exams of primary school. The heterogeneity analysis shows that high-ability and wealthy students are those who suffer the most from exposure to crime. I find evidence of decreasing marginal sensitivity to crime, as pupils living in less criminal areas suffer the most from exposure to crime. Overall, I interpret this evidence as consistent with a story of scarring effect and adaptation.

JEL Classification: I20, K42, R23.

Keywords: Neighbourhood; Crime; Academic Performance.

*I am very grateful to my supervisors Francesco Fasani and Marco Manacorda. I thank Sebastian Axbard, Anna Bindler, Eric Battistin, Rocco Macchiavello, Barbara Petrongolo, Anna Raute, Andrea Tesei, Paolo Pinotti, Olmo Silva, and all participants to the 4th IZA Workshop on the Economics of Education and to the 11th Transatlantic Workshop on the Economics of Crime for valuable comments and discussion. A special thank to the NPD staff. The views expressed here are those of the author alone.

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1 Introduction

Crime constitutes a deadweight loss for the society. Beyond its direct costs associated to victimisation, policing and the judiciary system, little is known about its indirect costs, which potentially affect a much larger share of the population. Indeed, crime causes distress and anxiety also to people not directly touched by victimisation. However, despite their potential, indirect costs of crime have received little empirical attention so far. Indeed, although crime cost is regularly appraised, official estimates do not include in their calculations consequences of fear to the general public and to communities in high crime areas (Dubourg et al., 2005; Cohen and Bowles, 2010; Heeks et al., 2018), which are key inputs for the estimation of the optimal level of public investment in the fight against crime.

This paper tries to fill the gap by studying the impact of exposure to crime at an early stage of education. Specifically, I attempt to answer the following question: does exposure to crime affect children performance at school? Exposure to a criminal environment is associated with emotional and cognitive stress as well as symptoms of post-traumatic stress disorder (Gorman-Smith and Tolan, 1998; Delaney-Black et al., 2002; Ozer and Weinstein, 2004). Stress can reduce working memory and increase cognitive distractions that lead students to perform poorly on tests. Furthermore, along with influencing students' performance in the short-term, shocks due to exposure to crime might also affect long-term outcomes which are determined by academic achievement. By answering this question, I therefore consider exposure to crime as an input that directly enters the education production function and has the potential to impair academic performance at early age.

I specifically focus on the context of potential high-stake exams and on a stage of life where external shocks are more likely to affect the development of socio-emotional skills (Cunha and Heckman, 2007; Heckman, 2006; Chetty et al., 2016). In lieu of considering secondary schools and colleges, I remove the risk of youth's direct involvement into crime and look at the first phase of education, whose long-run effects are already well established.

My empirical strategy produces estimates of the effect of exposure to crime on achievement of pupils who live in the same area where the crime takes place. To address the potential endogeneity of crime, I employ two highly-detailed datasets. I combine a unique set of geo-referenced data on the universe of police criminal records with pupil-level data for all the students enrolled in public primary schools in London. By geo-coding the exact location of the criminal incidents and of the schools and pupils' addresses, I build areas of exposure to crime around pupils' residences and identify postcode-level variation within narrowly defined neighbourhoods.[1] The very fine spatial nature of the data provides the unique opportunity to isolate the impact of crime from the neighbourhood effect. Furthermore, having access to the universe of crimes recorded by the police, I gain flexibility in the choice of the most relevant type of crime and in the design of the areas of exposure around pupils' homes.

To estimate the effect of living in a criminal area, I exploit hyperlocal variation in exposure to crime across areas where pupils live and I compare outcomes of pupils who go to the same school and take the exam in the same academic year, reside in the same neighbourhood, are exposed to the same local conditions and display the same observable characteristics. The empirical strategy relies on the assumption that there is no correlation in unobservable traits of pupils living in different sites within school catchment areas. In order to remove families' endogenous sorting into neighbourhoods, I condition on a full set of neighbourhood and time fixed effects, as well as individual controls. By adding school-time fixed effects, I capture all time-varying determinants of parental preferences over schools that are related to school inputs, such as schools, teachers and peers' quality. Finally, I absorb part of the selection of families into postcodes by conditioning on house prices and house characteristics, measured at the building level. Importantly, including house prices and conditions provides a proxy for local amenities, which are likely to play a relevant role in families' decisions of where to live. I run a number of tests to assess the validity of the identifying assumption and I find no evidence in favour of the fact that families select into specific locations within a neighbourhood based on crime realisations (Bayer et al., 2008).

Within-school estimates show that pupils who are more exposed to crime where they live perform worse at the final exams of primary school. To give a sense of the magnitude, one s.d. increase in local crime decreases reading or math test scores by 1% of standard deviation of test scores. These results are consistent with Chetty et al. (2018), who find that "a child's immediate surroundings '*within half a mile*' are responsible for almost all of the association between children's outcomes and neighbourhood characteristics". Results are robust to the inclusion of a full plethora of fixed effects and to a set of time-varying controls which absorb individual and postcode-specific housing characteristics. Results are significant for different types of

[1] My definition of neighbourhood refers to the one of school catchment area, which includes all pupils attending a certain school and living in its surroundings. The average radius of a school catchment area is 1.2 km (see Section 2 for further details). In the UK, a postcode unit generally represents a street, a single address or a single property. In London in particular, given the high urban density, postcodes alone refer to single buildings and can therefore be matched to a pair of geographical coordinates.

crime, and under all specifications stronger for violent crimes and anti-social behaviour offences which are likely to be more visible to the local community: this evidence supports the idea that information on crime likely reaches families through informal channels. To further assess the magnitude of my findings, I compare these estimates to the effect of another fundamental school input, namely school quality: I find that the impact of one s.d. increase in exposure to crime is around one-tenth of the effect of an increase in school quality. Back-of-the-envelope calculations based on estimates from Rivkin et al. (2005) reveal that each school should spend around £50,000 more per year in teaching staff in order to offset the learning loss due to exposure to crime.

The heterogeneity analysis reveals that pupils who suffer the most from exposure to crime are female, high-ability and non-disadvantaged students. Furthermore, I provide evidence of diminishing marginal sensitivity to local crime: pupils living in areas with less crime are those who are more subject to negative effects. Overall, I interpret this evidence as consistent with a story of adaptation or "scarring" effect.[2]

This paper makes several contributions with respect to previous work. Firstly, empirical knowledge about the spillovers of criminal activities is so far limited and only few papers have tried to shed some light on the link between crime and schooling outcomes. Grogger (1997) estimates the effect of local violence, defined as the sum of school and neighbourhood violence, on educational attainments using principal records and finds that it affects high school graduation rates and college attendance. Similarly, Aizer (2008) analyses the effect of neighbourhood crime on children well-being in Los Angeles. However, given the cross-sectional nature of the data, previous works encounter serious endogeneity concerns, which make difficult for them to claim causality. More recent studies evaluate instead the short-term effect of violence focusing on a sample of teenagers in Chicago and New York (Sharkey (2010), Sharkey et al. (2014)). Under the assumption that the timing of crime is orthogonal to the timing of the test, they estimate a negative effect of exposure to violent crimes on reading test scores only, stronger for black students. I improve upon existing work exploring the impact of exposure to local crime on primary school students. I use longitudinal data and exploit repeated information on both pupils' test scores and local crime to eliminate potential sorting bias. I remove the threat of

[2]This term was firstly used by Clark et al. (2001) (see also Clark (2003) and Clark and Georgellis (2013)) to describe that, despite a general negative effect on well-being of unemployed, workers who have been unemployed for few times become used to the situation and suffer less. The psychological basis of the reasoning is the following: judgement on the current situation depends on the experience of similar situations in the past, and higher level of past "consumption" or experience may offset higher current levels (see Kahneman (1994)).

reverse causality focusing on pupils aged 11 at the time of their final exam (Key Stage 2), who are arguably not directly involved in criminal activities.

Secondly, this paper is closely related to the literature that studies the impact of external shocks on students' outcomes.[3] I add to existing work defining arguably exogenous crime shocks and focusing on a stage of life where external events are more likely to affect the development of socio-emotional skills (Cunha and Heckman, 2007; Chetty et al., 2016) and to impair pupils' learning process and performance during exams. Empirical evidence has already established that shocks at early age jeopardise long-term human capital accumulation (Heckman, 2006) and have implications for the intergenerational transmission of economic advantage. If adverse shocks occurring at early age produce long-term effects, and given the relevance of education across domains (Angrist and Keueger, 1991), this in turns translates into large repercussions on the long-run outcomes of underprivileged communities. Despite not directly tackling the long-term consequences, I aim to explain the role that crime has in feeding education inequality.

Finally, I complement the literature that directly measures the neighbourhood effect by providing insights on the link between neighbourhood and schooling (Katz et al., 2001; Kling et al., 2005, 2007): indeed, I focus on one of the possible drivers behind the neighbourhood effect by isolating the pure crime effect while controlling for the local conditions.

To my knowledge this is the first analysis to be carried out in the UK and in London.[4] London provides the ideal setting to isolate causal estimates of crime spillovers in a developed urban area for two main reasons. Firstly, the high-quality administrative data on crime, together with data on the population of students, allows me to overcome identification issues, such as measurement error and correlation with unobservables. Second, London is similar to other major cities in the western world in terms of overall security and crime.[5] While several studies have so far documented extreme or endemic episodes of violence in developing countries (Monteiro and Rocha, 2016; Koppensteiner and Menezes, 2017) or in contexts of conflicts (Brück et al., 2014; Shany, 2017), my strategy has the advantage to have relevant implications for a broader audience of policy makers in a standard developed urban context.

The paper proceeds as follows. Section 2 explains the context of my analysis and the datasets

[3]For instance, see Ebenstein et al. (2016) on air pollution and Lindo et al. (2012) on college sports events.

[4]Around 20% of crimes registered in the UK are committed in London.

[5]The 2017 Economist Safe Cities Index, which ranks 60 major cities around the globe, placed London in the 20th spot for overall safety, between Chicago (19) and New York (21). Appendix Figure A1 compares crime trends between Chicago, London, and New York over the past two decades.

I employ on local crime and pupils' performance. Section 3 presents a conceptual discussion and the empirical strategy implemented. Section 4 and 5 provide the results and the robustness checks of the analysis. Section 6 concludes.

2 Background and Data

I build a unique dataset combining various sources of information on schooling, crime and housing market in London.

Student-level data I use information from the National Pupil Database, a unique dataset which contains the universe of students in state-funded primary schools in England.[6] The dataset includes detailed demographic information on pupils such as gender, ethnicity, language spoken at home, special-education-need (SEN) and free-school-meal (FSM) status, pupils' post-code of residence, as well as information on student achievement.

Pupils are assessed at the end of Key Stage 1 (KS1) and Key Stage 2 (KS2). At the end of KS1, pupils are evaluated by their teachers: these assessments are hardly comparable across schools, but constitute a good proxy for students' ability before the beginning of KS2, when they are aged 7. Pupils take KS2 exams when they are 11. These exams are instead standardised tests necessary for the transition to secondary school.[7] They are national tests in math and English, homogeneous across schools and marked by external examiners, therefore easily comparable across schools. In the empirical analysis, I use KS2 test scores as main outcome variable, while I control for KS1 scores, which represent a good proxy for pupils' pre-determined ability.

I match this dataset with the school census, which contains school-level information such as identifier, address, type of school and number of pupils enrolled. The restricted version of the school census allows me to follow the residential history of each pupil, retrieving the information on whether pupils changed home or school during the school cycle.

For the purpose of this paper, I consider academic years from 2010/11 to 2015/16, hence six repeated cross-sections.[8] I restrict the analysis to the population of students in London enrolled

[6] State-funded schools enrol around 90% of the student population and over 95% of primary school population in England (Department for Education, 2018). Private schools in England do not follow the National Curriculum or participate in the national KS2 evaluation. Because of this, data on these schools are not published by the Department of Education.

[7] In the UK, grammar schools select on the basis of the performance at the test at age 11 (Key Stage 2). Those from disadvantaged backgrounds rarely get into grammar schools.

[8] 2015/16 contains measures for test outcomes not perfectly comparable with previous years, therefore I standardise them by year.

in year 6 and eligible for Key Stage 2 final exam. As a result, the final sample contains 1,960 public-funded primary schools located in London and 497,062 pupils, living in 101,322 postcodes.

The neighbourhood definition used throughout this analysis is the one of school catchment area, which gathers all the postcodes where pupils enrolled in a school live.[9] In England, postcodes are abbreviated forms of address, which identify single addresses or buildings. I therefore take advantage of this crucial feature, and I map each postcode to a pair of geographical coordinates, geo-coding the exact location where pupils live.

Figure 1 provides an illustrative example of a school catchment area in the London borough of Tower Hamlets. The average radius of a school catchment area in London is 1.2 km and on average each school catchment area contains 38 postcodes (for 43 students enrolled). To give a sense of magnitude, school catchment areas contain around 14 Lower Super Output Areas, the smallest statistical units in England, which correspond to around 7 census tracts in the US.[10]

Crime data Crime data are drawn from the UK Police, which collects the universe of recorded crimes. The dataset includes information starting from December 2010 on type of crime, monthly date, and geographical coordinates where the crime was committed. Crimes are classified according to sixteen categories. For the sake of the analysis, I group crimes in six categories: property crimes, violent crimes, drug related crimes, anti-social behaviour, public order. Table A1 in the Appendix illustrates the definitions of each crime group.

I restrict the analysis to urban areas, and specifically to London only.[11] During the sample period (from December 2010 to July 2016), around 20% of crimes were committed in London, affecting 13% of the total UK population. In particular, 12 among the 15 top local authorities by number of crimes occurred are London districts.

I geo-code crime locations, pupils' and schools' addresses. I therefore build areas of exposure to crime around pupils' residences considering all the crimes recorded at most at 500 meters of

[9]Catchment areas are within local authorities: on average only 4% of students in my sample live in a different local authority than their school's.

[10]The average population per LSOA in London is 1,650, while in New York the average population per census tract is 3,000-4,000.

[11]Urban areas provide nearly all the variation in crime. According to the police records, from 2010 to 2017 only around 23% of crimes were committed in rural areas. Within London, I drop observations from the borough of City of London or Westminster due to measurement issues.

distance from pupils' postcodes.[12] Figure 2 illustrates an example of area of exposure to crime. Since the police might often report the approximate location of a crime instead of its exact position for anonymity reasons, I cope with measurement error issues by flexibly drawing areas of exposure around pupils' residences. I firstly consider an area around pupils' postcodes large enough to offset small measurement imprecisions and I then vary the radius of the exposure to crime area to test the robustness of the estimates.

Housing characteristics and Census I collect a third set of data in order to add housing characteristics at postcode level. I therefore combine several information on housing conditions, which I will use as building level controls in the main equation.[13]

Firstly, I use administrative records from the Land Registry, which contains the universe of residential sales between 1995 and 2015. Each recorded transaction reports the date of transfer, the sale price, and property type and the geo-coded address. Furthermore, I extract from the Energy Performance of Buildings additional housing characteristics. This dataset contains all the Energy Performance Certificates (henceforth, EPC) issued since 2008 for buildings sold, constructed or let. As for the current regulation, EPC is a compulsory requirement for any building. Each EPC record contains information on the address of the building and on housing conditions such as type of property, floor area in squared meters per property, number of habitable rooms, number of heated rooms, floor height. For the purpose of this analysis, I consider only domestic buildings and I geo-code the addresses in order to match them with pupils' postcodes.

Combining these two sources I build housing measures at baseline: for house prices, I use the postcode-level average prices in the five years before the beginning of the school cycle (between $t-3$, i.e. beginning of KS2, and $t-8$). For EPC data, I build a within-postcode average between 2008-2010 as before 2008, when the regulation became effective, data are very scarce.[14]

Each pupil's postcode is therefore assigned to baseline prices and baseline housing conditions.

Finally, I also use the Census 2001 to extract neighbourhood characteristics at baseline for the Lower Super Output Area (LSOA), such as share of flats, and share of social rented housing,

[12]The definition of the treatment area is coherent with recent work by Chetty et al. (2018), who conclude that "a child's immediate surroundings - within about half a mile - are responsible for almost all of the association between children's outcomes and neighbourhood characteristics.".

[13]On average there are only 1.6 pupils living in the same postcode.

[14]In a robustness check, I include in the empirical specification an indicator for whether postcode housing information are missing as well as different definition of baseline house prices. Results are not sensitive to the inclusion of such controls. Results are available upon request.

deprivation component indicators and baseline population. I will use this information as additional control in a robustness check.

Table 1 reports the descriptive statistics for demographic composition, crime and housing characteristics. On average, 580 criminal records, out of which 120 violent crimes, are committed throughout an academic year around a pupil's residence. The population of pupils in London is very heterogeneous: 41% of students are white and 52% are natives. Around a quarter of pupils are free-school-meal or with special education needs. The median grade for both reading and math test is 4, which is in line with the national average.

3 Empirical strategy

The empirical analysis investigates the effects on pupils' achievement of exposure to crime around pupils' homes.[15] I exploit variations across pupils' homes within narrowly defined neighbourhoods, i.e. school catchment areas. I therefore compare pupils living in different postcodes, having different degrees of exposure to crime, but going to the same school.

I estimate the following regression equation:

$$y_{i,p,s,t} = \beta_0 + \beta_1 crime_{p,t} + X'_{i,p,t}\gamma + Z'_{p,t}\delta + \phi_s + \phi_t + \varepsilon_{i,p,s,t} \tag{1}$$

where $y_{i,p,s,t}$ is the outcome of pupil i living in postcode p attending school s during academic year t. The main outcome variables are test scores in Math and Reading exams at the end of KS2. $Crime_{p,t}$ is the number of crimes recorded in an area of radius 500 meters around postcode p during academic year t. $X'_{i,p,s,t}$ is a vector of individual characteristics, that absorb part of the pupils' selection into schools. I also include the KS1 test score ($KS1_{i,p,t}$) and compute a pupil-specific value-added equation.[16] $Z'_{p,t}$ is a vector of baseline housing characteristics at the postcode level: this includes baseline prices and baseline housing conditions for each postcode of residence where pupils live. Finally, ϕ_s and ϕ_t are respectively school and academic year fixed effects. In the final specification, I also include the interaction of school-by-academic

[15] I have results on both test scores, levels and teacher assessments' levels. In the main analysis I show results on test scores, following Gibbons et al. (2008).

[16] The value-added approach is widely used in the literature to estimate achievement since it is considered a sufficient statistic for unobserved input histories and unobserved endowment of ability. See, for example, discussion in Hanushek et al. (1996) and citekrueger2003economic. In my case, KS1 and KS2 exams are not directly comparable, since only KS2 exams are standardised tests: for this reason, I include KS1 as a control.

year fixed effects, $\phi_{s,t}$.[17]

The parameter of interest is β_1, the effect of local crime on pupils' outcomes. The causal estimation of this parameter presents few identification challenges. Firstly, isolating the causal effect of crime from confounding factors related to the neighbourhood is hard. Crime is highly correlated with neighbourhood characteristics, such as poverty and socio-economic disadvantage. Criminal activities tend to concentrate in poor geographical areas because of peer interactions, less social stigma and a lower actual and/or perceived probability to be caught. More generally, the coefficient β_1 might reflect not only the effect of local crime, but also of all the unobserved time-varying postcode-level characteristics correlated with crime that might affect student achievement. Secondly, families' decisions of moving in a location are typically endogenous and sorting into neighbourhoods is the result of a non-random selection. If families choose to settle in areas where criminality is lower while at the same time investing more in their children education, then causal estimates would be confounded by unobserved factors. Specifically, if residents' choices are motivated by observed realisations of crime in specific locations, then the coefficients would be biased.

My empirical strategy arguably deals with both issues. Firstly, I add a vector of neighbourhood dummies (ϕ_s), which controls for all the time-invariant characteristics of the neighbourhood as well as the average level of crime in the area. Since I define neighbourhoods as school catchment areas, ϕ_s absorb also all unobserved time-invariant school characteristics as well. I therefore take advantage of variation within school-catchment area, exploiting deviations from the average neighbourhood crime.

I then solve the selection issue in several ways: by including school fixed effects I exploit only variation within neighbourhood, and therefore I capture the constant determinants of families' selection into neighbourhoods as well as the composition of local schools and areas. In this way I compare similar families having homogeneous preferences over schools and neighbourhood quality. In addition, I include a large set of time-varying individual characteristics (gender, ethnicity, free-school-meal, special-education-need, language spoken at home, indicators for change in school or home) which control for family background and changes in composition over time. Finally, I add postcode-level housing characteristics at baseline (housing prices, average floor area, average number of habitable rooms, average floor height), which remove part

[17] I cannot use postcode fixed effects since I do not have enough within-postcode variation (on average there are 1.62 pupils living in a postcode per year). To overcome this issue, I add additional controls at postcode level and as a robustness check I add fixed effects for groups of postcodes.

of the selection into postcodes. Importantly, including housing prices and conditions provide a proxy for local amenities, which are likely to play a relevant role in families' decisions of where to live.[18]

In the empirical strategy, I also add to Equation 1 school-time specific fixed effects, which absorb all time-varying neighbourhood and school characteristics, such as changes in the school supply and in pupils' intake overtime. For instance, exposure to greater violence might change the propensity of teachers to work in schools: this would increase wages demanded by teachers, or, especially in the short run, raise schooling staff absenteeism, which in turns would echo on pupils' performance (Chetty et al., 2011). Including $\phi_{s,t}$ removes the plausible concern that crime impacts on educational outcomes through school supply, school quality and teachers, who directly enter the education production function as an input. Finally, controlling for time-specific school shocks also absorbs any change that happens at a broader geographical level, such as at the local authority level. For instance, a potential source of time-varying differences are differential changes in police resources or in school funding across local authorities, which would be controlled for under this specification.

As a robustness check, in order to further control for neighbourhood composition and local amenities, I include a number of measures of baseline characteristics at the local level (Lower Super Output Area) from the Census. I also deal with the fact that crime is often subject to under-reporting. I compare estimates pooling together all the crime types with those of violent crimes only: as violent crimes are often more visible, they are likely to be less subject to misreporting. Finally, focusing on the primary phase of education only, I remove any threat of reverse causality, which would be relevant in the context of high-school students.

3.1 Validating the empirical strategy

The analysis is based on the consideration that, although families choose where to live, they are unable to fully characterise a precise location within a larger neighbourhood. This assumption arises from few considerations. At the time of the house purchase or lease, households get a reasonable sense of the socio-demographic structure of the neighbourhood in which they want

[18] There is a large literature of school quality and house prices showing that parental valuation of school quality is reflected in house prices and that, for instance, more disadvantaged households may face barriers in exerting school choice, such as high house prices close to high-quality schools (see, for instance, Black (1999), Gibbons et al. (2013a), and Battistin and Neri (2017)). Furthermore, house characteristics such as floor height, number of habitable rooms and energy performance strongly reflect the socio-economic status of the inhabitants.

to live. However, the variation within area is less easily observable: families lack of information to anticipate differences in neighbourhood characteristics within a bigger area, and even more to anticipate information on the exact crime location.

In addition, the housing market is quite thin at low levels of geography: the nature of randomness of the housing search, especially in the short-term, implies that families are restricted in their ability to choose over the precise location in the neighbourhood they have picked. For instance, only 12% of households in London moved house in the last year, while majority of households tend to remain longer in the same house.[19] Therefore, it might be difficult for families to select a house available in the exact location they want. As Bayer et al. (2008) and Linden and Rockoff (2008), I claim that the assumption of conditional exogeneity is reasonable because of the feature of randomness of the housing search, especially in the short term. Indeed, individuals may choose neighbourhoods with specific characteristics, but, within a fraction of mile, the exact location available at the time individuals seek to move into an area is arguably exogenous. Furthermore, even if we assume that families have perfect information over the distribution of crime realisations across available postcodes, they are unlikely to predict whether in the following year the crime around their residence will actually be above or below the neighbourhood average.[20]

In order to provide evidence in favour of this assumption, I empirically assess if realisations of past or current crime induce families to change home or school. Figures 5 and 6 show that neither current nor lagged crime are meaningful predictors of the probability to move, once taking into account school catchment area fixed effects, pupils and housing characteristics.

I therefore build on Bayer et al. (2008) and I implement a within-neighbourhood empirical strategy.[21] The identifying assumption is that, once controlling for the characteristics of the larger neighbourhood selected by the families, the remaining spatial variation across postcodes is arguably exogenous. My empirical strategy retrieves causal estimates of the impact of exposure to crime on pupils' outcomes as long as there is no correlation between unobserved factors and pupils' outcomes for those pupils that go to the same school but live in different postcodes. Additionally, including pupils' housing characteristics as controls, I compare similar families

[19] 59% of households live in their current home since more than 5 years, and 42% since more than 10 years. The corresponding mobility rate for rented units is larger (Greater London Authority, 2017).

[20] Appendix Figure A2 shows an illustrative example of information on neighbourhood criminality that are publicly available on the MET police website. Information on recorded crimes are aggregated at a larger geographical level than the one of my analysis.

[21] In order to identify neighbourhood effect, they isolate block-level variation in the characteristics of neighbours within narrowly defined neighbourhood reference groups (i.e. Census block groups).

living in similar building with homogeneous preferences over local amenities and schools. This identifying assumption is impossible to directly test, but I run a number of tests supporting it. This is crucial to establish a causal interpretation of the effect of exposure to crime on pupils' outcomes.

The first test comes from Bayer et al. (2008).[22] If the identification assumption is valid, then the correlation between pupil and neighbourhood characteristics should be zero, once absorbing neighbourhood fixed effects and individual controls. I therefore define the neighbourhood as composed by all the pupils attending the same school but living in different postcodes, and I study the correlation between predetermined characteristics of a pupil and those of his schoolmates. Following Bayer et al. (2008), I compute for each pupil the average characteristics of his schoolmates, excluding the pupil herself.[23] I therefore measure the correlation between the characteristics of a randomly drawn individual and the leave-out school averages.

Table 17 shows the results: the first column shows the unconditional correlation, the second conditions on time and school fixed effects, the third adds time-school fixed effects. Once absorbing the fixed effects, the correlations go to zero and become insignificant.[24] The results suggest that at least the extent of sorting based on observables is lower within school catchment areas than across neighbourhoods (column 1 versus column 3). Furthermore, these attributes would at least partially constitute the characteristics that are most immediately observed at the time of moving into a new residence. Therefore, when these observables are controlled for, sorting within school catchment area based on other (not observed) characteristics is less extensive. I argue that since the within-school catchment area correlation in observables does not contribute significantly to pupils' outcomes, the key identifying assumption on unobserved characteristics is at least plausible Altonji et al. (2005).

The second set of tests consists of balancing regressions: the aim is to examine the relationship between the observed baseline conditions and the subsequent changes in crime. Any association between baseline conditions and subsequent crime, once controlling for school catchment area and academic year fixed effects may indicate that postcodes that differ in terms of crime, also differ in terms of time-varying unobserved factors. Said in other words, if current or past crime predicts individual characteristics, than it might reveal that families select into neighbourhoods

[22] See also Battiston (2018).

[23] As explained in Bayer et al. (2008) and Battiston (2018), I avoid the mechanical bias of leave-one-out correlations by sampling one pupil per school when computing the correlations.

[24] Significance levels are bootstrapped by repeating 500 times the procedure of sampling one pupil per school catchment area.

based on crime realisations.

I therefore run the main specification from Equation 1 using as explanatory variable the number of crime recorded around pupils' houses on a set of pre-determined individual characteristics. Figure 5 shows the results. I plot for each row the estimated coefficient of a separate regression with the 95% confidence intervals. I first show that crime and individual characteristics strongly correlate. However, once conditioning on the set of fixed effects and controls that I use in my main specifications, the coefficients become smaller and non-significant. Figure 6 performs the same exercise regressing past crime on pre-determined pupil characteristics, while Figure 7 does the same restricting the crime population to violent crimes only. In both cases, introducing school fixed effects and individual and housing controls eliminates the correlation of crime with observables. Provided that the amount of selection on the observable explanatory variables provides a guide to the degree of correlation with the unobservables (Altonji et al., 2005), this evidence supports the exogeneity of the variation of exposure to crime within school catchment areas where pupils live.

In order to further control for residential sorting into different neighbourhoods and different schools, I also exploit the information on whether pupils changed home or school during the school cycle. I include these controls in the main regression and I see that results are robust to their inclusion. Furthermore, as a robustness check I split the sample in pupils who did and did not change school/home and check whether the estimates are actually driven by these sub-samples.

4 Results

4.1 Impact of pupil achievement

Table 2 shows the main results of the empirical analysis. Column 1 displays the simple cross-sectional correlation, column 2 adds school fixed effects, column 3 adds individual and housing controls, and finally column 4 reports the full specification of Equation 1, with the entire set of fixed effects and controls.

The cross-sectional estimates identify simple correlations between crime and pupils' test scores showing that pupils in more criminal areas perform worse than pupils in less criminal areas. However, crime might be correlated with socio-economic factors and in general economic disadvantage. I therefore try to isolate the impact of crime alone from confounding factors correlated with crime, such as neighbourhood deprivation and family economic status, using school fixed effects and additionally controlling for individual and housing characteristics.

Column 4 shows the estimates from the preferred specification, with the full plethora of individual and housing controls, school and time fixed effects as well as their interaction. The effects are smaller but still significant: one standard-deviation increase in crime decreases reading (math) test scores by to 1% of the standard deviation of reading or math test scores, which is around 1 mark point in the final tests.

To gain further insight on the magnitude of these estimates, I compare the effect of an increase in exposure to crime to what the literature has found so far. My results are in line with what the literature on violence and schooling has found (see Table A2): for instance Schwartz et al. (2016) evaluated the context of Afro-American students enrolled in public schools in New York and found a similar effect of exposure to homicides of around 1% sd. I further compare the crime effect that I estimate to the effects of other school inputs that the literature has focused on, such as teacher quality, to understand the relative importance of exposure to crime for pupils' achievement. My estimate corresponds in absolute terms to around 10% of the effect due to an improvement in school quality, as estimates by Rivkin et al. (2005). To give a sense of how economically relevant my estimates are, back-of-the-envelope calculations based on estimates from Rivkin et al. (2005) reveal that each school should spend around £50,000 more per year in teaching staff in order to offset the learning loss due to exposure to crime.[25]

Table 2 shows results grouping crime into five macro classes (see Table A1 for a description of the crime categories). For instance, I define the category of violent crimes putting together violence and sexual offences, common assaults and murders, and robberies. Table 3 shows the results by single type of crime, according to the classification into 16 categories made available by the police. The estimates confirm the evidence from the aggregate classification of crime: the stronger impacts come from violent offences, such as robberies and violent crimes, as well as the most visible types of crime, such as anti-social-behaviour.

Given the high spacial resolution of the data, a concern would be that crime and pupils' characteristics might be spatially correlated. I therefore also report Conley Standard errors (Conley,

[25] I use estimates from Rivkin et al. (2005), who show that the high-quality teacher effect is equivalent to a decrease in class size by 10 pupils. I therefore compare how much the latter would mean in terms of monetary investment in teaching staff. Using the NPD dataset which collects information about school income and expenditure from the Consistent Financial Reporting (CFR), I estimate that each school of my sample spends on average around £500,000 in teaching stuff per year. I therefore take the 10% of such expenditure, which corresponds to the amount that a relative loss in crime would cost.

1999) in order to account for both spacial (across postcodes within school catchment area) and serial correlation (within postcode across time periods) of the errors. Table A3 reports both robust and Conley standard errors, setting a cutoff distance of 2 km, close to the mean size of a school catchment area.[26]

In order to assess the robustness of the results, I perform a direct falsification exercise by regressing current pupils' test scores on future crime, precisely on crime recorded during the summer months following the end of the school (i.e. June and July) and before the beginning of the new academic year. This is a powerful test to check if the estimates are actually driven by unobserved factors. Table 4 shows the estimates of a regression of test scores on current crime, recorded during the academic year, and future crime, recorded during June and July. Once included the full set of fixed effects, estimates of future crimes are not significant. I interpret this table as evidence that future realisations of crime do not predict current test scores.

Finally, I investigate the underlying mechanisms. Exposure to crime might potentially affect academic achievement in two distinct manners. First, pupils being exposed to crime just before the exam might suffer from stress and anxiety which directly affect their performance while sitting the exam.[27] The alternative explanation has been put forward in the psychological literature (Gorman-Smith and Tolan, 1998; Delaney-Black et al., 2002; Ozer and Weinstein, 2004; Lacoe, 2020) and is instead that exposure throughout the academic year disrupts the learning process of children and thus is reflected in worse academic achievement in the final exams. An intuitive test to empirically assess which channel is more likely to matter is to define the exposure to crime based on the timing of the crimes. Specifically, in Table 5 I compare the effect of the cumulative exposure to crime throughout the academic year to the effect of exposure to crime recorded just in the month before the exam, i.e. April. The two coefficients are statistically identical, suggesting that what seems to matter is not only crime before the exam, but also the crime cumulatively experienced throughout the year.

[26] I have created a new STATA routine based on the one from Hsiang et al. (2011) (ols_spatial_HAC.ado) and its extension to multidimensional fixed effects by Thiemo Fetzer (reg2hdfespatial.ado). I perform robustness checks varying the cutoff distance to 4, 6, 10 km. Results are available upon request.

[27] This is the main explanation that the papers analysing the impacts of exposure to contexts of war or pervasive violence have suggested. See, for instance, Monteiro and Rocha (2016), Koppensteiner and Menezes (2017), Shany (2017) and Ang (2021).

4.2 Distance between pupils and schools

In this subsection, I examine how the relationship between crime and pupil achievement affects the size of the school catchment areas. As illustrated in Section 3, the full specification includes school-time fixed effects, which absorb any time-varying school component as well as any compositional change affecting the neighbourhood. However, if local crime crime affects neighbourhood composition and shapes families' decisions over school choice, then the changes in the size of the catchment areas might be endogenous, being a direct consequence of exposure to crime. For instance, if a neighbourhood experiences a sharp rise in crime, families might react shifting their school choices further away: in this way, less local families would state their preference for the local school, decreasing school demand due to local crime and mechanically increasing the radius of the local school catchment area. A change in the size of the catchment area would represent a threat to the identification strategy as long as it is driven by changes in crime, given that I exploit variation within catchment areas.

In order to assess the plausibility of this claim, I perform the following exercise: for each school, I keep the size of the school catchment area fixed at baseline and I run the main specification. Indeed, if parents select into a neighbourhood based on its criminality, the demand for a local school might in turn depend on variations in local recorded crime, which could potentially change the local school composition. Given that the main criterion for admission into state-funded schools is distance from home, a change in school demand would directly translate into an increase in the size of the catchment area. In order to check for the endogeneity of the catchment areas, I attribute to each school only students whose home postcode is within the radius of the catchment area in the first year of the sample period.[28] Thanks to this exercise, I condition on the initial selection of families into schools and neighbourhoods. Table 6 shows the estimates: the estimates are very similar to the main ones in Table 2. This alleviates the concern that results are driven by an endogenous enlargement of the school catchment areas due to pupils' exposure to crime. This exercise provides additional evidence against selection of families into areas based on deviations from local crime. I then further investigates this issue in Section 5, specifically looking at sub-samples of school and house movers.

[28] I define the size of the catchment area based on the distance between the school and each postcode of pupils' enrolled in the school in the first year of the sample (2010). I therefore keep fixed the maximum radius for each catchment area to its baseline maximum distance. I try the same with other measures, such as 99th and 95th percentiles and results do not vary.

4.3 Distance between pupils and crimes

I also examine how the relationship between crime and pupil achievement varies with the distance between crime offences and pupils' postcodes. Throughout the analysis, I define exposure to crime as the number of offences recorded by the police in an area of 500 meters radius around where pupils' live. On the one side, a crucial question is how close to home a crime must be committed to affect pupils' test scores. On the other side, setting a narrow area might result in measurement error, as the police often anonymises criminal records shifting slightly the geographical coordinates. In this case, one concern might be that the estimates with a large number of fixed effects suffer from attenuation bias because of measurement error in the crime variables. Indeed, this noise is exacerbated when using fixed effects, in particular given the high level of serial correlation in the local crime within neighbourhood.

In order to assess the sensitivity of the buffer choice, I follow the benchmark specification, but varying the buffer size in which I compute the exposure to crime variables. Table 7 shows the results. Each column displays results for a different type of crime, while each row for a different buffer size. For each buffer radius, I count the number of offences recorded at a distance of 50 meters, 100 meters, 250 meters, 500 meters, 1km, 2km and 3km. In the benchmark specification, I set buffer size to 500 meters. Although the smallest buffer is likely to suffer more from measurement error, the larger the buffer radius, the more estimates shrink and converge to precisely estimated zeros.

4.4 Heterogeneity analysis by students' characteristics

I complement the discussion on the results by analysing heterogeneous effects across pupils. I exploit the exceptionally rich dataset in order to provide some insights on the characteristics that pupils most seriously affected by exposure to crime display.

As first evidence, I split the sample into different sub-populations. This way I am able to estimate non-parametrically the different effect of exposure to crime in different sub-samples. Table 8 and 9 perform Equation 1 (including the entire arsenal of fixed effects) keeping only specific sub-populations and comparing the estimates with the full sample analysis. This exercise is useful to shed light on the mechanisms that are likely to drive the results.

The effects seem to be driven by non-disadvantaged (non-FSM) and high-ability students for

both exams.[29] An increase in 1 sd in crime reduces test scores by up to 1.2% of sd in math test scores, and up to 1.3-1.4% of sd if pupils are exposed to an increase in violent crimes or anti-social behaviour incidents. Similarly, the effect seems to come from female students, and specifically those coming from non-disadvantaged families, while the coefficients for male students are almost never significant for both math and reading exams (Table 10 and e 11).[30]
Overall, given the empirical findings, these effects seem to depend on the level of tolerance, or habituation: pupils from wealthier families are those who suffer the most. The results of non-disadvantaged kids are consistent with the fact that this sub-group might represent to the policy-relevant segment on which it is possible to measure the actual effect.[31] The differential effects on gender are harder to explain but are in line with similar studies on the neighbourhood effect.[32] For instance, Kling et al. (2007) found disproportionate long-run effects of living in a better quality neighbourhood across gender: a positive, beneficial effect on female youth, while a negative and adverse effect on male youth. Similarly, in England Gibbons et al. (2013b) shows that boys and girls respond differently to neighbourhood changes. Kling et al. (2005) found similar gender differences in the youth propensity to commit a crime: while in the short run both male and female perpetrate less violent crimes, in the long run males show a higher propensity to commit property crimes. The authors ascribe it to a different capacity of adapting to a new environment.

4.5 Heterogeneity analysis by area's characteristics

I also examine if local characteristics of the neighbourhoods where pupils live help explain the results. For instance, we could expect that pupils living in more violent areas are more sensitive to exposure to crime. I therefore define neighbourhoods (LSOAs) as above or below the median crime rate, population and poverty recorded in London at the baseline year.[33]

[29]High-ability (bottom) students are defined as those whose average test scores during KS1, when pupils are aged 5-7, where above the 75th percentile (below the 25th percentile) of the distribution.

[30]As a further check, I also perform a heterogeneity analysis where I add a double interaction between female and FSM, or high ability. The results confirm the previous conclusions under the sample analysis.

[31]This is similar to what found by Fort et al. (2020) in a context where they look at the costs related childcare for children from advantaged families.

[32]This is also in line with evidence from the literature on education interventions showing that girls are more affected than boys (Anderson, 2008; Angrist and Lavy, 2009; Lavy and Schlosser, 2011).

[33]Population and poverty data are from the 2001 Census in order to exclude reverse causality. Crime rate are computed for 2010, the first available year of crime data.

Table 12 shows the results when I split the sample according to these dimensions.[34] Results are stronger in less criminal and more populated areas, while there are no significantly different effects for poor versus rich areas. Figure 8 complements Table 12 by plotting the coefficients of separate regressions of student achievement on exposure to crime, each computed stratifying the dataset into percentiles based on the baseline crime rate in the LSOA where pupils live. The figure shows that for each type of crime the coefficients are strongly negative for the bottom tercile only, i.e. for kids living in areas at the bottom of the crime distribution. In terms of magnitude, an increase in one sd of total crimes decreases test scores by around 1.2% of sd for those kids living in less criminal areas. If they are exposed to a 1 sd increase in violent crimes, they are subject to a decrease in final math test scores of up to 3% of sd. The effect then shrinks and becomes almost zero in the top tercile. A similar pattern holds for reading test scores (Figure 9). This evidence suggests that pupils who are more sensitive to crime exposure are those who are less used to it.

Overall, the evidence from the heterogeneity analysis suggests a potential mechanism through which crime affects pupils' outcomes. Indeed, results are consistent with an adaptation or habituation effect, although other mechanisms are plausible. In order to provide a comprehensive answer, however we first need to consider alternative explanations. For instance, how individuals actually learn about crimes happening around them might be an important factor to consider and visibility of crime itself could be a potential channel. Individuals might also get information about crime from the media, and media reporting has been shown to be highly selective, focusing on the most serious examples of crime (Greer, 2007). In contrast, the lower level property offences that make up the majority of recorded crime are given sparse attention.[35] According to this explanation, in our case we would expect to retrieve results only for the most prominent types of crime, such as violent crimes (which include homicides). The estimates instead, although stronger for violent crimes, are significant for other types of crime too (see Tables 2 and 3). For instance, effects are stronger for exposure to anti-social-behaviour, a typically visible type of offence that however is likely not to be reported in the news. We can also reasonably exclude that the effect passes entirely through the media, since in this setting the effect of local press constitutes a common shock to the local authority that is absorbed by the school (and

[34] Splitting the sample I am still able to control for neighbourhood characteristics. In this case, I define neighbourhood as LSOA.

[35] As an example, Cornaglia et al. (2014) analyse local print media in Australia in 2001 to 2006 and find 600 media mentions of violent crime each year, compared to 230 mentions of property crime. For most people, the main source of information on crime is the local and national media.

school-time) fixed effects.

5 Robustness checks

Identification lies on the following consideration: once absorbed the catchment area average characteristics and controlled for individual and housing features, there is no remaining correlation in omitted factors across pupils' residences that potentially affect both local crime and pupils' educational outcomes. If this is true, then the empirical design should recover the causal estimate of exposure to crime on pupils' outcomes. I want therefore to make sure this is the case, and test this assumption.

Selection and pupils' mobility

I perform the analysis splitting the sample in two different sub-samples: dropping pupils who moved residence during the previous academic year (9% of observations) or pupils who changed school during primary school (around 13% of the observations). The School Census specifically contains a variable that states whether a pupil has changed school or house throughout the previous academic year.[36] I therefore exploit this information in order to understand if the effect is driven by pupils who are exposed for longer period to the same neighbourhood. The concern here is that families might decide to leave or stay at a school or neighbourhood depending on their tolerance towards crime.

Table 15 show the results when dropping from the sample pupils who changed school: coefficients are not significantly different from the full sample analysis (column 4 and 8 of Table 15), suggesting that families are unlikely to change school due to crime in the middle of the primary school cycle. Table 16 shows instead the results from the main specification when splitting the sample into those who did or did not change home during the previous academic year. Here, coefficients are stronger for movers, although these estimates have to be interpreted with cautiousness. Indeed, results might depend on the lagged effects due to exposure to crime in the old neighbourhood where pupils lived.

One possible explanation for these results is that families might select in neighbourhoods or schools based on crime as well. Still, a concern would arise if the composition of the neigh-

[36] These are pupils who changed school during the previous 3 years, that is, between year 3 and year 6 of primary school.

bourhood changes overtime and the decision of families to move depends on previous crime. Fortunately, the likelihood that families' movements are induced by realizations of crime in the previous period can be assessed empirically. In order to make sure that this is not the case, I check whether crime recorded around the previous area of residence determines the decision to move home or school in the next period. Figure 5 and 6 show that changes in current and past crime don't seem to correlate with the probability of changing school or home.

LSOA controls

In the main specification, I control for individual- and postcode-level characteristics. I therefore exploit variation in narrowly defined, homogeneous areas, and I compare pupils having similar observable characteristics, similar family background and living in similar buildings. I augment the model with 1,960 school fixed effects and interact them with year dummies, including in total 11,760 dummies for fixed effects, in addition to a vector of observable pupils' and buildings' features.

As a robustness check, I also add controls for local baseline characteristics, defining neighbourhood as the Lower Super Output Area (LSOA) where students live. LSOAs are the smallest geographical unit in the UK statistical geography. In a school catchment area in London, there are on average 14 LSOAs. They correspond to small and narrowly-defined geographical areas: to make a comparison, one LSOA is on average half the size of a census tract in the US.

These additional controls are meant to absorb very local neighbourhood components which might affect both local crime and pupils' performance and are not already absorbed by individual features. For instance, local deprivation is correlated with crime and has a separate effect on pupils' outcomes, which does not pass through family background or housing characteristics. On the other side, family economic status is already proxied by the free-school-meal and special-education-needs indicators and included in the main equation. Furthermore, given that school catchment areas are likely to be homogeneous, characteristics that are common to LSOAs within catchment areas are already absorbed by the school fixed effects. Similarly, I also include the share of FSM living in a radius of 100 meters around a pupil's house in order to additionally assess whether the effect is confounded by neighbourhood disadvantage. Finally, although there is not enough variation to include postcode fixed effects, I add dummies for outward postcodes, which aggregate group of postcodes.[37]

[37] In London there are around 300 Outward Postcodes. On average each outward code include 500 postcodes and around 30 LSOAs.

I therefore add these controls to the equation and see if results change. Table 13 and 14 show the results. The coefficients are not statistically different from the one of the main specification in Table 2, and remain strong and significant for violent crimes and anti-social behaviour.

6 Conclusions

This paper contributes to the growing literature studying the effects of growing up in a criminal neighbourhood on pupils' achievement. This highly debated topic among social scientists and psychologists has not found empirical evidence yet in economics. I take advantage of very detailed and geographically fine data and I match pupils' and schools' geo-coded addresses to crimes recorded around them. Conditioning on a large set of fixed effects, I exploit postcode-level variation in exposure to crime within narrowly defined school catchment areas. I find significant negative results, stronger for violent crimes. Results from the heterogeneity analysis show that pupils suffering the most from exposure to crime are high-ability, non-disadvantaged female students. A further analysis of the results based on the type of neighbourhood illustrates that those who actually live in less criminal areas suffer the most from exposure to crime. These are typically the relevant marginal subjects to be considered in the evaluation of any neighbourhood policy in advanced countries with relatively low crime incidence. I therefore provide the first evidence of an explored channel, that is decreasing marginal sensitivity to crime as the magnitude of these negative effects increase with family income. Policy-makers, when deciding over investments in crime prevention, should therefore take into account this channel of impact too.

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Tables

Table 1: Descriptive statistics

Variables	mean	sd
Panel A: Individual characteristics		
male	0.5	0.5
sen	0.22	0.41
white	0.42	0.49
black	0.22	0.41
asian	0.21	0.4
other ethnicities	0.14	0.35
eligible for free school meal	0.24	0.43
english spoken at home	0.54	0.5
pupil's postcode changed since previous year	0.09	0.28
school changed since previous year	0.13	0.34
distance current school	1.2	1.55
distance nearest school	0.36	0.2
Panel B: Individual characteristics		
reading test scores	30.91	9.49
math test scores	72.31	19.69
Panel C: Crimes (in hundreds)		
total crimes	5.79	4.83
violent crimes	1.16	0.96
property crimes	2.17	2.09
drug related crimes	0.55	0.82
anti-social-behaviour	1.71	1.5
public order offences	0.2	0.25
Panel D: Housing characteristics		
total floor area	39.41	40.82
number habitable rooms	2.47	1.61
floor height	1.81	0.79
house price	148,722.40	174,791.12
number heated rooms	2.32	1.53
Observations	441,003	441,003

Table 2: Pupils's test score and crime: Benchmark results

	Reading test scores [sd]				Math test scores [sd]			
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
All crimes	-0.062***	-0.024***	-0.005**	-0.006***	-0.046***	-0.001	-0.006***	-0.006***
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.004]	[0.002]	[0.002]
Panel B								
Violent crimes	-0.082***	-0.029***	-0.007***	-0.007***	-0.059***	0.001	-0.005**	-0.007***
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.004]	[0.002]	[0.002]
Property crimes	-0.038***	-0.010***	-0.002	-0.004**	-0.029***	0.002	-0.003	-0.004**
	[0.006]	[0.002]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.002]
Drugs crimes	-0.053***	-0.017***	-0.004*	-0.004**	-0.040***	0.001	-0.005**	-0.002
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.002]
Public order	-0.051***	-0.012***	-0.002	-0.004**	-0.038***	0.004	-0.000	-0.004**
	[0.005]	[0.003]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.002]
Anti-social behaviour	-0.072***	-0.029***	-0.004	-0.006***	-0.053***	-0.008**	-0.008***	-0.007***
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.004]	[0.002]	[0.002]
Observations	441,003	441,003	441,003	441,003	441,003	441,003	441,003	441,003
School FE	No	Yes	Yes	Yes	No	No	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind and housing controls	No	No	Yes	Yes	No	Yes	Yes	Yes
School-year FE	No	No	No	Yes	No	No	No	Yes

Note. The table shows OLS regressions of KS2 reading score and KS2 math score on a measure of exposure to crime around pupils' house (radius of 500 meters). Each row indicates a separate regression of crime on test scores. Panel A shows results pooling together all types of crime, panel B separates crime types. Column (1) and (5) include time fixed effects, column (2) and (6) add school fixed effects, column (3) and (7) control for individual and housing characteristics and column (4) and (8) include school-time fixed effects. Standard errors, shown in brackets, are clustered at the level of the school catchment. Individual controls include: gender, ethnicity, FSM, SEN, language spoken at home, student's average point score at KS1. Housing controls (at baseline) include: average floor area, average number of habitable rooms, average floor height, average price, average LSOA population. Crime measures and outcomes are standardised. *** p<0.01, **p<0.05, * p<0.1

Table 3: Pupils's test score and crime: broken-down types of crime

	Reading test scores				Math test scores			
Independent variable	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
ASB	-0.072***	-0.029***	-0.004	-0.006***	-0.053***	-0.032***	-0.008***	-0.007***
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.002]
Bycile theft	-0.005	0.003	-0.001	-0.001	-0.008*	0.003	-0.001	-0.001
	[0.005]	[0.003]	[0.003]	[0.002]	[0.004]	[0.003]	[0.003]	[0.002]
Burglary	-0.041***	-0.009***	0.000	-0.002	-0.032***	-0.011***	-0.001	-0.002
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.002]
Criminal damage and arson	-0.084***	-0.022***	-0.002	-0.007***	-0.067***	-0.023***	-0.003	-0.007***
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.002]
Drugs	-0.050***	-0.012***	-0.001	-0.005***	-0.037***	-0.011***	-0.001	-0.003*
	[0.006]	[0.002]	[0.002]	[0.002]	[0.005]	[0.002]	[0.002]	[0.002]
Other crimes	-0.037***	-0.012***	-0.004	-0.001	-0.029***	-0.012***	-0.005*	-0.000
	[0.005]	[0.003]	[0.003]	[0.002]	[0.004]	[0.003]	[0.003]	[0.002]
Other theft	-0.021***	-0.006***	-0.000	-0.004**	-0.017***	-0.008***	-0.003	-0.004**
	[0.005]	[0.002]	[0.002]	[0.002]	[0.004]	[0.002]	[0.002]	[0.002]
Possession of weapons	-0.046***	-0.006**	-0.004	-0.001	-0.033***	-0.004	-0.001	-0.002
	[0.005]	[0.003]	[0.002]	[0.002]	[0.004]	[0.003]	[0.003]	[0.002]
Public disorder and weapons	-0.036***	-0.007***	0.004*	-0.002	-0.030***	-0.011***	-0.000	-0.003*
	[0.004]	[0.003]	[0.002]	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]
Public order	-0.044***	-0.007**	-0.005*	-0.004*	-0.031***	-0.002	-0.000	-0.003*
	[0.005]	[0.003]	[0.003]	[0.002]	[0.005]	[0.003]	[0.003]	[0.002]
Robbery	-0.064***	-0.020***	-0.003	-0.006***	-0.044***	-0.018***	-0.003	-0.005***
	[0.006]	[0.003]	[0.003]	[0.002]	[0.005]	[0.003]	[0.003]	[0.002]
Shoplifting	-0.013***	-0.003	0.000	0.000	-0.008***	-0.001	0.001	0.001
	[0.003]	[0.002]	[0.001]	[0.001]	[0.003]	[0.002]	[0.001]	[0.001]
Theft from person	-0.016***	-0.003	-0.003	-0.004**	-0.012***	-0.001	-0.000	-0.002
	[0.004]	[0.002]	[0.002]	[0.002]	[0.004]	[0.002]	[0.002]	[0.002]
Vehicle crime	-0.046***	-0.013***	-0.006**	-0.004**	-0.033***	-0.017***	-0.009***	-0.005***
	[0.006]	[0.003]	[0.002]	[0.002]	[0.006]	[0.003]	[0.003]	[0.002]
Violence and sexual offences	-0.079***	-0.013***	-0.009**	-0.008***	-0.054***	-0.006*	-0.001	-0.006**
	[0.006]	[0.004]	[0.004]	[0.002]	[0.006]	[0.004]	[0.004]	[0.002]
Violent crime	-0.080***	-0.021***	0.003	-0.005**	-0.066***	-0.028***	-0.005	-0.008***
	[0.006]	[0.003]	[0.003]	[0.002]	[0.005]	[0.004]	[0.004]	[0.002]
Observations	441,003	441,003	441,003	441,003	441,003	441,003	441,003	441,003
School FE	No	Yes	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind and housing controls	No	No	Yes	Yes	No	Yes	Yes	Yes
School-year FE	No	No	No	Yes	No	No	No	Yes

Note. The table shows OLS regressions of KS2 reading score [column 1 to 4] and KS2 math score [column 5 to 8] on a measure of exposure to crime around pupils' house [radius of 500 meters]. Each row indicates a separate regression of crime on test scores. Column [1] and [5] include time fixed effects, column [2] and [6] add school fixed effects, column [3] and [7] control for individual and housing characteristics and column [4] and [8] include school-time fixed effects. Standard errors, shown in brackets, are clustered at the level of the local authority of pupils' residence. Individual controls include: gender, ethnicity, indicator for change in home, indicator for change in school, FSM, SEN, language spoken at home, student's average point score at KS1. Housing controls [at baseline] include: average floor area, average number of habitable rooms, average floor height, average price, average LSOA population. Crime measures are standardised. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Pupils's test score and future crime

Independent variable	Reading test scores (1)	(2)	Math test scores (3)	(4)
All crimes - *year t*	-0.010*	-0.011	-0.004	-0.019***
	(0.006)	(0.007)	(0.006)	(0.007)
All crimes - *june*	0.007		-0.001	
	(0.006)		(0.005)	
All crimes - *july*	-0.002		-0.001	
	(0.005)		(0.005)	
All crimes - *year t+1*		0.006		0.014**
		(0.007)		(0.007)
Violent crimes - *year t*	-0.012***	-0.005	-0.009**	-0.009
	(0.005)	(0.006)	(0.005)	(0.006)
Violent crimes - *june*	0.002		0.004	
	(0.003)		(0.003)	
Violent crimes - *july*	0.003		-0.002	
	(0.003)		(0.003)	
Violent crimes - *year t+1*		-0.003		0.001
		(0.006)		(0.006)
Observations	361,590	361,590	361,590	361,590
Individual and housing controls	Yes	Yes	Yes	Yes
School-year FE	Yes	Yes	Yes	Yes

Note: The table shows OLS regressions of KS2 reading score (column 1 and 2) and KS2 math score (column 3 and 4) on exposure to crime around pupils' house (radius of 500 meters) during the academic year and either in the months after the exam, i.e. June and July, or in the following year (year $t + 1$). Each row indicates a separate regression of crime on test scores. Crime measures and outcomes are standardised. See notes to Table 2 for details on controls. *** p<0.01, **p<0.05, * p<0.1

Table 5: Pupils's test score and timing

	Read test scores (sd)				Math test scores (sd)			
	Previous academic year	Month before exam	Excluding last month	Excluding last 2 months	Previous academic year	Month before exam	Excluding last month	Excluding last 2 months
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All crimes	-0.006***				-0.006***			
	(0.002)				(0.002)			
		-0.006***				-0.006***		
		(0.002)				(0.002)		
			-0.006***				-0.006***	
			(0.002)				(0.002)	
				-0.007***				-0.006***
				(0.002)				(0.002)
Violent crimes	-0.007***				-0.007***			
	(0.002)				(0.002)			
		-0.007***				-0.005***		
		(0.002)				(0.002)		
			-0.008***				-0.007***	
			(0.002)				(0.002)	
				-0.008***				-0.007***
				(0.002)				(0.002)
Observations	441,003	441,003	441,003	441,003	441,003	441,003	441,003	441,003
School, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table shows OLS regressions of KS2 reading score (column 1 and 4) and KS2 math score (column 5 and 8) on exposure to crime around pupils' house (radius of 500 meters) during: the previous academic year (column 1 and 5), the month before the exam (i.e. April) (column 2 and 6), the period September to March before the exam (column 3 and 7), and the period from September to February (column 3 and 7). Each row indicates a separate regression of crime on test scores. Crime measures and outcomes are standardised. See notes to Table 2 for details on controls. *** p<0.01, **p<0.05, * p<0.1

Table 6: Impact of pupils' outcomes using baseline catchment areas

	Reading test scores [sd]				Math test scores [sd]			
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All crimes	-0.062***	-0.023***	-0.004*	-0.005**	-0.046***	-0.023***	-0.005**	-0.004**
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.002]
Violent crimes	-0.082***	-0.027***	-0.006***	-0.007***	-0.059***	-0.024***	-0.004*	-0.006***
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.002]
Property crimes	-0.038***	-0.009***	-0.001	-0.003*	-0.029***	-0.010***	-0.002	-0.003
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.002]
Drugs crimes	-0.053***	-0.016***	-0.004*	-0.003*	-0.040***	-0.016***	-0.005**	-0.001
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.002]
Public order	-0.051***	-0.010***	-0.002	-0.003	-0.037***	-0.008***	0.000	-0.003
	[0.005]	[0.003]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.002]
Anti-social behaviour	-0.072***	-0.028***	-0.003	-0.005**	-0.053***	-0.030***	-0.007***	-0.006***
	[0.006]	[0.003]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.002]
Observations	432,071	432,071	432,071	432,071	432,071	432,071	432,071	432,071
R-Squared	0.004	0.104	0.503	0.543	0.002	0.082	0.527	0.572
School FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind and housing controls	No	No	Yes	Yes	No	No	Yes	Yes
School-year FE	No	No	No	Yes	No	No	No	Yes

Note. The table shows OLS regressions of KS2 reading score and KS2 math score on a measure of exposure to crime around pupils' house (radius of 500 meters). Each row indicates a separate regression of crime on test scores. Panel A shows results pooling together all types of crime, panel B separates crime types. Column (1) and (5) include time fixed effects, column (2) and (6) add school fixed effects, column (3) and (7) control for individual and housing characteristics and column (4) and (8) include school-time fixed effects. This table keps the same of the catchment areas fixed in 2010, the first year in which crime data are available. Standard errors, shown in brackets, are clustered at the level of the school catchment. Crime measures and outcomes are standardised. *** p<0.01, **p<0.05, * p<0.1

Table 7: Pupils' test score and crime by distance to crime

Independent variable	Reading test scores (sd)						Math test scores (sd)					
	All crimes	Violent Crimes	Property crimes	Drugs	Public order	ASB	All crimes	Violent Crimes	Property crimes	Drugs	Public order	ASB
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Buffer Radius:												
50m	-0.110	-0.481***	0.294	0.255	-0.215	-0.139	-0.057	-0.402**	0.186	-0.029	-0.014	-0.008
	(0.182)	(0.154)	(0.206)	(0.187)	(0.172)	(0.113)	(0.189)	(0.159)	(0.207)	(0.212)	(0.155)	(0.119)
100m	-0.198***	-0.253***	-0.032	-0.058	-0.103***	-0.158***	-0.138***	-0.210***	-0.027	-0.014	-0.086**	-0.101***
	(0.049)	(0.045)	-0.05	(0.039)	(0.040)	(0.032)	(0.049)	(0.045)	(0.049)	(0.042)	(0.039)	(0.035)
250m	-0.029***	-0.040***	-0.008	-0.014*	-0.011	-0.039***	-0.027***	-0.041***	-0.011	-0.007	-0.012	-0.031***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
500m	-0.006***	-0.007***	-0.004**	-0.004**	-0.004**	-0.006***	-0.006***	-0.007***	-0.004**	-0.002	-0.004**	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
1km	-0.001***	-0.001***	-0.000***	-0.001***	-0.000***	-0.001***	-0.001***	-0.001***	-0.000***	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2km	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
3km	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	441,003	441,003	441,003	441,003	441,003	441,003	441,003	441,003	441,003	441,003	441,003	441,003
Ind and housing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table shows OLS regressions of KS2 reading score and KS2 math score on measures of exposure to crime around pupils' house. Each row indicates a separate regression of crime on test scores. Columns indicate the type of crime, rows indicate the radius of the buffer area around pupils' postcodes (from 50 meters to 3 km). Standard errors, shown in brackets, are clustered at the level of the school catchment. Crime measures and outcomes are standardised. *** p<0.01, **p<0.05, * p<0.1

Table 8: Reading test scores and crime: heterogeneity by pupils' characteristics

	Reading tes scores [sd]						
	native	no native	female	male	free-school-meal	no free-school-meal	top students
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All crimes	-0.003	-0.006**	-0.008***	-0.003	-0.002	-0.005**	-0.009***
	[0.003]	[0.002]	[0.002]	[0.003]	[0.003]	[0.002]	[0.003]
Violent crimes	-0.006**	-0.006**	-0.010***	-0.004	-0.002	-0.007***	-0.011***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]	[0.003]
Property crimes	-0.002	-0.004*	-0.007***	-0.001	-0.003	-0.003	-0.005
	[0.003]	[0.002]	[0.002]	[0.003]	[0.003]	[0.002]	[0.003]
Drugs crimes	-0.003	-0.003	-0.005**	-0.002	-0.001	-0.003	-0.009***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]	[0.003]
Public order	-0.001	-0.004*	-0.005**	-0.001	-0.001	-0.004*	-0.006**
	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]	[0.003]
Anti-social behaviour	-0.002	-0.006**	-0.006**	-0.004	-0.001	-0.006**	-0.011***
	[0.003]	[0.002]	[0.003]	[0.003]	[0.003]	[0.002]	[0.003]
Observations	240,213	200,456	219,430	221,421	104,451	335,982	104,613
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind and housing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table shows OLS regressions of KS2 reading scores on exposure to crime around pupils' houses (radius equal meters). Each row indicates a separate regression of crime on test scores. The top row shows results pooling together all crime. Each column stratifies the sample based on pupil's observable characteristics: origin, gender, FSM, KS1 test scor (bottom) students are defined as pupils above the 75th percentile (below the 25th percentile) of the distribution of KS1 t Standard errors, shown in brackets, are clustered at the level of the school catchment. For individual and housing control of Table 1. Crime measures are standardised. *** p<0.01, **p<0.05, * p<0.1

Table 9: Pupils's test score and crime: heterogeneity by pupils' characteristics

	Math test scores						
	native	no native	female	male	free-school-meal	no free-school-meal	top students
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All crimes	-0.007***	-0.002	-0.007***	-0.004*	0.001	-0.007***	-0.012***
	[0.003]	[0.002]	[0.003]	[0.003]	[0.003]	[0.002]	[0.003]
Violent crimes	-0.010***	-0.003	-0.009***	-0.004*	0.001	-0.008***	-0.013***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]	[0.002]	[0.003]
Property crimes	-0.006**	-0.001	-0.005**	-0.003	0.001	-0.005**	-0.006**
	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]
Drugs crimes	-0.002	-0.000	-0.002	-0.002	0.001	-0.003	-0.011***
	[0.003]	[0.002]	[0.003]	[0.003]	[0.003]	[0.002]	[0.003]
Public order	-0.006**	-0.002	-0.004*	-0.003	0.003	-0.005***	-0.009***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]
Anti-social behaviour	-0.007***	-0.004*	-0.009***	-0.006**	-0.000	-0.009***	-0.014***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]	[0.002]	[0.003]
Observations	240,213	200,456	219,430	221,421	104,451	335,982	104,613
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind and housing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-year FE	Yes	Yes	Yes	Yes	Yes	Yes	No

Note. The table shows OLS regressions of KS2 math scores on exposure to crime around pupils' houses (radius equal to meters). Each row indicates a separate regression of crime on test scores. The top row shows results pooling together all crime. Each column stratifies the sample based on pupil's observable characteristics: origin, gender, FSM, KS1 test scor (bottom) students are defined as pupils above the 75th percentile (below the 25th percentile) of the distribution of KS1 t Standard errors, shown in brackets, are clustered at the level of the school catchment. For individual and housing control notes of Table 1. Crime measures are standardised. *** p<0.01, **p<0.05, * p<0.1

Table 10: Heterogeneous effects on test scores for female students

Sample: Female

	Reading tes scores [sd]						Math tes scores [sd]					
	native	no native	free-school-meal	no free-school-meal	top students	bottom students	native	no native	free-school-meal	no free-school-meal	top students	bottom students
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
All crimes	-0.005	-0.011***	-0.001	-0.010***	-0.009**	-0.006	-0.007*	-0.006*	0.003	-0.009***	-0.010**	-0.009
	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.007)
Violent crimes	-0.008**	-0.011***	0.002	-0.013***	-0.014***	-0.007	-0.011***	-0.007*	0.002	-0.012***	-0.014***	-0.014**
	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.007)
Property crimes	-0.004	-0.009***	-0.001	-0.009***	-0.004	-0.011*	-0.004	-0.004	0.003	-0.007**	-0.004	-0.009
	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.007)
Drugs crimes	-0.002	-0.009***	-0.004	-0.005*	-0.007*	0.006	-0.003	-0.002	0.003	-0.005	-0.008**	-0.001
	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.006)
Public order	-0.005	-0.005	0.003	-0.007***	-0.005	-0.008	-0.006*	-0.002	0.004	-0.006**	-0.010***	-0.006
	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)
Anti-social behaviour	-0.002	-0.010***	0.000	-0.009***	-0.011**	-0.002	-0.008**	-0.008**	0.002	-0.011***	-0.013***	-0.007
	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.006)
Observations	119,466	99,171	51,684	166,735	56,506	41,511	119,466	99,171	51,684	166,735	56,506	41,511
Ind and housing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table shows OLS regressions of KS2 reading scores on exposure to crime around pupils' houses (radius equal to 500 meters). Each row indicates a separate regression of crime on test scores. The top row shows results pooling together all types of crime. Each column stratifies the sample based on pupil's observable characteristics: origin, gender, FSM, KS1 test scores. Top (bottom) students are defined as pupils above the 75th percentile (below the 25th percentile) of the distribution of KS1 test scores. Standard errors, shown in brackets, are clustered at the level of the school catchment. For individual and housing controls see notes of Table 1. Crime measures are standardised. *** p<0.01, **p<0.05, * p<0.1

Table 11: Heterogeneous effects on test scores for male students

Sample: Male

	Reading tes scores [sd]						Math tes scores [sd]					
	native	no native	free-school-meal	no free-school-meal	top students	bottom students	native	no native	free-school-meal	no free-school-meal	top students	bottom students
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
All crimes	-0.001	-0.001	-0.002	-0.000	-0.009**	-0.006	-0.007*	-0.001	-0.000	-0.004	-0.010**	-0.009
	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.007)
Violent crimes	-0.004	-0.001	-0.004	-0.000	-0.014***	-0.007	-0.008*	0.000	0.002	-0.005	-0.014***	-0.014**
	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.007)
Property crimes	0.001	-0.001	-0.003	0.001	-0.004	-0.011*	-0.005	0.001	0.000	-0.002	-0.004	-0.009
	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.007)
Drugs crimes	-0.004	0.000	-0.000	-0.001	-0.007*	0.006	-0.002	-0.001	-0.001	-0.002	-0.008**	-0.001
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)
Public order	0.004	-0.003	-0.002	0.001	-0.005	-0.008	-0.004	-0.002	0.002	-0.004	-0.010***	-0.006
	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)
Anti-social behaviour	-0.001	-0.002	-0.001	-0.002	-0.011**	-0.002	-0.007*	-0.002	-0.001	-0.006	-0.013***	-0.007
	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.006)
Observations	120,313	100,308	51,230	169,068	56,506	41,511	120,313	100,308	51,230	169,068	56,506	41,511
Ind and housing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table shows OLS regressions of KS2 reading scores on exposure to crime around pupils' houses (radius equal to 500 meters). Each row indicates a separate regression of crime on test scores. The top row shows results pooling together all types of crime. Each column stratifies the sample based on pupil's observable characteristics: origin, gender, FSM, KS1 test scores. Top (bottom) students are defined as pupils above the 75th percentile (below the 25th percentile) of the distribution of KS1 test scores. Standard errors, shown in brackets, are clustered at the level of the school catchment. For individual and housing controls see notes of Table 1. Crime measures are standardised. *** p<0.01, **p<0.05, * p<0.1

Table 12: Heterogeneous effects by type of area

	Reading test scores						Math test scores			
	Baseline crime rate		Baseline population		Baseline poverty		Baseline crime rate		Baseline population	
	> median	< median	> median	< median	> median	< median	> median	< median	> median	< median
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
All crimes	-0.003	-0.014***	-0.008***	-0.002	-0.001	0.000	-0.002	-0.013***	-0.008***	-0.004
	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)
Violent crimes	-0.004*	-0.015***	-0.010***	-0.005	-0.001	-0.003	-0.004*	-0.012***	-0.008***	-0.007**
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)
Property crimes	-0.002	-0.013***	-0.007***	-0.000	-0.002	0.001	-0.001	-0.011***	-0.006**	-0.002
	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.003)
Drugs crimes	-0.003	-0.007**	-0.005**	-0.002	-0.001	-0.002	0.001	-0.007*	-0.004*	-0.001
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.003)
Public order	0.000	-0.013***	-0.007***	0.001	-0.001	0.004	-0.001	-0.010***	-0.006***	-0.001
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)
Anti-social behaviour	-0.003	-0.010***	-0.008***	-0.001	-0.001	0.002	-0.003	-0.012***	-0.009***	-0.005
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	220,738	219,779	218,854	221,835	228,644	211,138	220,738	219,779	218,854	221,835
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind and housing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table shows OLS regressions of KS2 reading score (column 1 to 6) and KS2 math score (column 7 to 12) on a measure of exposure to crime around pupils' house (radius equal to 500 meters). Each rov of crime on test scores. Each column include the full set of fixed effects and individual and housing controls. Median crime is defined as the median median crime rate across LSOAs in 2010. One LSOA is below above/below the baseline median London crime rate (the same holds for population or poverty). Column (1)-(2) and (7)-(8) split the sample according to median crime; Column (3)-(4) and (9)-(10) split the samp population; Column (5)-(6) and (11)-(12) split the sample according to median poverty. Standard errors, shown in brackets, are clustered at the level of the school catchment. For individual and housing controls s measures are standardised. *** p<0.01, **p<0.05, * p<0.1

Table 13: Pupils's test score and crime: LSOA controls for neighbourhood peers' composition

	Reading test scores (sd)					Math test scores (sd)				
Baseline controls at LSOA level	share of FSM	share of SEN	share of ethnic groups	share of female	share of natives	share of FSM	share of SEN	share of ethnic groups	share of female	share of natives
Independent variable	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
All crimes	-0.003	-0.005***	-0.004**	-0.003*	-0.003	-0.003	-0.005**	-0.005***	-0.004**	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Violent crimes	-0.004*	-0.007***	-0.005***	-0.004**	-0.003*	-0.004*	-0.006***	-0.007***	-0.005**	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Property crimes	-0.002	-0.004**	-0.003	-0.003	-0.002	-0.002	-0.003*	-0.004**	-0.003*	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Drugs crimes	-0.002	-0.003*	-0.002	-0.001	-0.001	-0.000	-0.001	-0.002	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Public order	-0.001	-0.003*	-0.002	-0.002	-0.001	-0.002	-0.003*	-0.004**	-0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Anti-social behaviour	-0.002	-0.005**	-0.003*	-0.003	-0.002	-0.004**	-0.006***	-0.007***	-0.006***	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	440,799	440,799	440,799	440,799	440,799	440,799	440,799	440,799	440,799	440,799
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LSOA Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table shows OLS regressions of KS2 reading score and KS2 math score on a measure of exposure to crime around pupils' house (radius of 500 meters). Each row indicates a separate regression of crime on test scores. Each column includes as additional control a measure of peer composition in the neighbourhood, displayed in the column title. For instance, share of FSM is computed as the number of FSM kids living at baseline in the same block over the total number of kids living in that area at baseline. Standard errors, shown in brackets, are clustered at the level of the school catchment. Crime measures and outcomes are standardised. *** p<0.01, **p<0.05, * p<0.1

Table 14: Pupils's test score and crime: additional controls

	Reading test scores		Math test scores	
Baseline control:	number of FSM around postcode (radius 100m)	Outward Postcode Fixed effect	number of FSM around postcode (radius 100m)	Outward Postcode Fixed effect
Independent variable	(1)	(2)	(1)	(2)
All crimes	-0.005***	-0.002	-0.005***	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Violent crimes	-0.006***	-0.005**	-0.006***	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Property crimes	-0.004**	0.000	-0.004**	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Drugs crimes	-0.003*	-0.001	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Public order	-0.003*	-0.001	-0.004**	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
Anti-social behaviour	-0.004**	-0.003	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	439,768	440,994	439,768	440,994
Controls	Yes	Yes	Yes	Yes
School-year FE	Yes	Yes	Yes	Yes
LSOA Controls	Yes	Yes	Yes	Yes

Note. The table shows OLS regressions of KS2 reading score and KS2 math score on a measure of exposure to crime around pupils' house (radius of 500 meters). Each row indicates a separate regression of crime on test scores. Column 1 adds the number of FSM pupils living in an area of radius 100 meters around where pupil i lives. Column 2 add Outward Postcode fixed effects. Standard errors, shown in brackets, are clustered at the level of the school catchment. Crime measures and outcomes are standardised. *** p<0.01, **p<0.05, * p<0.1

Table 15: Heterogeneous effects by type of pupil: school movers

	Reading test scores				Math test scores			
	changed school=1		changed school=0		changed school=1		changed school=0	
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All crimes	0.004	0.005	-0.006***	-0.006***	-0.008	-0.003	-0.005**	-0.005**
	(0.006)	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)	(0.002)	(0.002)
Violent crimes	-0.000	0.001	-0.007***	-0.008***	-0.008	-0.004	-0.004	-0.006***
	(0.006)	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)	(0.002)	(0.002)
Property crimes	0.003	0.004	-0.002	-0.005**	-0.008	-0.002	-0.002	-0.003*
	(0.006)	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)	(0.002)	(0.002)
Drugs crimes	0.001	-0.000	-0.006**	-0.004**	-0.000	0.001	-0.006**	-0.001
	(0.005)	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)	(0.002)	(0.002)
Public order	-0.003	-0.002	-0.002	-0.004**	-0.011*	-0.005	0.002	-0.003
	(0.005)	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)	(0.002)	(0.002)
Anti-social behaviour	0.009	0.010*	-0.006**	-0.007***	-0.006	-0.005	-0.008***	-0.006***
	(0.006)	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)	(0.002)	(0.002)
Observations	57,884	56,850	383,119	383,052	57,884	56,850	383,119	383,052
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind and housing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-year FE	No	Yes	No	Yes	No	Yes	No	Yes

Note. The table shows OLS regressions of KS2 scores on exposure to crime around pupils' house (radius equal to 500 meters). Each row indicates a separate regression of crime on test scores. The top row shows results pooling together all types of crime. The table splits the sample based on pupil's change of school. Column (1) to (4) takes as dependent variable KS2 reading test scores; column (5) to (8) takes as dependent variable KS2 math test scores.Standard errors, shown in brackets, are clustered at the level of the school catchment level. Crime measures and outcomes are standardised. *** p<0.01, **p<0.05, * p<0.1

Table 16: Heterogeneous effects by type of pupil: house movers

	Reading test scores				Math test scores			
	changed postcode=1		changed postcode=0		changed postcode=1		changed postcode=0	
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All crimes	-0.012**	-0.020***	-0.003	-0.004*	-0.012**	-0.018***	-0.005**	-0.004*
	(0.005)	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)	(0.002)	(0.002)
Violent crimes	-0.018***	-0.024***	-0.005**	-0.005**	-0.015***	-0.020***	-0.003	-0.005**
	(0.006)	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)	(0.002)	(0.002)
Property crimes	-0.007	-0.016***	-0.001	-0.003	-0.009*	-0.015***	-0.002	-0.002
	(0.005)	(0.006)	(0.002)	(0.002)	(0.005)	(0.006)	(0.002)	(0.002)
Drugs crimes	-0.007	-0.016***	-0.004*	-0.002	-0.008	-0.015**	-0.005*	0.000
	(0.005)	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)	(0.003)	(0.002)
Public order	-0.012**	-0.017***	-0.001	-0.002	-0.011**	-0.016***	0.001	-0.002
	(0.005)	(0.006)	(0.002)	(0.002)	(0.005)	(0.006)	(0.002)	(0.002)
Anti-social behaviour	-0.011**	-0.018***	-0.003	-0.004*	-0.011*	-0.015**	-0.007***	-0.005**
	(0.006)	(0.006)	(0.002)	(0.002)	(0.006)	(0.006)	(0.003)	(0.002)
Observations	38,891	37,580	402,112	402,100	38,891	37,580	402,112	402,100
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind and housing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-year FE	No	Yes	No	Yes	No	Yes	No	Yes

Note. The table shows OLS regressions of KS2 test scores on exposure to crime around pupils' house (radius equal to 500 meters). Each row indicates a separate regression of crime on test scores. The top row shows results pooling together all types of crime. The table splits the sample based on whether pupils change residence during the previous academic year. Column (1) to (4) takes as dependent variable KS2 reading test scores; column (5) to (8) takes as dependent variable KS2 math test scores. Standard errors, shown in brackets, are clustered at the level of the school catchment level. Crime measures and outcomes are standardised. *** p<0.01, **p<0.05, * p<0.1

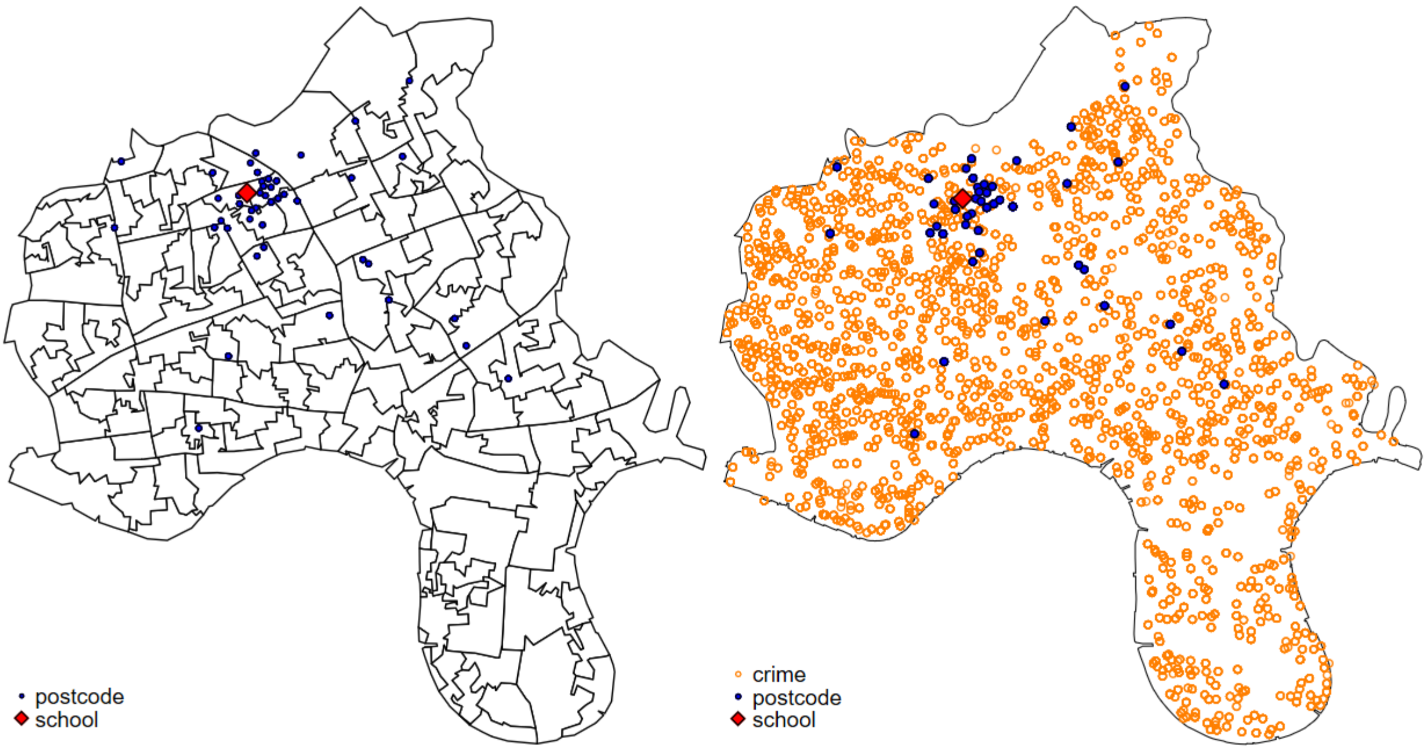
Table 17: Correlation of individual and neighbourhood characteristics

Characteristics	Unconditional correlation (1)	Conditional on school FE (2)	Conditional on Year x School (3)
Male	0.0003***	0.000	0.000
SEN	0.0011***	0.0001***	0.000
White	0.0013***	0.000*	0.000
Black	0.0008***	0.000	0.000
Asian	0.0007***	0.000*	0.000
Other ethnicity	0.0001***	0.000	0.000
FSM eligible	0.0006***	0.000***	0.000
Native	0.0016***	0.000	0.000
Changed postcode	0.000***	0.000	0.000
Changed school	0.0006***	0.0001***	0.000
Distance current school	0.0226***	0.0006	0.000
Distance nearest school	0.0001***	0.000	0.000

Note: The table displays estimates of the correlation between individual and average neighbours' characteristics. Unbiased estimates are obtained by sampling one random pupil per neighbourhood per year (see Bayer et al. (2008)). As in the all analysis, I define the neighbourhood as the school catchment area and the set of neighbours as the set of pupils enrolled in year 6 in the same school and living in the same area. Column (1) shows unconditional correlations, Column (2) controls for School FE, Column (3) adds time-specific School FE. Significance levels are bootstrapped repeating 500 times the sampling procedure of drawing one individual per neighbourhood (Battiston, 2018).

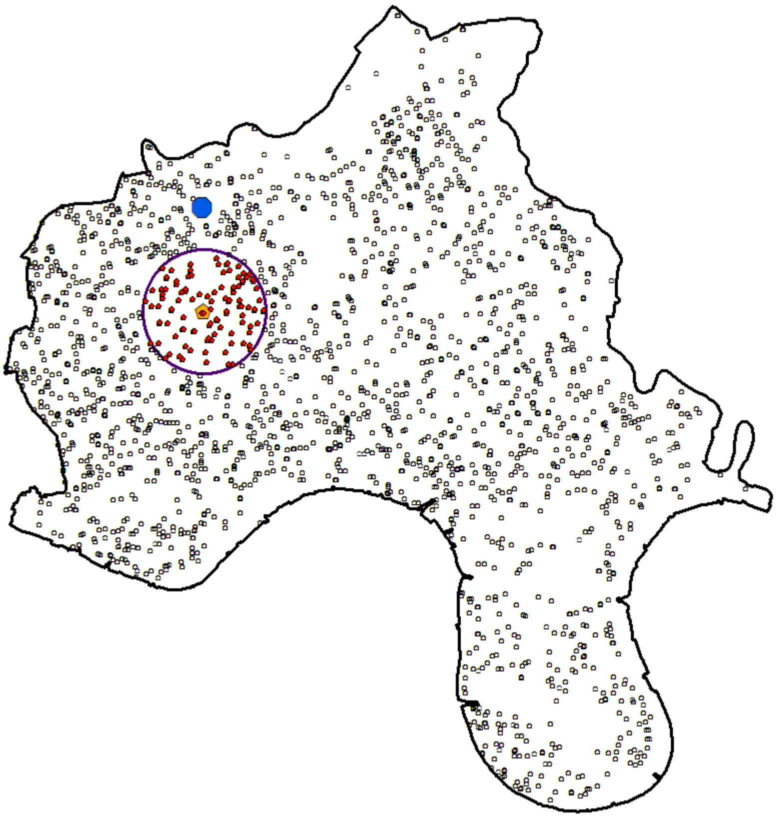
Figures

Figure 1: Example of catchment area



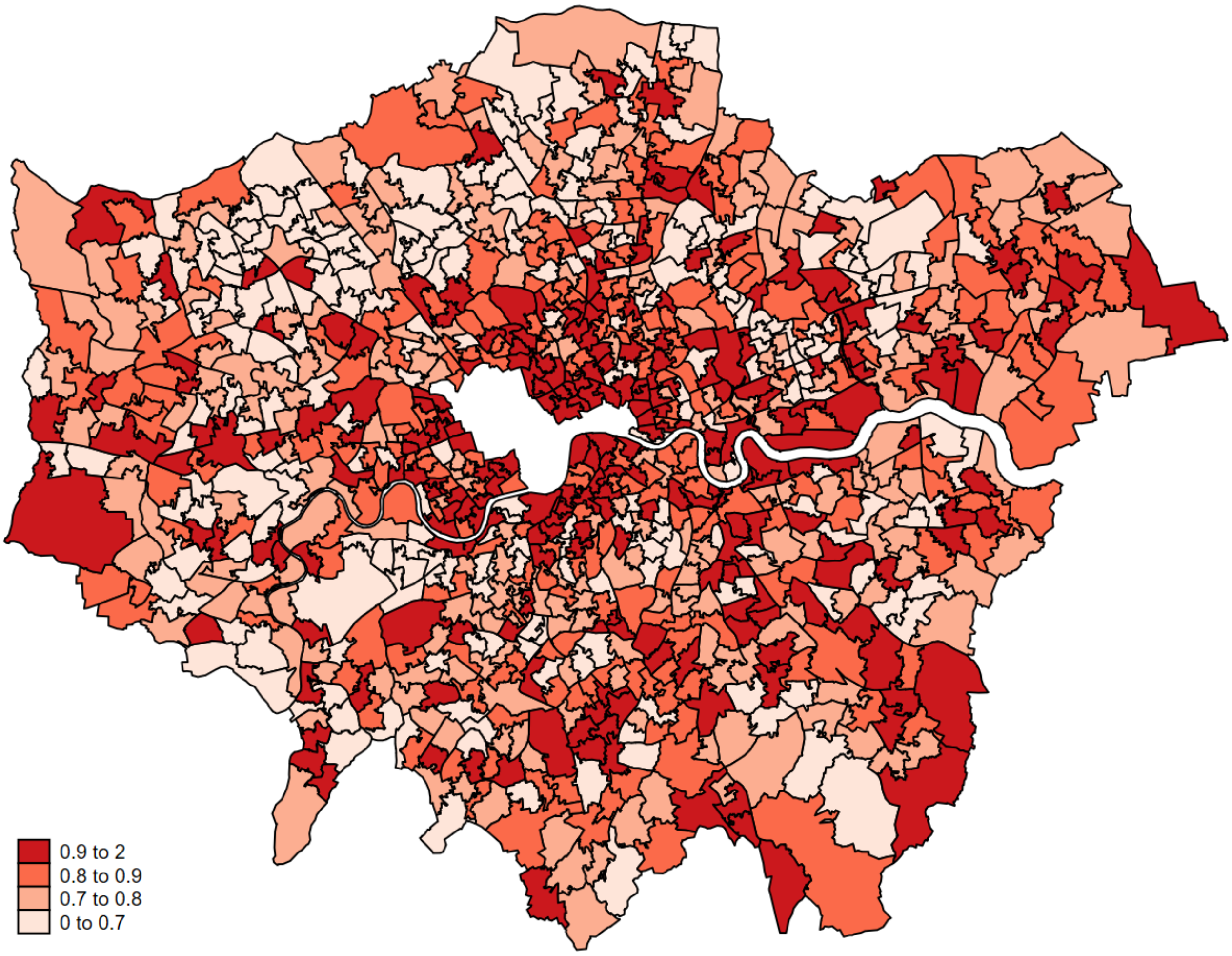
Note: The left panel shows the London borough of Tower Hamlets, composed by 130 LSOAs (grey outline), with one illustrative school (red dots) and the corresponding listing of postcodes of pupils enrolled in that school (blue dots) superimposed. In this illustrative example, during the academic year 2014/2015 60 pupils, living in 45 different postcodes (blue dots), were enrolled in the last year of primary schools. The right panel superimposes the listing of crimes occurred in Tower Hamlet in a representative year (orange dots). In the text, school catchment areas correspond to sets of postcodes of pupils enrolled to the same school.

Figure 2: Example of area of crime exposure



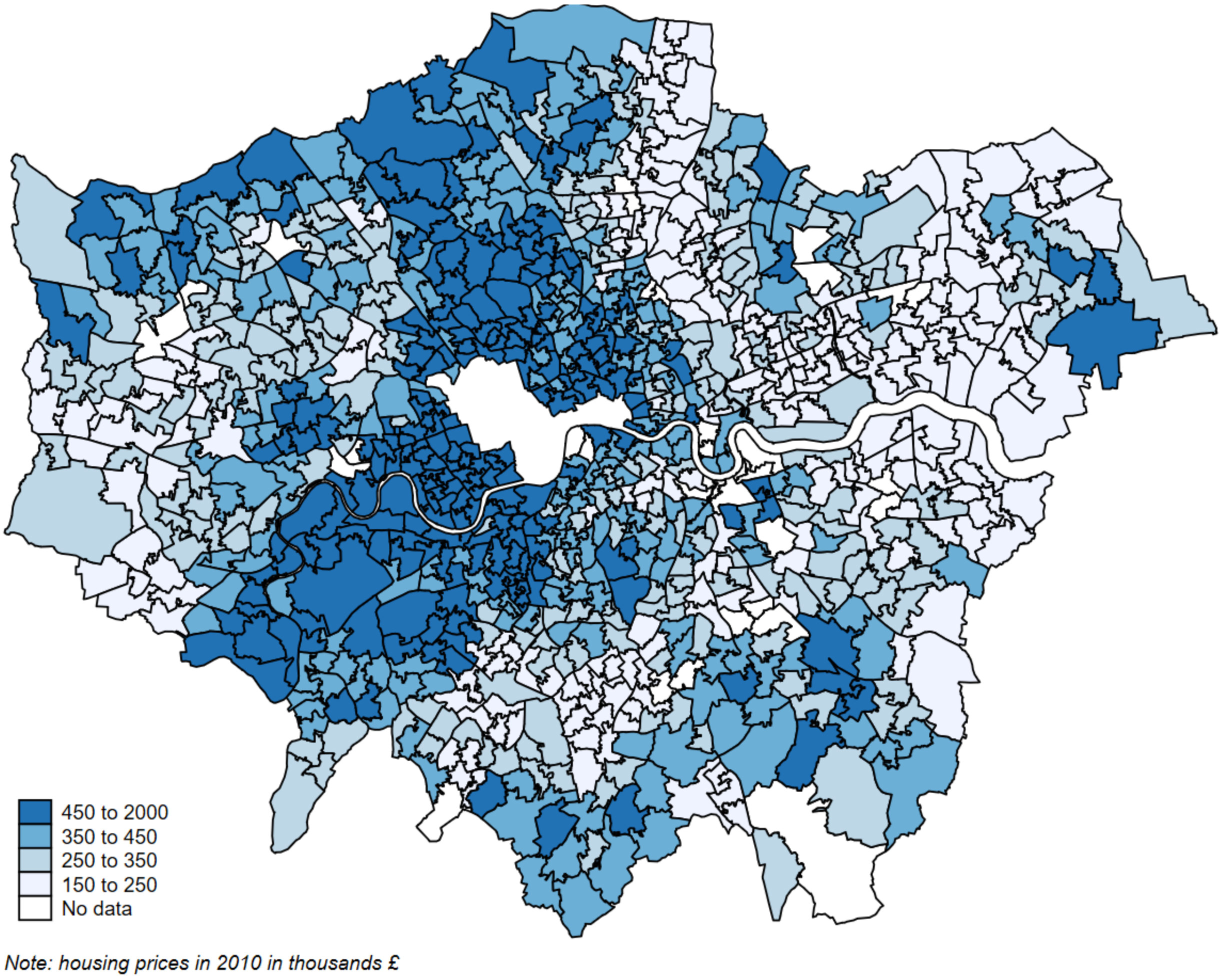
Note: The figure shows the London borough of Tower Hamlets with the corresponding listing of crimes recorded in a representative year superimposed (grey dots). I highlight one illustrative school (blud dot) where one illustrative pupil is enrolled (orange house). The blue circle describes an area of 500 meters of radius around an illustrative pupil house (orange house), the red dots correspond to all the crimes within 500 meters from the house. In the text, exposure to crime sums the number of crimes recorded around pupils' houses.

Figure 3: Distribution of crime rate in London in 2010



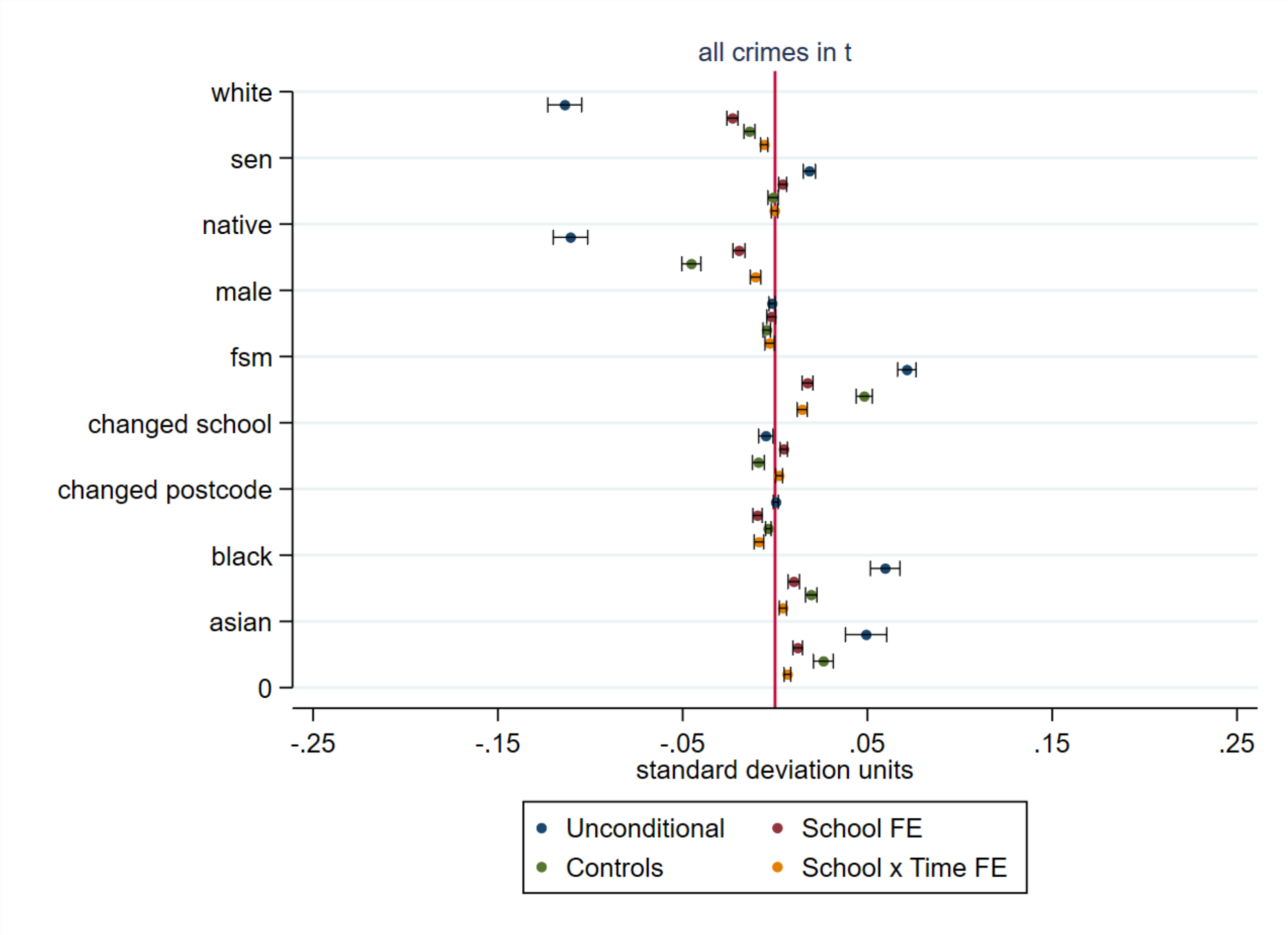
Note: This map displays the average monthly MSOA (Middle Super Output Area) crime rate during the academic year 2010-2011. Source: MET Police records.

Figure 4: Distribution of housing prices in London in 2010



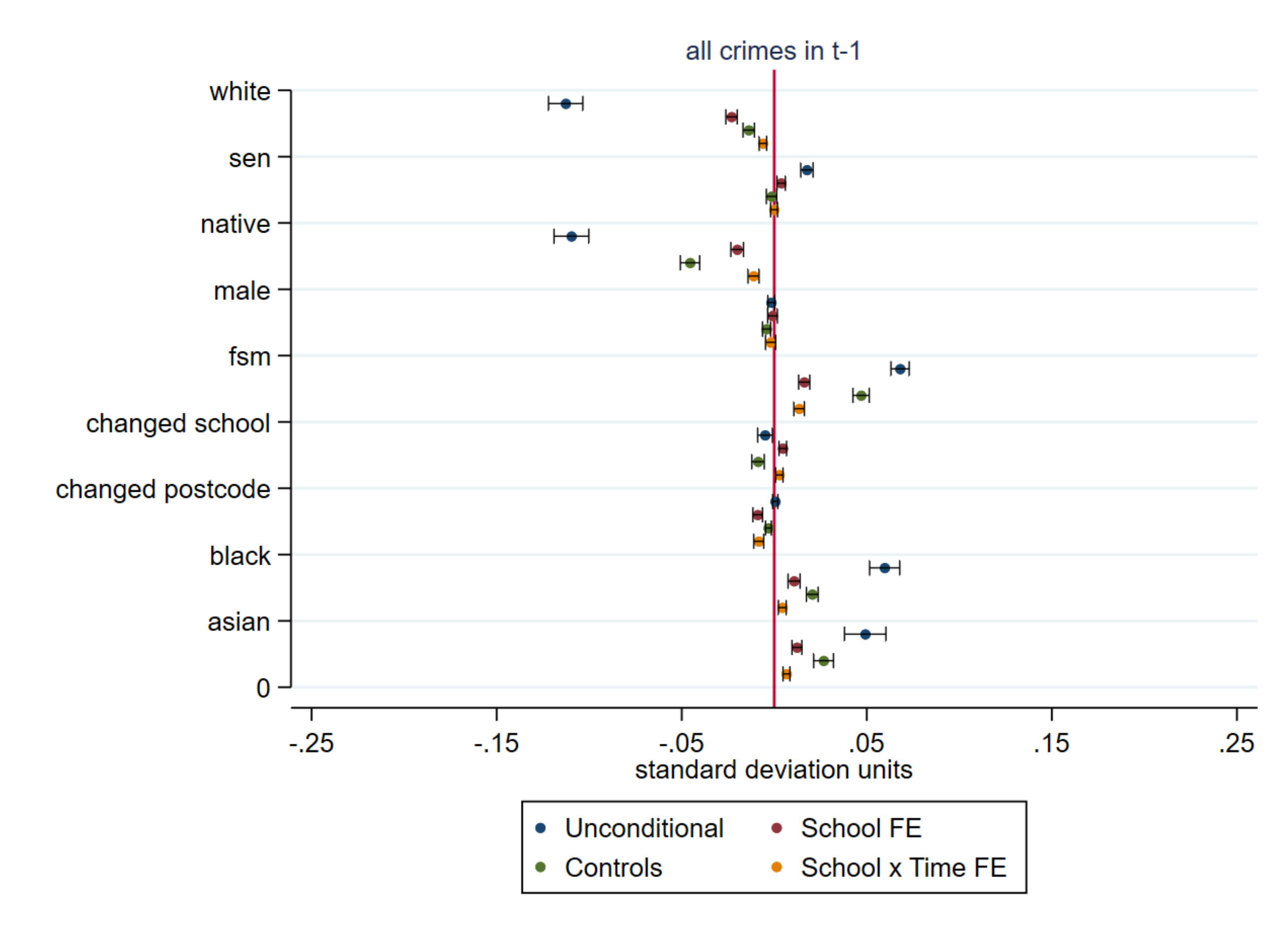
Note: This map displays the average MSOA (Middle Super Output Area) housing prices in 2010 expressed in £1000. Source: Land Registry.

Figure 5: Balance of predetermined characteristics on current crime



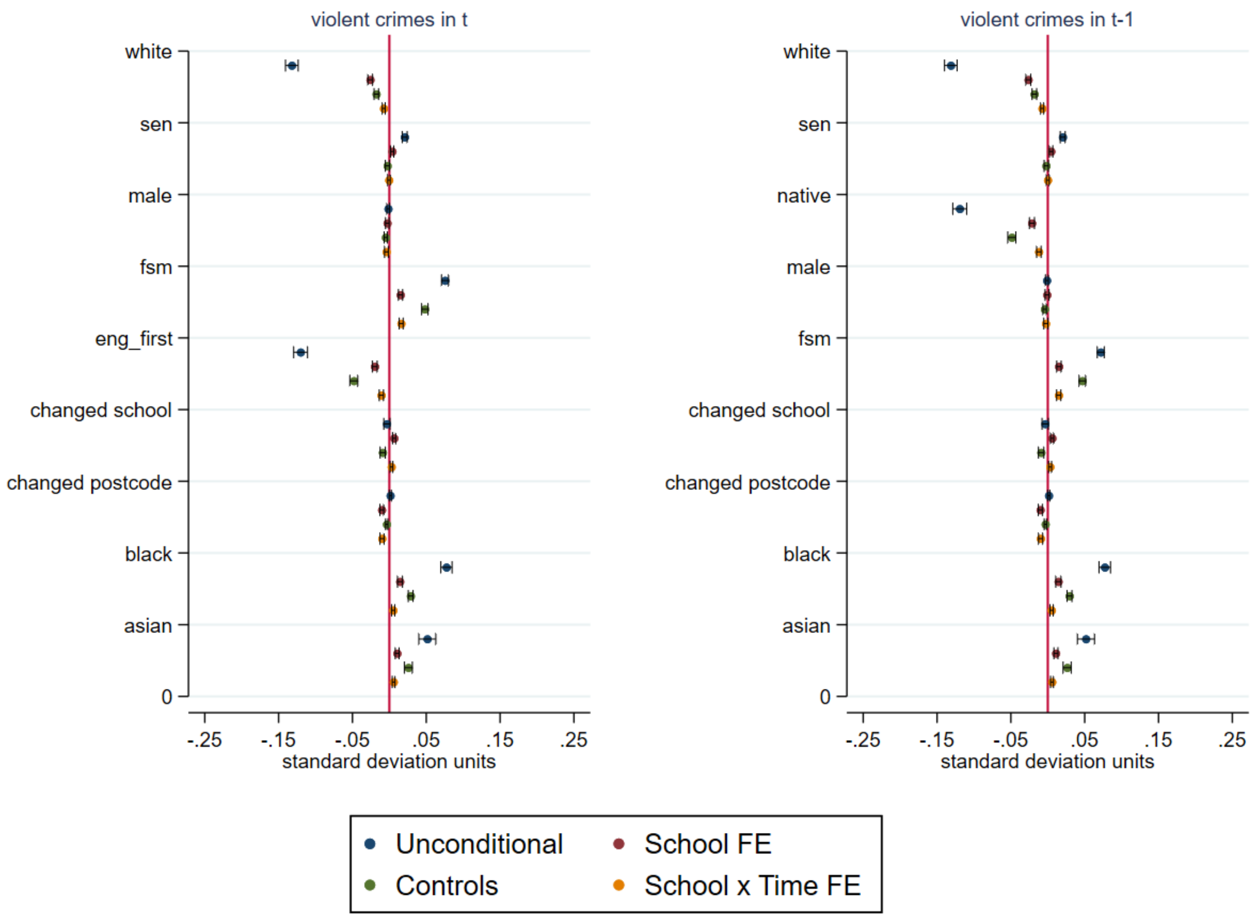
Note: This graph displays the OLS estimates of regressions of predetermined individual characteristics on current crime. Each row plots estimates from a different regression. "Unconditional" estimates control only for time FE. "School FE" estimates add school FE. "Controls" additionally control for individual and housing characteristics. Finally "School x Time FE" adds the interaction between School and Time FE. Standard errors are clustered at the level of the school catchment area.

Figure 6: Balance of predetermined characteristics on past crime



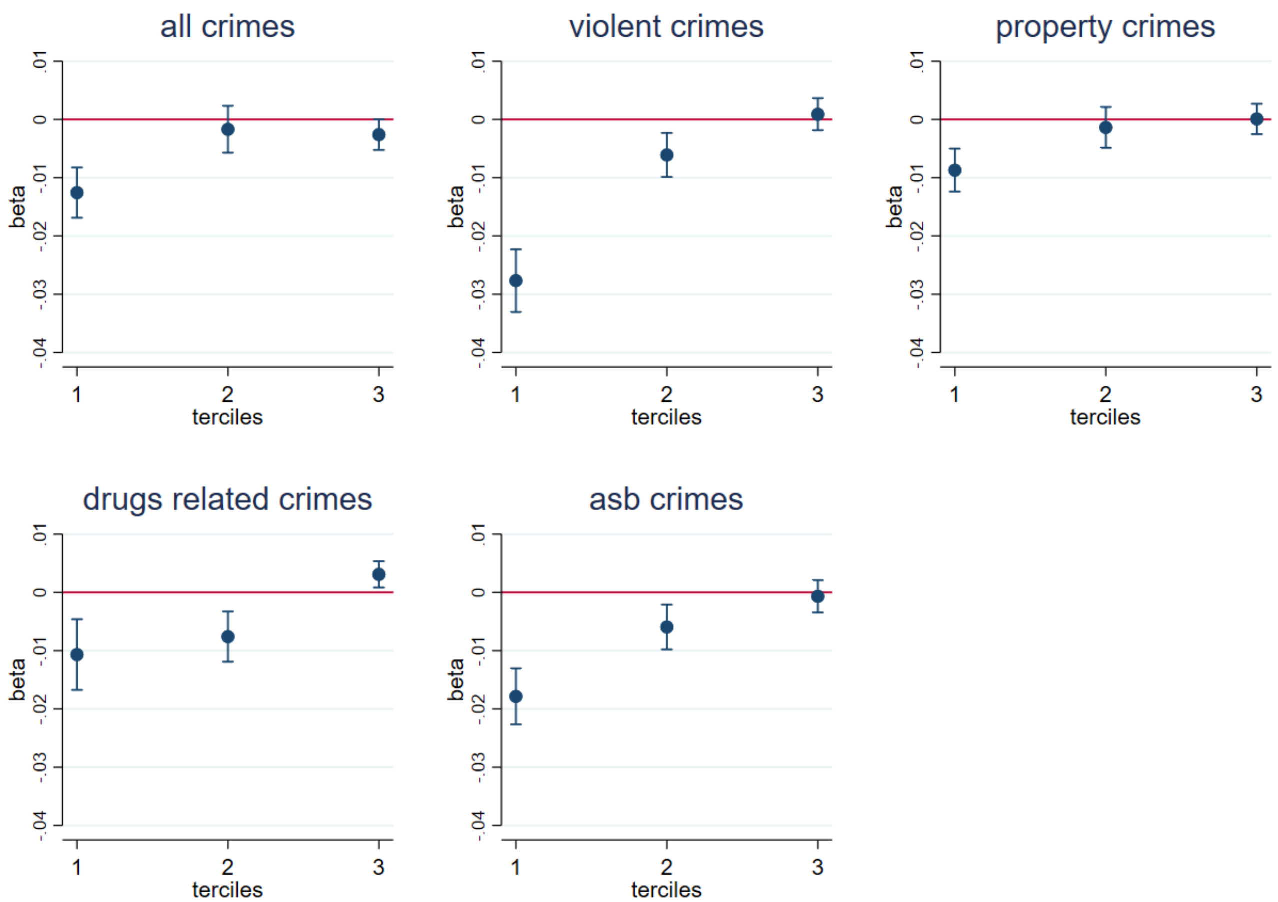
Note: This graph displays the OLS estimates of regressions of predetermined individual characteristics on past crime. Each row plots estimates from a different regression. "Unconditional" estimates control only for time FE. "School FE" estimates add school FE. "Controls" additionally control for individual and housing characteristics. Finally "School x Time FE" adds the interaction between School and Time FE. Standard errors are clustered at the level of the school catchment area.

Figure 7: Balance of predetermined characteristics on violent crimes



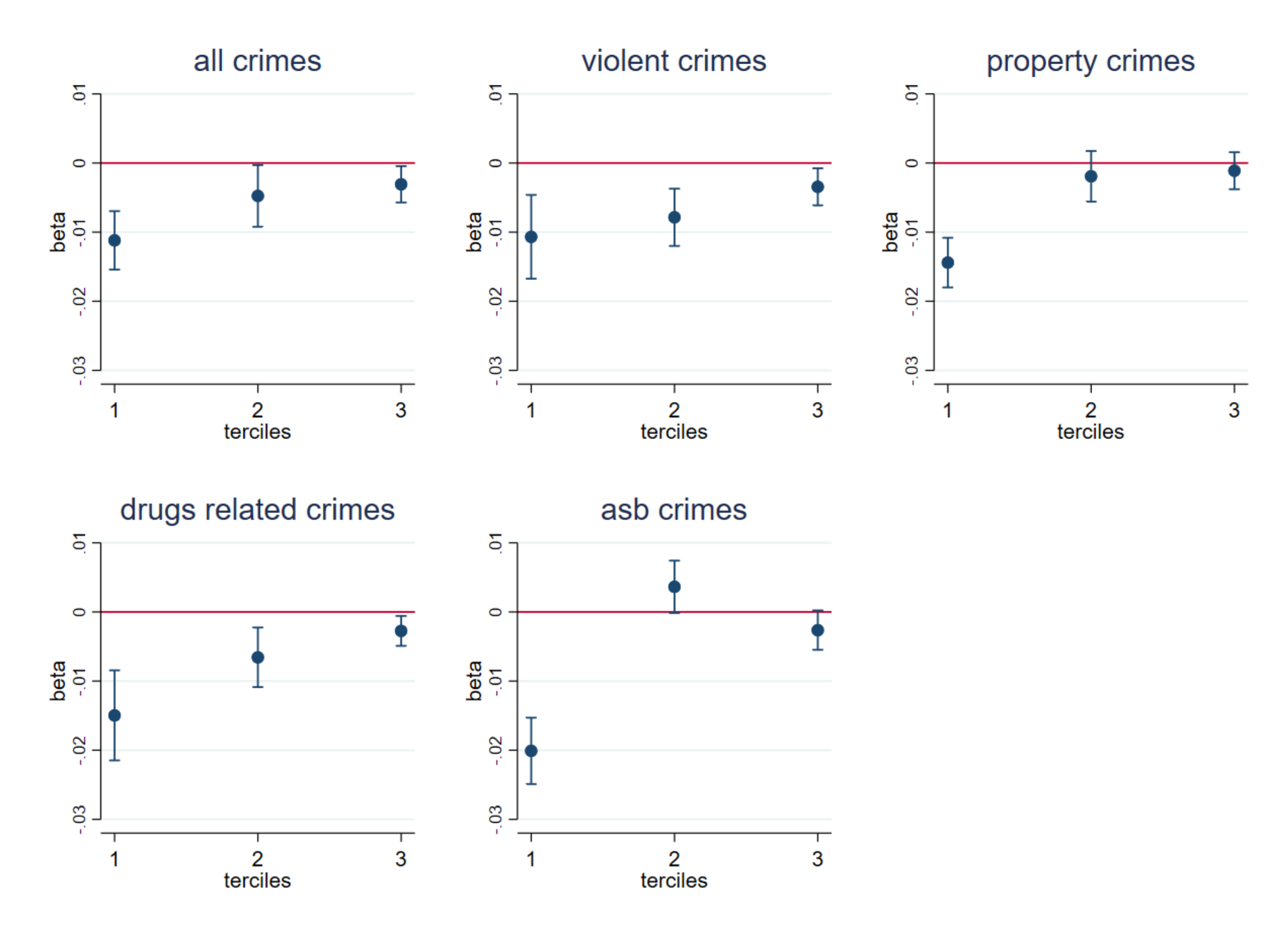
Note: This graph displays the OLS estimates of regressions of predetermined individual characteristics on current (Panel A) or past violent crime (Panel B). This graph displays the OLS estimates of regressions of predetermined individual characteristics on past crime. Each row plots estimates from a different regression. "Unconditional" estimates control only for time FE. "School FE" estimates add school FE. "Controls" additionally control for individual and housing characteristics. Finally "School x Time FE" adds the interaction between School and Time FE. Standard errors are clustered at the level of the school catchment area.

Figure 8: Impact on math test scores by percentile of crime rate



Note: This graph displays the OLS estimates of the benchmark regressions of math test scores on crime by baseline crime rate. Each panel computes exposure by type of crime (violent crimes, property crimes, drugs, asb). The x axis indicates the tercile of crime rate distribution in which the dataset is stratified. Baseline crime rate is computed at the LSOA level in 2010. Standard errors are clustered at the level of the school catchment area.

Figure 9: Impact on reading test scores by percentile of crime rate

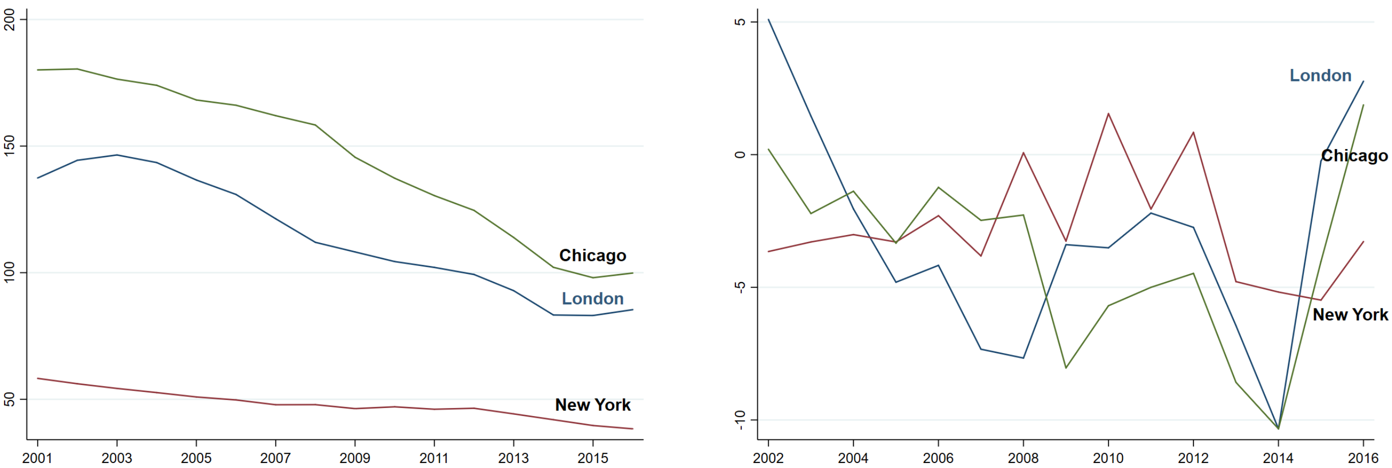


Note: This graph displays the OLS estimates of the benchmark regressions of reading test scores on crime by baseline crime rate. Each panel computes exposure by type of crime (violent crimes, property crimes, drugs, asb). The x axis indicates the tercile of crime rate distribution in which the dataset is stratified. Baseline crime rate is computed at the LSOA level in 2010. Standard errors are clustered at the level of the school catchment area.

Appendix

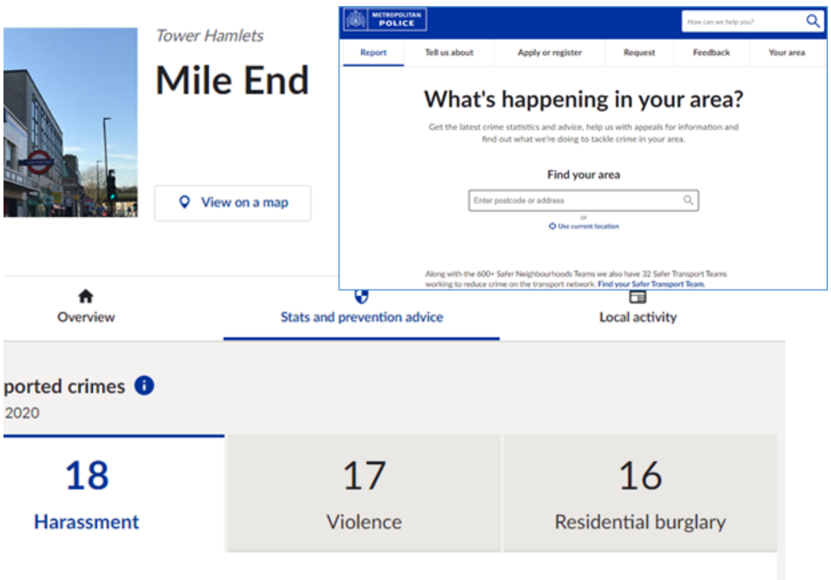
Figure A1: Comparison of crime trends in Chicago, London and New York

(a) Crime rate (per 1000 ppl) (b) Crime rate growth



Note: Source: Chicago Police Department, FBI UCS Annual Crime Reports, MET Police

Figure A2: Public available information on local crime rate



Note: This picture shows a screen-shot from the MET Police website https://www.met.police.uk/a/your-area/.

Table A1: Definition of crime categories

Types of crime	Category definitions
Anti-social behaviour	anti-social behaviour
Drugs	Drugs and other crime
Property crimes	Bicycle thefts, other thefts, theft from the person, shoplifting, vehicle crimes, burglary, vehicle crime, criminal damage and arson
Public order and weapons	Possession of weapons, public disorder and weapons, public order
Violent crime	Violence and sexual offences and violent crime (common assault and murder), robbery

Table A2: Reconciling the results with existing estimates

Study	Setting	Shock	Effect	Relative effect
Sharkey et al. (2016)	New York - afican-american students in public schools	1 sd increase in violent crimes	1% sd	
Monteiro and Rocha (2017 Restud)	Rio de Janeiro	exposure to gangs gunfights	5% sd	
Rivkin et al. (2005 Econometrica)	US	school input - teachers' quality and class size		10%
Adda et al. (2011)	Sweden	parental death		5%
Gibbons et al. (2013 EJ)	UK	neighborhood effect	0 effect	
Effect of being FSM	my sample	Effect of being FSM		9%

Note: This table shows the comparison of my estimates with the existing ones from the literature. Column 1 refers to the paper taken as comparison; column 2 illustrates the setting of the study; column 3 explains the type of shock explored in the study while Column 4 reports the estimates from the mentioned paper. Column 5 provides instead the comparison with my estimates. For instance, my effect corresponds to around 10% of the effect of an increase in school quality based on estimates from Rivkin et al. (2005).

Table A3: Pupils' test scores and crime: standard errors

	Reading test scores [sd]				Math test scores [sd]			
	Distance cutoff: 2 km	Distance cutoff: 4 km	Distance cutoff: 6 km	Distance cutoff: 10 km	Distance cutoff: 2 km	Distance cutoff: 4 km	Distance cutoff: 6 km	Distance cutoff: 10 km
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All crimes	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Violent crimes	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Property crimes	-0.004**	-0.004**	-0.004**	-0.004**	-0.005**	-0.005**	-0.005**	-0.005**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Drugs crimes	-0.003**	-0.003**	-0.003*	-0.003*	-0.002	-0.002	-0.002	-0.002
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Public order	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004***	-0.004**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]
Anti-social behaviour	-0.006***	-0.006***	-0.006***	-0.006***	-0.007***	-0.007***	-0.007***	-0.007***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Observations	441,003	441,003	441,003	441,003	441,003	441,003	441,003	441,003
R-squared	0.465	0.465	0.465	0.465	0.485	0.509	0.485	0.509
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind and housing controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table shows OLS regressions of KS2 reading score (column 1 to 4) and KS2 math score (column 5 to 8) on exposure to crime around pupils' house (radius equal to 500 meters). Each row indicates a separate regression of test scores on a specific crime category. Panel A shows results pooling together all types of crime, panel B separates crime types. Column (1) and (5) include time fixed effects, column (2) and (6) add school fixed effects, column (3) and (7) control for individual and housing characteristics and column (4) and (8) include school-time fixed effects. Individual controls include: gender, ethnicity, FSM, SEN, language spoken at home, student's average point score at KS1. Housing controls (at baseline) include: average floor area, average number of habitable rooms, average floor height, average price, average LSOA population. Crime measures are standardised. I report robust standard errors clustered at the level of the school catchment (shown in parentheses) and Conley standard errors (in square brackets, computed at 2km cutoff). *** p<0.01, **p<0.05, * p<0.1