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# Looking Ahead in Anger. The effects of foreign migration on youth resentment in England

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**Abstract.**

Figures are showing that ethno-cultural issues are increasingly related to most school bullying incidents happening lately. While many theoretical arguments and empirical investigations scrutinize the effects of foreign migration on hostile behaviours enacted by the adult population, there is insufficient evidence on the effects of immigration on youth. This paper provides evidence by exploiting the shock from migration which occurred in the UK after the 2004 European Union Enlargement to estimate the magnitude and the directionality of the effect exerted by the resulting inflow of migrants on school bullying. Multilevel Logit, Generalized Estimating Equations and Control Function with Two-Stage Residual Inclusion are used on a novel dataset containing spatially fine-grained observations on school bullying across the UK. Findings highlight a relevant effect of the shock from migration in triggering bullying, which is robust to the accounting for potential endogeneity with respect to immigrants' location choice. The role of existing language barriers as channel for the effect of the migration shock is also scrutinized, to find that they increase its effect.

**Keywords**: school bullying, migration, conflict, cultural threat, inequality, language barriers, resentment

**JEL codes:** F22, I31, J15

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# 1. INTRODUCTION

30% of students aged 13-15 experiences bullying globally and among OECD countries the share amounts to 18% (OECD, 2017; UNESCO, 2018). Lately, figures show a sharp rise in the count of the cultural-based episodes of school bullying (Marsh & Mohdin, 2018; OECD, 2017; Sime et al., 2017; Southern Poverty Law, 2019; Weale, 2019). Relating these figures to the existing evidence on the causal links between foreign migration and adverse behaviors enacted by adult cohorts (Card, Dustmann, & Preston, 2012; Rodrik, 2018), it appears that little is known about the effects of foreign migration on youth resentment. This paper addresses this question through a statistic strategy which allows to assess both the magnitude and the direction of the relationship. The issue deserves attention, since understanding how immigration contributes to shape young cohorts' behaviors undoubtedly matters for a better comprehension of how adult cohorts will behave.

Different strands of literature support the analysis of the effects of a local shock from migration on school bullying. First, bullying-studies evidence provides for intolerant behaviors enacted by pupils at school mimic the adults' intolerant behaviors in the same community (Pells, Ogando Portela, & Espinoza, 2016; Sime et al., 2017; Southern Poverty Law, 2019; Vertovec & Coen, 2002). This first set of evidence also corroborates the effect of the local environment on what happens inside the school walls (Espelage, 2014; Juvonen & Graham, 2014; Kardefelt-Winther & Maternowska, 2019). Second, social science evidence shows that resentful behaviors among adult population arise as reaction to large inflows of unknown immigrants and the cultural threat they represent (*i.a.* Goodwin & Milazzo, 2017; Halla, Wagner, & Zweimüller, 2017; Hangartner, Dinas, Marbach, Matakos, & Xefteris, 2018; Kinnvall, 2017; Newman, 2013). By combining these two research strands, it appears possible that a cultural shock from migration fuels school violence. The latter happens because pupils emulate adults' reactions to the shock happening at the community level. This paper

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investigates this hypothesis providing an empirical measure of the effect of a migration shock occurring in a place on the local level of school bullying.

The analysis considers the total level of school bullying, irrespective of the target being a newcomer or a native, as hate literature details that oppressive violence against minorities triggers retaliation by members of the victimized group (Banks, White, & McKenzie, 2019; Tausch et al., 2011). The same pattern is observed in bullying, where data show that victims often turns into perpetrators, having retaliation as a driver (Walters & Espelage, 2018). Hence, racist bullying against newcomers by members of the dominant ethic group opens up to retaliatory bullying against them. If the cultural threat due to the migration shock affects bullying, it does so on the total magnitude of school violence.

A first contribution of the present investigation is overcoming the recognized limitations of school-bullying research focusing only on the individual/family dimension in the analysis of risk factors (Álvarez-García, García, & Núñez, 2015; Cook, Williams, Guerra, Kim, & Sadek, 2010; Tippett & Wolke, 2014), by acknowledging the role of a spatial socioeconomic feature like foreign migration. Second, the paper opens up to bridging the bullying literature and the socioeconomic literature on the influence of foreign migration on social anxiety. Within the latter, increasing emphasis is placed on local demographic changes caused by migration inflows as source of threat (Hopkins, 2010; Newman, 2013), since these changes threaten the *status quo* by affecting extant expectations of the incumbent population about the composition of the local community. In other terms, the analysis focuses on the behavioral effects of the exposure to newcomers considering the prior socioethnic structure. On this, the multicultural "*defended neighbourhood*" hypothesis states that a large migration influx is most culturally threatening for citizens residing in contexts with minimal pre-existing experience of the population that is moving to their place (Newman, 2013). Pre-existing experience of incoming migrants eases the mitigation of the cultural shock since the receiving place is already familiar with their cultural outlook.

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The current research builds upon these developments, by bringing them together in the form of empirically assessing whether school bullying is determined by sudden and sizeable inflows of an immigrant group in places where the immigrant group has largely been absent. The resulting evidence shows that immigration of unfamiliar cultural groups is a trigger for youth resentment. The role of immigration of previously unknown cultural groups in determining harassment among young cohorts holds also controlling for other fundamental individual and local socioeconomic features that extant literature acknowledges as relevant in explaining intolerant behaviors, such as inequality, poverty, social strain (Goodwin & Milazzo, 2017; Krosch, Tyler, & Amodio, 2017; Wilkinson & Pickett, 2017). Hence, the findings support a *"defended school"* hypothesis with respect to young cohorts, analogously to what has been demonstrated for the "*defended neighbourhood*" hypothesis for adult cohorts.

In the paper, the "*defended school*" hypothesis is analyzed with respect to the impact on school bullying of the fast and large migration influx which occurred in England after the 2004 EU Enlargement. The considered age cohort is given by 15-years-old, an age group just 3 years away from voting and experiencing a local milieu which overcomes the borders of family and school to reach the more complex local socioeconomic structures. England is considered for two reasons. First, the UK displays a remarkably high share of school bullying victimization, ranking 4th among OECD countries in terms of highest rate (OECD, 2017). Second, the 2004 EU Enlargement generated a sizeable shock from Eastern European (A8) migration which is recognized as a potential trigger for sociocultural threats for England (Becker & Fetzer, 2017; Goodwin & Milazzo, 2017). Anecdotal evidence depicts that hate crimes against A8 migrants sharply rose after the Enlargement (Human Rights First, 2008; Rzepnikowska, 2019). In 2013 one person every 14 hours had been arrested for hate crimes against Polish people[1] in England (Mcdevitt, 2014). Furthermore, following the Enlargement, British voters became increasingly concerned about the effects of immigration (Goodwin & Milazzo, 2017; Meleady, Seger, & Vermue, 2017).

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In the current research, the A8 migration shock is combined with new data on school bullying from the 2014 What About YOUth? Survey (WAY-2014) (Health and Social Care Information Centre of the UK Government, 2016) that covers the universe of 15-years-old pupils in England in 2014-15. The WAY-2014 data provides information about bullying victimization of respondents, their gender, their ethnic characteristics, the deprivation level of their residential neighbourhood and the local authority of residence. The combined database contains individual-level data on 15-years-old and spatial-level data on the A8 migration shock. Alongside, data on the spatial socioeconomic outlook are included to let the empirical investigation to control for spatial characteristics. The database allows to analyze, through estimation of a Multilevel Logit, a Generalized Estimation Equations Logit and a Control Function with Two-Stage Residual Inclusion, the effects exerted by the migration shock on bullying by controlling also for individual characteristics of the target and potential endogeneity in the A8 migrants' locational choices.

Estimation results support the "*defended school*" hypothesis. Local exposure to sharp and fast migration inflows of unfamiliar cultural groups emerges as a determinant for school bullying, even when individual-level features and other potential confounders are controlled for. This result is supported by accounting for the potential endogeneity of the scrutinized regressor, by means of instrumenting the local exposure to the A8 migration shock through a shift-share type of exogenous regressor. Hence, the current research provides evidence supporting A8 immigration as determinant of school bullying. The results also outline that language barriers increase the overall effect of a given level of cultural shock from immigration, acting as a moderating feature. This finding is consistent with existing research on the adult population (Newman, 2013) where language barriers have been assessed as hampering the level of cultural diversity assimilation. Additionally, the findings from the paper show that the local poverty level does not constitute a risk factor for bullying victimization, while places

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characterized by higher spatial polarization in terms of income are associated to more bullying.

The current investigation expands on previous research along three dimensions. First, it bridges bullying-related literature with socioeconomic research investigating the effects of foreign migration on the behaviors of the receiving populations. Second, the findings add to existing evidence on how perceived sociocultural threats determine social tension among adult cohorts. Third, the paper specifically addresses the salience of the spatial dimension through a comprehensive geographical approach across England. The spatial dimension has been largely under scrutinized in bullying-related research up to now, notwithstanding the non-negligible spatial heterogeneity in bullying rates at different geographic scales (Health and Social Care Information Centre of the UK Government, 2016; OECD, 2017). Overall, the results strongly support including within bullying-prevention programs both measures to favor the local assimilation of unassimilated cultural groups and measures to moderate economic inequality.

The remainder of the paper is organized as follows. Initially, a review of relevant research on bullying and sociocultural threat is outlined. Then, the data and the empirical strategies used in the empirical estimation are introduced and described. The results are then presented and discussed. Finally, concluding comments are presented.



## 2. REVIEW OF RELATED LITERATURE

Bullying is both a societal challenge and a public health concern (Ammermueller, 2012; Brown & Taylor, 2008; Tippett & Wolke, 2014). The negative effects caused by bullying, alongside its pervasiveness, have pushed it to the top of many institutional agendas (Council of Europe, 2015; United Nations, 2018). Seminal approaches on the identification of risk factors associated with school bullying focused on the link between bullying and individual/family characteristics, producing mixed empirical evidence up

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to the point that scholars have asserted the impossibility of identifying robust individual types for either bullying perpetrators or victims (Álvarez-García et al., 2015; Espelage, Van Ryzin, & Holt, 2018; Juvonen & Graham, 2014; OECD, 2017). The identification of this "*personalized bias*" has pushed research to broaden the scope of investigation to include the effects of places (Espelage, 2014; Migliaccio & Raskauskas, 2016; Tippett & Wolke, 2014), given also that findings from meta-analysis display a strong effect size of local factors (Cook, Williams, Guerra, Kim, & Sadek, 2010) and that ) and that schools are not "*hermetically sealed institutions*" (Southern Poverty Law, 2019).

The growing awareness of the influence of places opens up to bridge the literature on oppressive violence happening at school and the literature on the role of foreign migration in shaping local social anxiety. To this respect, the existing evidence shows that the incumbent population becomes hostile to foreign migrants through the perception of threats to its established sociocultural identity (Card et al., 2012; Enos, 2016; Hainmueller & Hopkins, 2014). Increasing emphasis is placed on local demographic changes caused by migration inflows (Hopkins, 2010; Newman, 2013), since these changes threaten the *status quo* by affecting extant expectations of the incumbent population about the composition of the local community. Thus, the focus of investigation is the size of the exposure to newcomers considering the prior socio-ethnic structure. On this, Newman (2013) has developed a multicultural "*defended neighborhood*" hypothesis stating that a large influx of migration is most culturally threatening for citizens residing in contexts with minimal pre-existing experience of the population that is moving to their place. Pre-existing experience of incoming migrants eases the mitigation of the cultural shock, since the receiving place is already familiar with their cultural outlook.

Within this setup, the fast and sizeable arrival of unfamiliar cultural groups in the UK after 2004 represents a potential sociocultural threat fitting within the "*defended neighbourhood*" hypothesis (Becker & Fetzer, 2017; Goodwin & Milazzo, 2017). In the

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aftermath of the 2004 European Union Enlargement, eight Eastern European (A8) countries, alongside Cyprus and Malta, joined the European Union. The UK did not enforce any transition rules with respect to the movement of people, experiencing a resulting mass migration significantly larger than anticipated.

**Figure 1: The geography of A8 migrants' settlements in 2001 and 2011 across the 150 England Upper Tier Local Authorities (UTLA) (A); (B)The 2001-2014 migration trend towards England from the countries which were part of the European Union before 2004 (EU14) (solid line) and the A8 countries (dotted line) (B).**

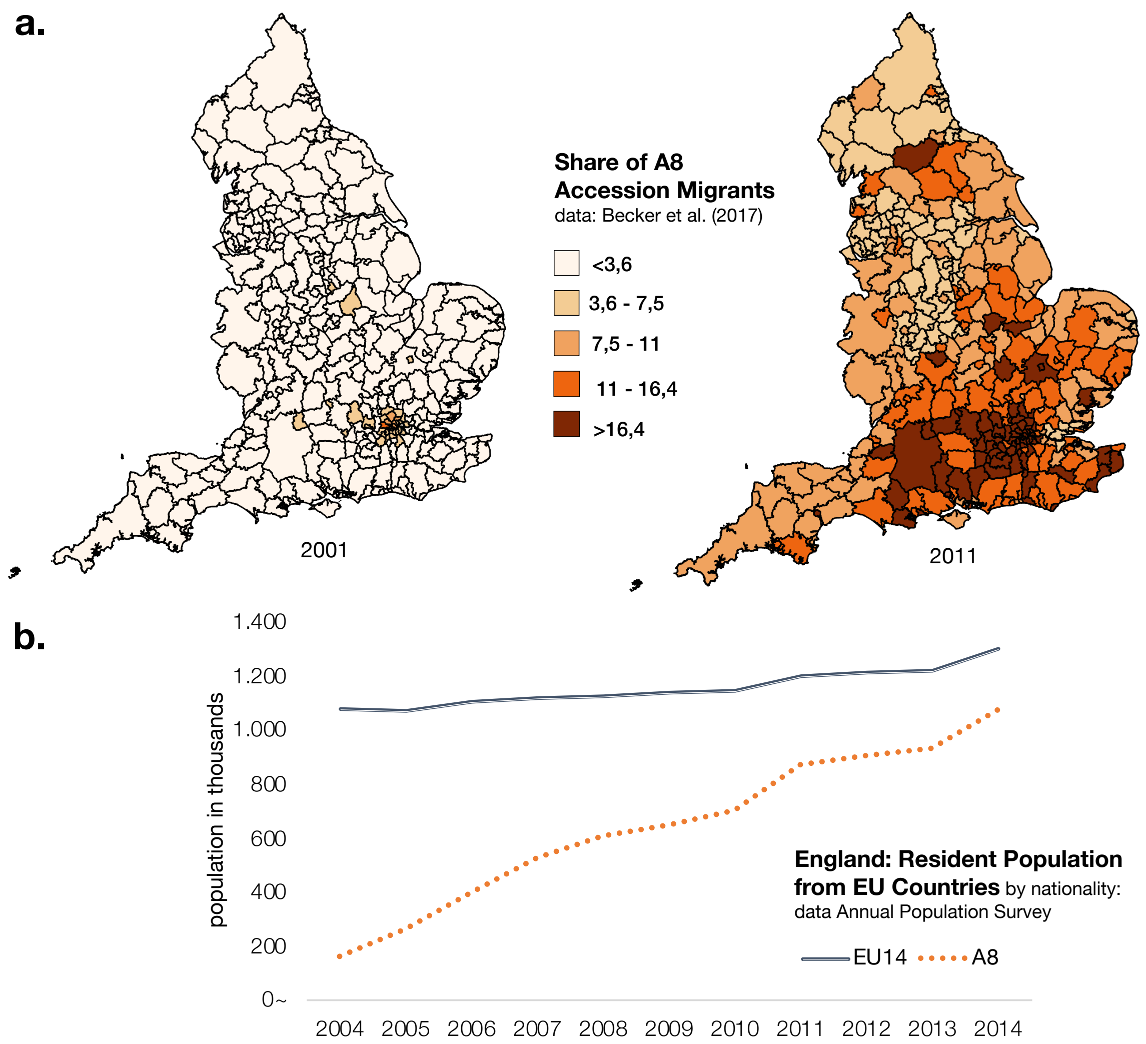


Figure 1 shows the sharp increase in A8 migrants arriving to England after 2004 compared to the trend of EU 14 citizens. Alongside, Figure 1 also portrays the spatial

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distribution of A8 migrants before and after 2004 to highlight the different pattern which occurred after 2004, since A8 migrants have been spreading throughout the place, with relevant settlements in small and rural areas which have previously attracted very few migrants (Pollard, Latorre, & Sriskandarajah, 2008). This fast and relevant arrival of unfamiliar cultural groups in many English areas after 2004 represents a potential sociocultural threat fitting within the "*defended neighborhood*" hypothesis (Becker & Fetzer, 2017). A8 migrants have settled in areas which were not previously familiar with Eastern European culture igniting the perception of cultural threat in the local population and triggering tension and disorder. Figures on the sharp increase in hate-crimes against A8 migrants occurring in England after 2004 further support the hypothesis (Human Rights First, 2008; Mcdevitt, 2014; Rzepnikowska, 2019). According to bullying related literature, pupils might mimic this social anxiety in the school environment by enacting cultural and ethnic violence to protect the established social identity. New anecdotal evidence suggests that the perceived threats to social identity posed by A8 migrants in the wider environment work also inside schools (Sime et al., 2017).

Hence, there is a rationale for empirically verifying whether the sociocultural threats arising from sudden inflow of migrants enact school violence in line with the "*defended neighborhood*" hypothesis. To deal with established concerns about endogeneity of immigrant's location choices, the outlook of the A8 migrants' geography in England is instrumented through shift-share with respect to the geography of A8 migrants in 2001. The paper also explores the role of pre-existing language barriers at local level in moderating the effects of the A8 migration shock. The presence of language barriers inhibits contact among diverse groups, resulting in increased perception of obstacles for the incumbent dominant cultural group posed by the out-groups and increased uneasiness toward them (Hainmueller & Hopkins, 2014). This increased uneasiness posed by language barriers may undermine the assimilation of cultural diversity, which in turn may boost the effect of a given level of cultural shock from inflows of new

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migrants. Evidence about England shows that speaking the language of the hosting country is a pivotal social norm for the incumbent cultural group[2] (NatCen Social Research, 2014), so cultural minorities have to abide to it to reduce the cultural distance from the dominant culture.

Additionally, the investigation performed in the paper also provides novel information with respect to the spatial socioeconomic determinants of violent behaviors targeting minorities and disempowered groups, relating to recent works on gender violence (Aizer, 2010; Alesina, Brioschi, & La Ferrara, 2020; Tur-Prats, 2019), hate groups, hate speech and hate manifestations (Medina, Nicolosi, Brewer, & Linke, 2018; Müller & Schwarz, 2018). Finally, the triggering effect exerted by migration inflows on school bullying outlined in this paper is also related to the thriving literature scrutinizing the geography of resentments (Dijkstra, Poelman, & Rodríguez-Pose, 2019; McCann, 2020).

## 3. DATA

Previous contributions on school bullying have mainly considered national and/or cross-country level surveys targeting limited samples of schools (Álvarez-García et al., 2015; OECD, 2017; Tippett & Wolke, 2014). This paper specifically addresses the salience of the spatial dimension through a comprehensive geographical approach across the 150 English Upper Tier Local Authorities[3] (UTLAs), by assembling an original dataset that matches novel data on 15-years-old's experience of being bullied resulting from the What About YOUth? 2014 survey (WAY-2014) with spatially fine-grained socioeconomic data. The targeted spatial dimension has been largely under scrutinized in bullying-related research up to now, notwithstanding the non-negligible spatial heterogeneity in bullying rates at different geographic scales (Health and Social Care Information Centre of the UK Government, 2016; OECD, 2017).

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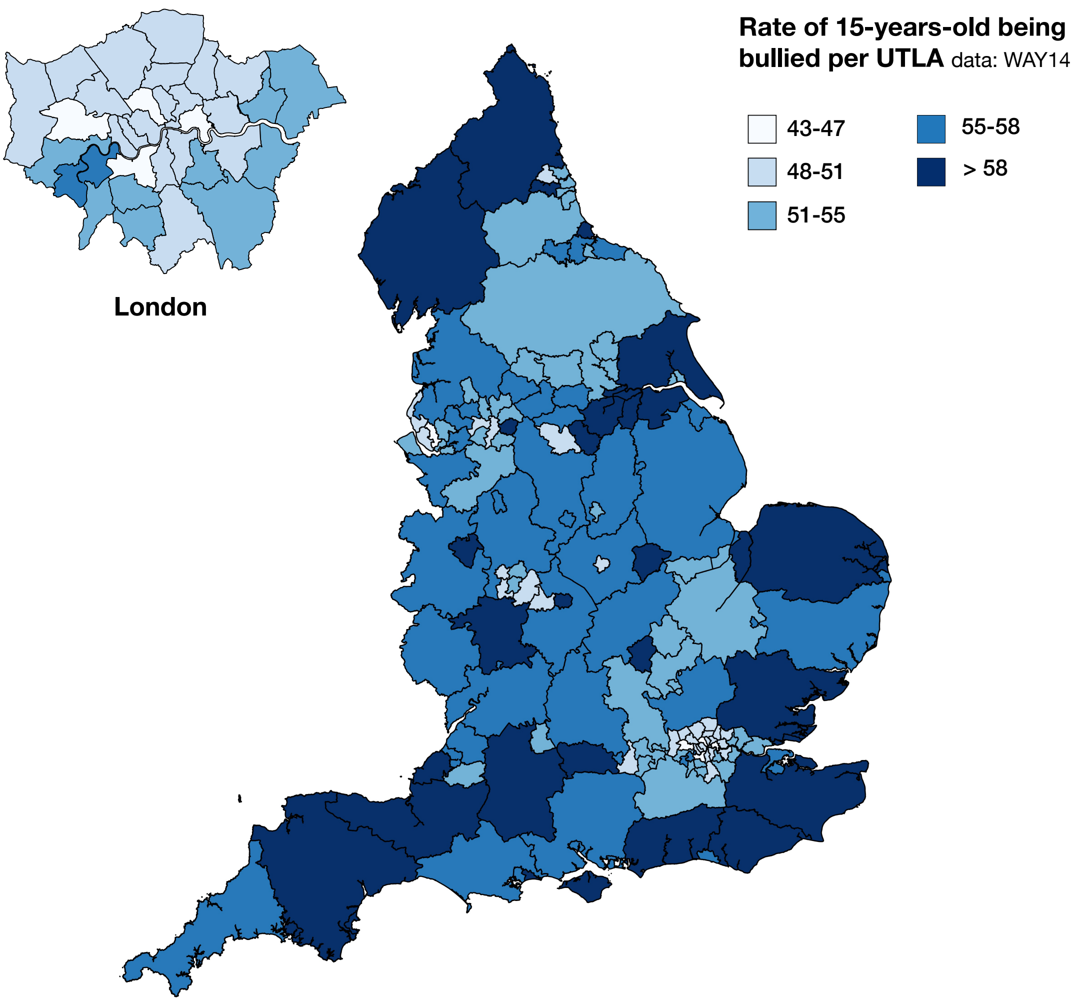
Measuring school bullying. School bullying is measured using the WAY-2014 data from NHS Digital. Data contain 110,788 individual observations corresponding to the number of survey participants having answered bullying-related questions between Sept. 2014 and Jan. 2015. For each respondent, the WAY-2014 database details whether he/she has been bullied or not (Yes/No), the gender, the ethnicity, the level of deprivation of the neighbourhood of residence and the Upper-Tier-Local-Authorities (UTLAs) of residence at the time of the survey.



**Figure 2: The geography of bullied 15-years old across the 150 England UTLAs as measured by the WAY-2014 survey.**



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Data are robust at UTLA level, accounting for a weighted population of 520,221 pupils (Health and Social Care Information Centre of the UK Government, 2015). More details are provided in the Appendix. Almost all previous studies have sampled less than 50,000 pupils, often across countries (Álvarez-García et al., 2015). This dataset entails suitable characteristics to provide a spatially robust proxy for bullying in England, allowing to develop an empirical estimation capable of sound inclusion of the spatial-level covariates. The geography of school bullying from WAY-2014 shows non-negligible spatial heterogeneity across the UTLAs, as outlined in Figure 2.

Measuring the spatial exposure to a migration shock. The fine-grained WAY-2014 data on bullying victimization are merged with administrative data, starting from the following measure for the A8 migration shock in UTLA *j* (Becker & Fetzer, 2017),

$$A8_j = \frac{A8\ Migrants_{UTLA_{j,2011}} - A8\ Migrants_{UTLA_{j,2001}}}{EU14\ Migrants_{UTLA_{j,2001}}} \tag{1}$$

where the numerator is given by the 2011-2001 difference in the size of UTLA *j* residents coming from A8 countries. The denominator is the size of 2001 UTLA *j* resident population coming from EU countries that have been members of the European Union before 2004. Eq.(1) accounts for both the magnitude of A8 migration and its effect relative to migration from Western European countries (Becker & Fetzer, 2017). The measure aligns with the "*defended neighbourhood*" hypothesis by taking into account that a great influx of any immigrant group will be perceived as more of a shock among incumbents in places where the same immigrant group had previously been largely absent. Given the central role of migration shock in the analysis, exposure to migration from other contexts is estimated both as a control variable and as alternative main variable of interest. It displays non significance in either case (See Appendix, Table 5).

Control variables. To include potential confounding issues that are relevant with respect to school bullying, several variables are considered. Recent research has been

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outlining the role of income inequality on school bullying at the cross-national level (Due et al., 2009; Elgar et al., 2013; Wilkinson & Pickett, 2017) and at the neighborhood level, although the latter has been mainly limited to urban settings (Juvonen & Graham, 2014; van der Ende et al., 2012). Evidence from behavioral studies outlines that in deprived contexts individuals display high level of prosocial behaviors, due to a higher awareness of being dependent on others to fulfil needs and goals (Manstead, 2018; Piff & Robinson, 2017; Stellar, Manzo, Kraus, & Keltner, 2012). The same effect of deprivation on pro-sociality and solidarity has been found analyzing young cohorts (Guinote, Cotzia, Sandhu, & Siwa, 2015). Additionally, inequality scholars have provided data supporting that absolute deprivation per se it is not a risk factor for school bullying, being inequality -rather than poverty- the trigger for social intolerance. In particular, more unequal places have higher levels of school violence both in deprived and non-deprived neighborhoods (Wilkinson & Pickett, 2017). Therefore, this paper considers both income deprivation and income inequality as potential confounders. The proxy for the former is conveyed through the Income Deprivation Average Score, which measures the relative income deprivation for local areas in England (Department for Communities and Local Governments of the UK Government, 2015). To grasp the inequality dimension, a measure for spatial income polarization is introduced, calculating the variation coefficient for the distribution of income across neighborhoods within the same UTLA using data on income level at neighborhood-scale.

Social frustration is measured through the number of children in need and the share of split population. Conversely, the share of same sex couples conveys a measure for openness. Also, UTLA population size and its ethnic composition are considered. Given the focus on the effect of a migration shock, local exposure to migration from other international contexts is assessed both as a cofounder and as a competitive treatment. The school ethnic composition at UTLA level is contemplated, due to the existing empirical evidence supporting its potential influence on bullying (Burgess & Platt,

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2018). A recent study on the US has highlighted that particularly predominantly white schools are more hostile environments for racial minorities (Rogers et al., 2017), hence the share of British white pupils is used to proxy established incumbent ethnicity[4]. Other cofounding factors are given by crime, identified by the literature as a local element that may influence school violence (Bowes et al., 2009) and unemployment share, another proxy for socioeconomic hardship (Guiso, Herrera, Morelli, & Sonno, 2017). Geography is considered in terms of rural/urban dichotomy since extant literature has identified that this distinction may play a role (Juvonen & Graham, 2014; Smokowski, Cotter, Robertson, & Guo, 2013). The WAY-2014 database contains also individual information on pupil's gender, ethnicity and neighborhood deprivation, which are among the most scrutinized individual-level features in bullying-related literature (Álvarez-García et al., 2015; Espelage, 2014; Hong & Espelage, 2012; Sykes, Piquero, & Gioviano, 2017; van der Ende et al., 2012). UTLA codes are used to match individual-level data and spatial level data. Tables 1-3 in the Appendix show summary statistics and further details for the data[5].

## 4. STATISTICAL ANALISYS

### 4.1 Baseline model

The impact of the spatial exposure to the cultural shock from A8 migrants on school bullying is estimated by regressing the likelihood of being bullied of pupil $i$ living in UTLA $j$ on the measure for the shock due to A8 immigration in UTLA $j$. In the WAY-2014 survey, each respondent is sampled to deliver robust data at UTLA level, hence she/he is nested in the corresponding UTLA. The 2-level nature of the dataset is exploited estimating a Multilevel (ML) logit model as preliminary estimation strategy, being that the ML logit allows the dependent variable under investigation to depend on variables belonging to different nested levels. Through the ML model it is also possible to investigate whether there are explanatory variables at the UTLA level

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serving as moderators of pupil-level relationships, *i.e.* to measure the relevance of cross-level interactions. Three meaningful cross-level interactions are considered among controls. First, the UTLA-level of income deprivation is studied as moderator for the effect of the level of deprivation of the neighbourhood of residency. Second, given the recent figures showing that predominantly white schools are more hostile environments for ethnic-cultural minorities (Rogers et al., 2017), the share of British white pupils at school level is considered as a moderator for the individual characteristic of belonging to a minority. Finally, the effect of spatial economic polarization on the level of deprivation of the neighbourhood of residency is introduced. Deprivation and inequality are highly correlated; hence two distinct ML logit specifications are estimated as summarized by eq. (2) and eq. (3) below. The dependent variable $y_{ij}$ takes value 1 if pupil $i$ living in UTLA $j$ has been bullied and 0 otherwise.

$$\begin{aligned}\Pr(y_{ij}=1) = {} & \alpha_0+\alpha_{0j}+\delta A8_j+\alpha_1 MIN_{ij}+\alpha_2 DEP_{ij}+\cdots+ \\ & +\beta_1 BW_j+\beta_2 POV_j+\gamma_1 MIN_{ij}\times BW_j+\gamma_2 DEP_{ij}\times POV_j+\cdots+\beta_m z_{mj}\end{aligned} \tag{2}$$

$$\begin{aligned}\Pr(y_{ij}=1) = {} & \alpha_0+\alpha_{0j}+\delta A8_j+\alpha_1 MIN_{ij}+\alpha_2 DEP_{ij}+\cdots+ \\ & +\beta_1 BW_j+\beta_2 POL_j+\gamma_1 MIN_{ij}\times BW_j+\gamma_2 DEP_{ij}\times POL_j+\cdots+\beta_m z_{mj}\end{aligned} \tag{3}$$

where $A8_j$ is the A8 migration shock in UTLA $j$ measured by eq. (1). Eq.(2)-(3) include also potential individual-level confounders identified by extant evidence (Álvarez-García et al., 2015; Espelage, 2014; Hong & Espelage, 2012; Sykes et al., 2017; van der Ende et al., 2012). Formally, $MIN_{ij}$, $DEP_{ij}$ and $GEN_{ij}$ are ethnicity, deprivation of the neighbourhood of residency and gender of pupil $i$ living in UTLA $j$. At the UTLA-level the $z$-controls are rurality, share of split population, children in need, share of same sex couples, income deprivation, share of British white pupils at secondary school, population size, ethnic composition, crime and unemployment. With respect to the cross-level interactions, $BW_j$ is the share of British white pupils attending secondary school in UTLA $j$. In eq (2), $POV_j$ is the income-deprivation measure for UTLA $j$;

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whereas in eq (3) $POL_j$ is the level of spatial income polarization of UTLA *j*. $\alpha_{0j}$ is the random intercept (RI) component, capturing the UTLA effect for each *j-th* UTLA; it is assumed to be independent of the model covariates and independent and identically distributed as follows: $\alpha_{0j} \sim N(0, \tau^2)$. Errors are clustered at UTLA level and variables are centered around the grand-mean. Survey weights are scaled to reduce bias estimation (Asparouhov, 2006; Carle, 2009; Rabe-Hesketh & Skrondal, 2006) (see Tables 13 and 14 in the Appendix) and the pertinence of the ML model is verified through postestimation diagnostics on the salience of the spatial dimension (Maas & Hox, 2005; Snjiders & Bosker, 2012) (see Figure 1 in the Appendix).

The analysis also estimates a Generalized Estimating Equations (GEE) logit model, representing a competing modelling strategy for nested data which does not require strong distributional assumptions to deliver robust and unbiased results. The GEE logit model provides consistent estimates of population-averaged effects even when dependency among individuals in clusters is not properly modelled (Rabe-Hesketh & Skrondal, 2012).

### 4.2 Addressing endogeneity of immigrants' localization choice.

Both the ML logit and the GEE logit estimates cannot be interpreted in a causal way. A threat is that the treatment variable is exposure to a migration shock, and A8 migrants are not randomly assigned across receiving places. Therefore, bias from sorting and reverse causality are possible (Jaeger, Ruist, & Stuhler, 2018). On the one hand, the arrival of unknown migrant population might trigger a cultural threat perception, fueling xenophobic violence in the receiving communities also at the school level. On the other hand, A8 migrants can choose to locate in places with low level of xenophobia at school to protect their children. To avoid or at least reduce this potential bias, a shift-share instrument is introduced, as typical in migration literature (Card, 2001; Mayda, Peri, & Steingress, 2021) and in empirical works on A8 migration patterns in the UK (Becker & Fetzer, 2017; Jaitman & Machin, 2013; Sá, 2015). The

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shift share instrument predicts the actual spatial distribution of A8 migrants exploiting their spatial distribution more than 10 years before. It is based on the assumption that 10-or-more-year lagged distribution of immigrants is not correlated with current outcomes for the native population other than via its impact on current immigration (Mayda et al., 2021). This lagged spatial distribution provides a set of weights (the shares) that are applied to the national immigrants' inflow rates (the shifts). Hence, variation at the local level is created exploiting variation in national inflows, that are less endogenous to local issues (Jaeger et al., 2018).

A further concern that the shift share instrument does not consider refers to potential omitted variable bias. Places might have local features appealing to immigrants and also affecting bullying. All estimations are performed with spatial fixed effects and socioeconomic controls at the UTLA level to contribute to reducing this concern.

Given the non-linear nature of the econometric model, the shift-share instrument is used in a Control Function approach with Two-Stage Residual Inclusion (CF-TSRI), following the literature on endogeneity with hierarchical data and binary outcome (Petrin & Train, 2010; Terza, Basu, & Rathouz, 2008; Wooldridge, 2010, 2014). The CF-TSRI approach estimates the potentially endogenous variable, $A8_j$ against the shift-share instrument in the reduced form equation alongside UTLA-level control variables from the structural equation. Then, the reduced form residuals are plugged into the structural equation together with the endogenous explanatory variable and the other control variables.

The shift-share instrument considers the interaction between national inflows by country of origin with immigrants' geographic distribution in 2001. Formally,

$$m_j = \sum_C \frac{M_{Cjt^0}}{M_{Ct^0}} \frac{\Delta M_C}{POP_{jt-1}} \tag{4}$$

where $\frac{M_{Cjt^0}}{M_{Ct^0}}$ identifies the share of immigrants from country-of-origin $C$ in place $j$ at reference date $t^0$, which precedes the date of the measurement of the endogenous

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regressor and that is set at 2001. $\Delta M_C$ is the country level number of new arrivals from country $C$ at the date of measurement of the endogenous regressor and $POP_{jt-1}$ is the population of UTLA $j$ in the previous period. This instrument is consistent with the exclusion restriction since it is more than plausible that neither the national size of A8 migrants in England after 2001 nor the local cultural outlook of more than a decade before the time in which bullying is observed have some direct effect on the current school bullying. The instrument summarized in eq. (4) is used as exogenous regressor in the following reduced form equation

$$A8 = \pi_1 m + \pi_2 \Omega + v_2 \tag{5}$$

where $A8$ is the potentially endogenous regressor, $m$ is the shift-share regressor and $\Omega$ includes all the UTLA-level continuous control variables used in the ML logit and GEE logit specifications. Following the CF-TSRI approach, first eq. (5) is estimated to get stage 1 residuals, $\hat{v}_2$. Then, stage 2 estimates the structural equation, which is given by the ML logit model described by eq. (2) with stage 1 residuals, $\hat{v}_2$, included among regressors. The structural equation is estimated through GLM. Both stages consider cluster robust standard errors and they are embedded in a bootstrapping program to account for improved efficiency and robustness of standard errors (Wooldridge, 2010). Existing research suggests to check the validity of shift-share estimation with respect to the geographic distribution of A8 migrants in 2004 (Jaitman & Machin, 2013). This is due to observed differences between pre- and post-2004 A8 migrants in the UK along several dimensions. Hence, the validity of estimates will be checked against an alternative shift-share instrument, which is formally given by eq (4) with 2004 as baseline year $t^0$.

Another relevant point to address refers to some caveats about shift-share instruments (Goldsmith-Pinkham, Sorkin, & Swift, 2020; Jaeger et al., 2018; Van Dijk, 2018). It has been showed that these instruments do not account for local adjustment dynamics which follow immigration shocks, and which could affect the investigated

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outcome. Similarly to Klaesson et al. (2020), the present investigation might be exempted from this adjustment dynamics issue, since it analyzes the effect of local variables on an individual outcome that has a very limited effect on local variables. In any case, the investigation will alleviate concerns about this potential bias by adopting the multiple instrumentation approach developed by Jaeger et al. (2018) among robustness checks. In practical terms, estimation will consider the effect of adjustment dynamics by adding a lagged exposure to the A8 migration shock among regressors in eq. (2) and instrumenting for this with an additional shift-share instrument.

**4.3 Language barriers as moderator for the immigration shock.**

Introducing language barriers as the moderating factor for the effect of A8 migration shock changes eq. (3) as follows,

$$\begin{aligned}\Pr(y_{ij}=1) = {} & \alpha_0 + \alpha_{0j} + \delta LB_j \times A8_j + \alpha_1 MIN_{ij} + \alpha_2 DEP_{ij} + \cdots + \\ & + \beta_1 BW_j + \beta_2 POL_j + \gamma_1 MIN_{ij} \times BW_j + \gamma_2 DEP_{ij} \times POL_j + \cdots + \\ & + \beta_m z_{mj}\end{aligned} \tag{6}$$

where $LB_j$ measure the exposure to language barriers in secondary school in UTLA $j$, given by the difference between the share of secondary school pupils not speaking English as first language at time $t$ and the share of secondary school pupils not speaking English as first language at time $t$-$s$. Data from the School Census show that more than 60% of pupils not speaking English as first language are not English fluent (Office for National Statistics - ONS, 2019), hence figure on the secondary school population not having English as first language can still provide with a broad indication of school level exposure to language barriers. Eq. (6) is estimated by applying the CF-TSRI approach to the ML logit with eq.(5) as the reduced form equation and eq.(4) as the extra-regressor.

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# 5. RESULTS

## 5.1 Baseline results

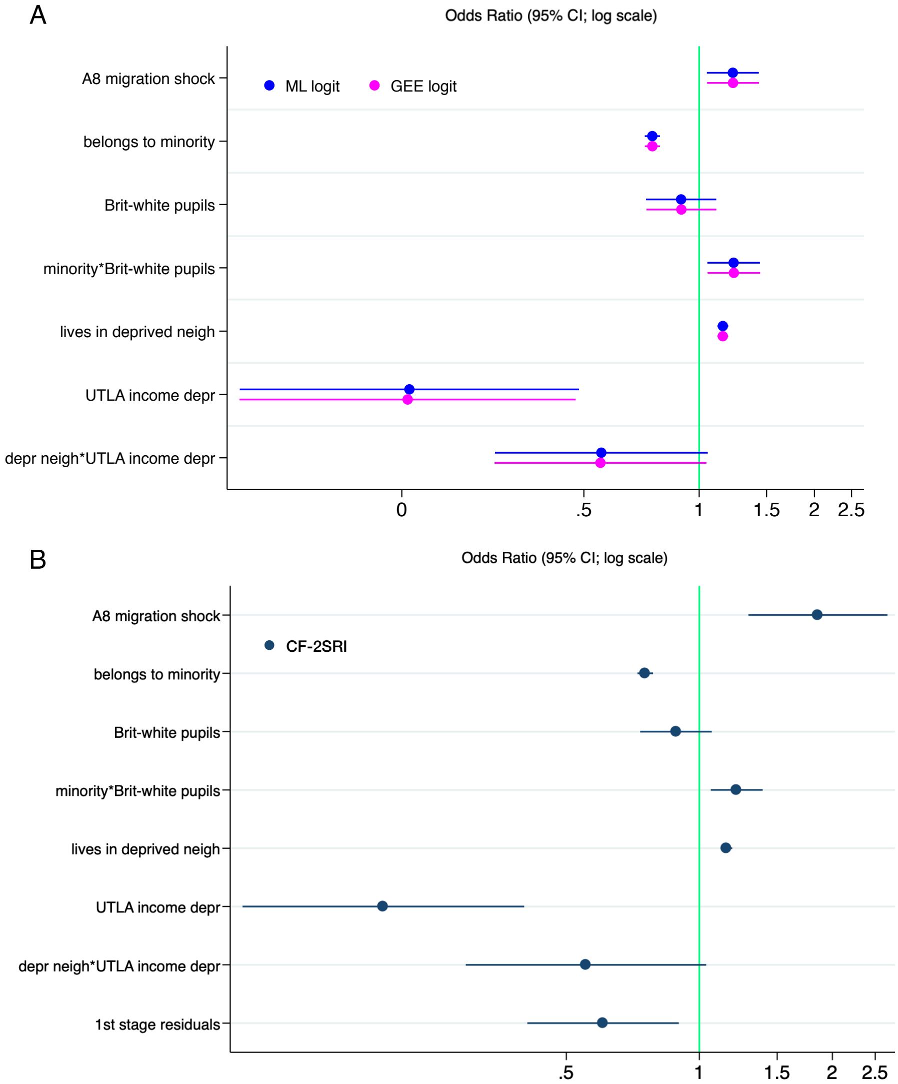


Figure 3. Plots of the estimated odds ratios and the corresponding 95% Confidence Intervals for the considered model specifications. Odds ratio as measures of associations for the A8 migration shock and the considered cross-level interactions from the estimation of a ML logit and a GEE logit (A); odds ratio as measure of causation for the A8 migration shock from the estimation of CF-TSRI (B). Errors are clustered at UTLA level for all model specifications. Control variables included in all model specifications: (i) individual-level: gender, minority, lives in deprived neighbourhood; (ii) UTLA-level: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area. CF-TSRI results after 1000 bootstrap replications. CF-TSRI 1st stage F-stat =15.58

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Figure 3.a displays the odds ratio plots for the estimated effects of A8 migration on school bullying for the baseline Multilevel (ML) logit model with Random Intercept (RI) (Odds ratio in blue in Figure 3.a), which are also detailed in Table 1 column 1.

**Table 1: Exposure to a cultural shock from migration and school bullying**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ML logit RI *interactions* | GEE logit *interactions* | CF 2SRI 2nd stage GLM ML logit *interactions* | |
| | Odds ratio | Odds ratio | Odds ratio | Coef. |
| **A8 Migration shock** | **1.225****<br>**[1.047,1.432]** | **1.226****<br>**[1.049,1.433]** | **1.922***** | 0.654***<br>(0.180) |
| Belongs to Minority | 0.755***<br>[0.721,0.790] | 0.755***<br>[0.721,0.790] | 0.755*** | -0.281***<br>(0.0212) |
| British White in School | 0.897<br>[0.726,1.108] | 0.899<br>[0.728,1.109] | 0.882 | -0.126<br>(0.0992) |
| Belongs to Minority*Brit White in School | 1.230**<br>[1.050,1.441] | 1.232**<br>[1.052,1.443] | 1.233** | 0.209**<br>(0.0735) |
| Lives in Deprived Neighborhood | 1.153***<br>[1.116,1.191] | 1.153***<br>[1.116,1.191] | 1.153*** | 0.142***<br>(0.0150) |
| UTLA Income Deprivation | 0.175***<br>[0.063,0.486] | 0.173***<br>[0.063,0.476] | 0.189*** | -1.665***<br>(0.330) |
| Deprived Neighborhood* UTLA Income Deprivation | 0.555*<br>[0.293,1.053] | 0.553*<br>[0.292,1.045] | 0.559* | -0.581*<br>(0.332) |
| CF Stage 1 residuals | | | 0.577** | -0.550**<br>(0.192) |
| *Individual level controls* | *YES* | *YES* | *YES* | YES |
| *UTLA level controls* | *YES* | *YES* | *YES* | YES |
| *DWH test (p-value)* | | | | 0.0047 |
| Log likelihood | -66114.119 | | | -66111.602 |
| Observations | 110788 | 110788 | 110788 | 110788 |
| Cluster | 150 | 150 | 150 | 150 |
| | | | CF 2SRI 1st stage OLS | |
| | | | | coef |
| Shift share | | | | -0.633***<br>(0.009) |
| Controls (all UTLA-level continuous covariates) | | | | YES |
| F-test ex instrument | | | | 15.58 |

*Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively; errors clustered at UTLA level; odds ratios are reported with their confidence intervals being odds ratios a nonlinear transformation of the logit coefficients.*

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In the ML logit regression, findings outline that a larger local exposure to the A8 migration shock is associated with a higher likelihood of school bullying. More into details, the odds of bullying victimization increase by a factor of 1.225 for an increase of 1 p.p in the exposure to the shock from A8 migration, holding all the other variables constant. Findings hold also when exposure to migration from the rest of the world is accounted for (See Table 5 in the Appendix). Several interactions for the A8 migration shock have been tested, all showing non-significance; the considered interactions are: the interaction between the migration shock and crime, the interaction between the migration shock and local economic deprivation and the interaction between the migration shock and local ethnic diversity (See Table 6 in the Appendix). To assess the relevance of the demographic changes rather than the static demographic outlooks, the local current share of A8 migrants has been considered instead of the local change in A8 migrants after the Enlargement, to get that there is no significant effect when levels rather than changes are considered (See Table 7 in the Appendix).

Another robustness check accounts for potential spatial spillovers to check for the potential influence of the neighboring UTLAs on local bullying, following existing evidence showing that failing to account for spatial spillovers may determine misspecification bias (Corrado & Fingleton, 2012; Mantegazzi, McCann, & Venhorst, 2020; Tselios, Noback, van Dijk, & Mccann, 2015). Three different sources for spatial spillovers from neighboring UTLAs are considered: the A8 migration shock, the socioeconomic features considered as control variable in eq (2), and bullying[6]. Estimations confirms findings from the baseline model specification (See Table 11- columns 1-2 in the Appendix). Finally, the estimated effect of the A8 migration shock is consistent also when the analysis considers either the subset of UTLAs with the strongest size of exposure to the shock (See Table 8 in the Appendix) or the subset of UTLAs without the big metropolitan contexts (See Table 10- column 1 in the Appendix). Similarly, results hold when existing spatial heterogeneity of UTLAs is accounted for in terms of *(i)* differences in the spatial scale of UTLAs and *(ii)* distance

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from the closest largest urban center in the region (See column 1 of Table 12.a and column 1 of Table 13 in the Appendix). Figure 3.a also displays the estimation results when the competing specification of the GEE logit is considered (Odds ratio in pink in Figure 3.a). The consistency of the results from the two considered competing model specifications means that the significant associations between risk factors, protective factors and school bullying are robust to the underlying assumption of spatial dependencies. Table 1 -column 2 details the estimation results.

Figure 3.a and Table 1 summarize additional results which are significant in both the ML logit and the GEE logit and which do not alter the estimated effect of the A8 migration shock. Living in a deprived neighbourhood has a positive direct association with bullying, displaying an odds ratio equal to 1.153 and a negative indirect association moderated by the overall local level of income deprivation, being that the interaction term has an odds ratio equal to 0.555. Then, belonging to a minority has a negative direct association with the odds of bullying, as highlighted by the odds ratio amounting to 0.755, which is countered by the share of British white pupils in the school, as attested by the odds ratio equal to 1.230 of the interaction between belonging to a minority and share of British white at school.

Table 18 columns 1 and 2 in the Appendix show the detailed estimates for the ML logit and the GEE logit respectively, for all the variables considered in the model.

### 5.2 Addressing endogeneity of A8 migrants' locational preferences

Figure 3.b outlines the estimation results from the CF-TSRI approach which allows to account for endogeneity in A8 migrants' locational choices. The findings, detailed in Table 1- columns 3-4, show that a larger local exposure to the A8 migration shock determines a higher school bullying, even when individual characteristics of the pupils as well as spatial socioeconomic features are included in the estimation. For an increase of 1 p.p in the exposure to the cultural shock from migration the odds of bullying victimization increased by a factor of 1.922. Residuals from the reduced form equation entered significantly in the second stage of the CF-TSRI approach (*DWH test*=

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0.0047), supporting that the A8 migrants' location choices after 2001 are endogenous. The results from the estimation of the reduced form equation of the first stage of the CF-TSRI approach show that the shift-share regressor is a negative significant predictor of A8 migrants' spatial preference in England: the coefficient of the shift-share regressor equals -0.633 with a Kleibergen-Paap Wald rk *F-test* equals to 15.58 suggesting that the regressor is not a weak instrument. The results from the reduced form equation align with existing evidence showing that A8 migrants into the UK after the EU Enlargement chose places with the smallest presence of A8 people already settled (Becker & Fetzer, 2017; Jaitman & Machin, 2013). This locational pattern can be related to the fact that the post 2004 A8 migrants were quite different from pre 2004 A8 migrants in terms of: demographic characteristics (age, gender, marital status) (Drinkwater, Eade, & Garapich, 2009), reasons for migration (economic, political) (Pollard et al., 2008) and geography of sending communities (rural, urban) (Okólski & Salt, 2014), up to the point of resembling two different groups (Becker & Fetzer, 2017). These differences support the evidence of negative ties between the actual geography of A8 settlements in England in 2014 and the synthetic geography resulting from the shift-share instrument. Accounting for endogeneity of the A8 migration shock results in a much larger impact of the migration shock on bullying. Since the shock remains at the same time highly significant, it appears that, among the sources of bias delivering attenuation, measurement error may play a role.

Existing differences between pre-2004 and post-2004 A8 migrants in the UK could influence locational preferences, which are the information used to design the shift-share instrument. Thus, it appears wise to check what happens when the shift share instrument considers 2004 as baseline year rather than 2001. Estimates from this alternative specification confirm that the places with higher exposure to A8 migration have higher likelihood of bullying victimization (see Table 9.a in the Appendix).

Finally, findings from the CF-TSRI are verified accounting for the potential adjustment dynamics that could bias the shift-share instrument. This is done following

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the multiple instrumentation approach (Jaeger et al., 2018). Formally, eq (2) is estimated through the CF-TSRI approach, adding a lagged exposure to the A8 migration shock among regressors, and also instrumenting for this with the analogous shift-share instrument. The lagged exposure is measured between 2006 and 1999. Estimates support the main findings, as summarized by Table 2.

Table 1, columns 3-4 show that estimates from the CF-TSRI approach confirm the additional results related to economic deprivation and ethnic groups composition at the school level. Living in a deprived neighbourhood still had a positive direct association with bullying, with an odds ratio equal to 1.153 and a negative indirect association moderated by the overall local level of income deprivation summarized by an odds ratio amounting to 0.559. Table 1, column 3, outlines that belonging to a minority had a negative direct association with bullying (odds ratio of 0.755), which is countered by the share of British white pupils in the school as shown by the odds ratio of the interaction between belonging to a minority and the share of British white at school equal to 1.233.

Estimation results hold also when causality is estimated through a Limited Information Maximum Likelihood (LIML) estimation (see Table 9.b in the Appendix), when the big urban contexts were removed (See Table 10 columns 3 and 4 in the Appendix), considering different sources for spatial spillovers (See Table 11 columns 5-8 in the Appendix) and accounting for UTLAs spatial heterogeneity (See Table 12.a and 12.b columns 5-8 and Table 13 columns 3 and 4 in the Appendix). The effect of immigration has been assessed accounting for potential confounding features, consistently with existing literature which highlights that economic features may constitute a relevant competing force in triggering intolerance (Anderson, Crost, & Rees, 2020; Elgar et al., 2013; Hainmueller, Hiscox, & Margalit, 2015).

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**Table 2. Multiple instrumentation approach estimation applied to CF-TSRI to account for adjustment dynamics affecting the shift-share instrument (Jaeger et al., 2018)**

| | (1) | (2) |
|---|---|---|
| | CF 2SRI<br>2nd stage GLM ML logit | |
| | Odds ratio | Coef |
| **A8 Migration shock** | **2.382*** ** | **0.868*** ** |
| | | **(0.249)** |
| **Lagged A8 Migration shock** | **0.920*** | **-0.083*** |
| | | **(0.045)** |
| CF Stage 1 residuals | 0.404** | -0.906* |
| | | (0.316) |
| Lagged CF Stage 1 residuals | 1.160** | 0.149* |
| | | (0.0670) |
| *Individual level controls* | *YES* | *YES* |
| *UTLA level controls* | *YES* | *YES* |
| *DWH test (p-value)* | | 0.0164 |
| Log likelihood | | |
| Observations | 110788 | 110788 |
| Cluster | 150 | 150 |
| *Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.<br>*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area, deprivation, school ethnic composition | | |
| **A8 Migration shock (2011-2001)** | | |
| Shift-share | | -0.711*** |
| | | (0.010) |
| Lagged Shift-share | | 4.112*** |
| | | (0.053) |
| Controls (all UTLA-level continuous covariates) | | *YES* |
| F-stat ex instrument | | 49.35 |
| **Lagged A8 Migration shock (2006-1999)** | | |
| Shift-share | | -2.749*** |
| | | (0.043) |
| Lagged Shift-share | | 2.888*** |
| Controls (all UTLA-level continuous covariates) | | *YES* |
| F-stat ex instrument | | 38.42 |

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively;*

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Figure 4 summarizes another finding relating to the economic dimension, which did not alter the estimated causal effect. Figures 4.A-4.B outline the opposite marginal effects of deprivation and spatial income polarization, also detailed in Table 3. Local deprivation had a negative marginal association (Figure 4.A), whereas spatial income polarization had a positive marginal association (Figure 4.B). These findings align with existing behavioral evidence detailing observed high level of prosocial behaviors in deprived contexts, due to a higher awareness of being dependent on others to fulfil needs and goals (Manstead, 2018; Piff & Robinson, 2017; Stellar et al., 2012). The same effect of deprivation on pro-sociality and solidarity has been found analyzing young cohorts (Guinote et al., 2015). Additionally, they are also consistent with existing literature showing that resentment is fueled by inequality rather than absolute deprivation (Côté, House, & Willer, 2015; Kunstman, Plant, & Deska, 2016; Layte & Whelan, 2014; Wilkinson & Pickett, 2017), also when young cohorts are considered (Elgar et al., 2015, 2013).

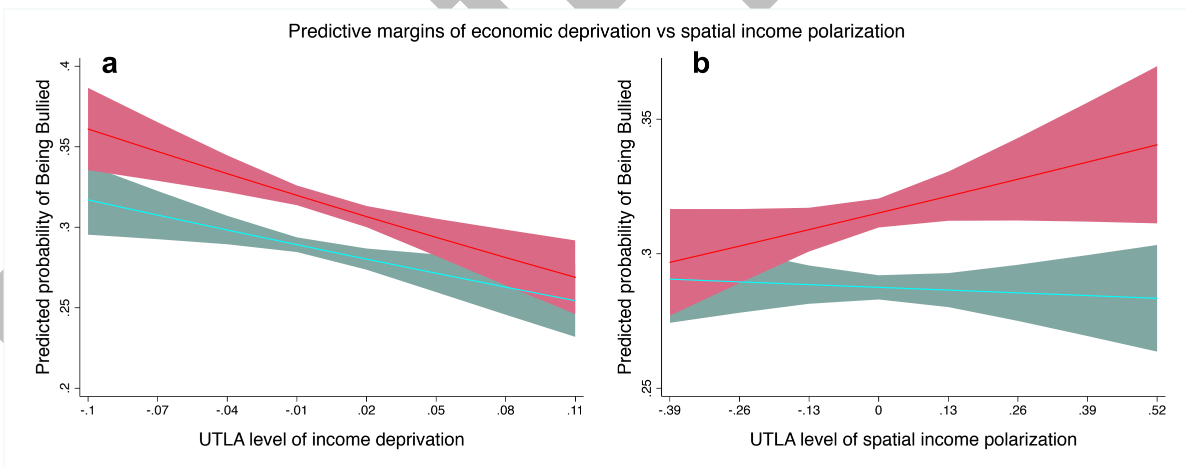


**Figure 4: Estimates of cross-level interactions from CF-TSRI approach with 95% Confidence Intervals. Moderating effect of: UTLA-level poverty and UTLA spatial income polarization. The likelihood of being bullied for a pupil living in a poor neighbourhood decreases for poor UTLAs (A). The likelihood of being bullied for a pupil living in a poor neighbourhood increases for spatially unequal UTLAs (B). Estimates holds for all the model specifications (ML logit, GEE logit and CF-TSRI).**

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**Table 3: ML logit and CF-TSRI estimates for spatial income polarization**

| | (1) | (2) | (3) |
|---|---|---|---|
| | ML logit RI interactions | CF 2SRI 2nd stage GLM logit interactions | |
| | Odds ratio | Odds ratio | Coef. |
| **A8 Migration shock** | **1.224**** | **2.024***** | **0.705***** |
| | **[1.022,1.466]** | | **(0.205)** |
| Belongs to Minority | 0.756*** | 0.756*** | -0.280*** |
| | [0.722,0.791] | | (0.0214) |
| British White in School | 0.891 | 0.873 | -0.136 |
| | [0.6974,1.137] | | (0.0911) |
| Belongs to Minority*Brit White in School | 1.254** | 1.255** | 0.227** |
| | [1.074,1.464] | | (0.0741) |
| Lives in Deprived Neighborhood | 1.1457*** | 1.145*** | 0.136*** |
| | [1.109,1.182] | | (0.0171) |
| Spatial Income Polarization | 1.081 | 1.097 | 0.0924 |
| | [0.890,1.313] | | (0.0899) |
| Deprived Neighborhood*Spatial Income Polarization | 1.304** | 1.293** | 0.257** |
| | [1.064,1.598] | | (0.104) |
| CF Stage 1 residuals | | 0.547** | -0.604** |
| | | | (0.237) |
| Individual level controls | YES | YES | YES |
| UTLA level controls | YES | YES | YES |
| DWH test (p-value) | | | 0.074 |
| Log likelihood | -52041.291 | -66120.154 | |
| Observations | 110788 | 110788 | 110788 |
| Cluster | 150 | 150 | 150 |

Individual level controls: gender, ethnicity, deprivation of neighbourhood of residency.
UTLA level controls: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area

| | CF 2SRI: 1st stage OLS |
|---|---|
| | coef |
| Shift share | -0.447*** |
| | (0.010) |
| Controls (all UTLA-level continuous covariates) | YES |
| F-Stat ex instrument | 11.47 |

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively; errors clustered at UTLA level; CF 2SRI is bootstrapped (1000 replications);*
*odds ratios are reported with their confidence intervals being odds ratios a nonlinear transformation of the logit coefficients.*

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### 5.3 The moderating role of language barriers

Finally, it is investigated whether language barriers would act as a channel for the cultural shock, by estimating their moderating role on the exposure to the A8 migration shock. The findings of the CF-TSRI approach applied to eq. (6) support the prediction. Larger local language barriers have a positive marginal effect on school bullying for any given level of the A8 migration shock, as detailed in Table 4 and summarized in Figure 5. Estimates show that when language barriers are considered, the overall effect of the A8 migration shock on bullying amounts to a direct effect measured by an odds ratio equal to 2.104 and an indirect effect measured by the odds ratio of the interaction terms which equals 1.093. Findings hold also for alternative timespans in the measurement of the exposure to language barriers (See Table 15 in the Appendix).

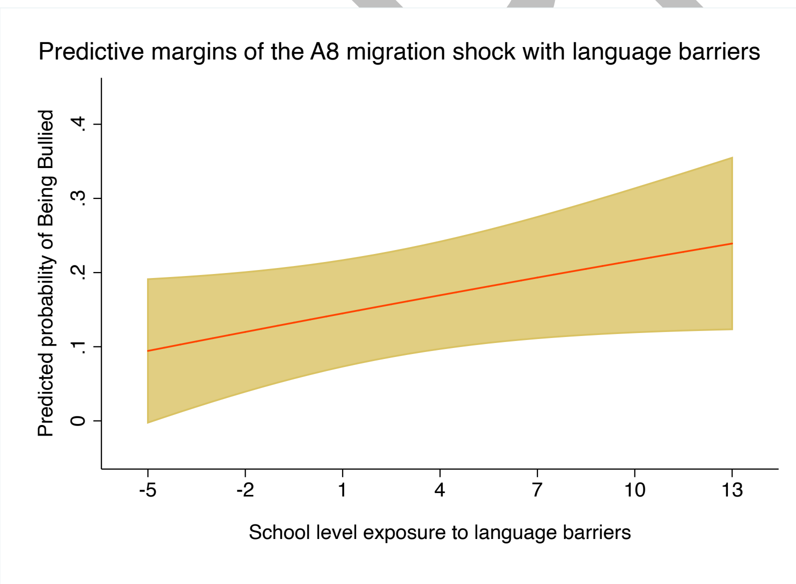


**Figure 5. Estimates of the moderating effect of existing language barriers on school bullying with 95% Confidence Intervals. The higher the exposure to language barriers, the stronger the overall effect of the cultural shock from A8 migration on school bullying**

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Table 4: CF-TSRI ML logit estimates with language barriers

| | (1) |
|---|---|
| | CF 2SRI<br>2nd stage GLM ML logit<br>Language barriers<br>2013-2009 |
| Language Barriers Exposure | 0.966* |
| | [0.831,1.002] |
| **A8 Migration shock** | **2.104*** ** |
| | **[1.388,3.190]** |
| **Lang. Barriers Exposure * A8 Migration shock** | **1.093** ** |
| | **[1.011,1.067]** |
| Stage 1 Residuals | 0.541** |
| | [0.348,0.843] |
| *Individual level controls* | *YES* |
| *UTLA level controls* | *YES* |
| *Cross level interactions* | *YES* |
| Log Likelihood | -66115.961 |
| Observations | 110788 |
| Cluster | 150 |

*Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency. *UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively; errors clustered at UTLA level; CF 2SRI is bootstrapped (1000 replications); odds ratios are reported with their confidence intervals being odds ratios a nonlinear transformation of the logit coefficients.*

### 5.4 Postestimation diagnostics and robustness checks

The ML logit estimation results presented in Table 1 refer to the fitted specification identified following a bottom-up approach. The model is developed stepwise, starting with a random intercept for each UTLA and subsequently adding predictors and random slopes. After each step, a log-likelihood ratio test gauges if the model constitutes a better fit to the data compared to classical logit, or a better fit compared to the previous step (Hox, 2010). The sample size is large, and the number of clusters exceeds 100, hence maximum likelihood estimation delivers accurate standard errors (Bryan & Jenkins, 2016). Further support for the role of UTLA-level features in

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influencing bullying victimization comes from Median Odd Ratios (MOR), above the threshold value of 1 (Austin & Merlo, 2017). Results also show that, by focusing the investigation on fine-grained spatial dimensions, it becomes possible to account for the existing geographic heterogeneity displayed by data on bullying. The considered spatial-level covariates substantially reduces the estimate of between-UTLA variance of school bullying. Hence, a large fraction of bullying spatial variance is explained by local features proxied by significant covariates. Wald test confirm significance of covariates (Rabe-Hesketh & Skrondal, 2012). The comment on Figure 1 in the Appendix details the aforementioned diagnostics. The model appears not to suffer from severe multicollinearity[7] (mean VIF = 3.85, EU 2004 migration accession VIF = 1.81). Following the bottom-up approach (Hox, 2010), other UTLA-level covariates have been assessed (juvenile crime, exposure to migration from other contexts, stock of human capital, religious outlook, adopted children, population density) showing both non-significance and no improvement in model fit.

As detailed in section 5.1, given the central role of migration shock in the analysis, different dimensions for migrations have been considered both as a control variable and as alternative main variable of interest to see that it does not influence the findings of the paper (see Table 5 in the Appendix). By the same token, it has been assessed the relevance of the exposure to changes in the local size of A8 migrants compared to the relevance of the static size, to see that the former is a robust determinant whereas the latter is no (see Table 7 in the Appendix). This robustness checks support the "*defended school*" hypothesis by stressing the role of demographic changes as trigger for unrest. Further support for the "*defended school*" hypothesis comes from another set of robustness checks where data are divided in subsets to account for the role of the ethnic dimension at the school level. The effect of the exposure to changes in the local size of A8 migrants holds when only UTLAs where British white students are the majority of the secondary school population, while it does not hold in the UTLAs where the incumbent leading ethnicity is the minority. These findings confirm that

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places with high level of multi-ethnicity are less unprepared to the arrival of newcomers, having already experience of different migration inflows, whereas places with a low level of multi-ethnicity feel more threatened by the arrival of new migrants (See columns 1 and 2 Table 14 in the Appendix).

Also, potential misspecification bias that can arise when potential spatial spillovers are not accounted for are assessed. In particular, the model specifications are estimated including spatial externalities from the 4 closest neighboring UTLAs in terms of: A8 immigration shock, control variables and bullying rates. Results are confirmed (see Table 11 in the Appendix) and they hold also when either the closest 3 or 5 neighboring UTLAs are considered. To gauge the influence of big urban contexts, the baseline specifications with cross-level interactions -ML, GEE and CF with 2SRI- are estimated also removing the big Metropolitan Boroughs: namely, London, Birmingham, Leeds, Sheffield, Bradford, Manchester, Liverpool, Bristol, Kirklees, Coventry, Leicester, Wakefield, Wigan, Wirral. Results are detailed in Table 10 in the Appendix. Results are confirmed also when only London is removed as well as when the 6 biggest cities are removed[8]. To further assess the effects of UTLAs heterogeneity, several other robustness checks are performed. First, the baseline specifications with cross-level interactions are also estimated by splitting them in term of spatial size and population size to see that findings are confirmed (see Table 12 in the Appendix). Second, results hold also when the distance from the closest core urban center in the region is included among controls (see Table 13 in the Appendix). Given the significance of the interaction between the A8 migration shock and language barriers, other potential interactions for the A8 migration shock have been tested to see that they are not significant (see Table 6 in the Appendix). Similarly, the relevance of the language barriers is tested by changing the timespan of exposure to language barriers to see that findings remain consistent (see Table 15 in the Appendix).

To control for potential concern about non-normally distributed residual errors, misspecification and outliers, the ML logit with RI is estimated both with cluster-

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robust standard errors and with White robust standard errors (Hox, 2010). Following the literature on multilevel estimation with survey data, the procedure to identify the fitted model as well as the estimations are performed for the unweighted ML logit model and for ML logit models with scaled survey weights (Rabe-Hesketh & Skrondal, 2006). Results align, therefore only results for the unweighted model are presented in the paper, while in Tables 16 and 17 in the Appendix are detailed the results for the convergence among weighted and unweighted model specifications.

## 6. DISCUSSION

The evidence presented in Tables 1-4 and in Figures 3 and 5 shows that the shock from A8 migration affects school bullying even when acknowledged individual and spatial risk factors are controlled for. Hence, for England, the sudden and sizeable upturns of migration inflows in places which are unfamiliar with the incoming group behave as determinants of school violence. This finding relates to the "*defended neighborhood*" hypothesis since the migration shock happening at the local level triggers a cultural threat perception in the incumbent population (Hangartner et al., 2018; Newman, 2013). Literature addressing adult cohorts has already highlighted that social tension is often the consequence of a perceived challenge to the social *status quo* posed by out-groups (Card et al., 2012; Hainmueller & Hopkins, 2014). Results from the empirical estimation presented in Table 1 confirm that young cohorts are not immune from these tensions and that cultural shock transmits to social disorders also in the school environment, as speculated in the literature (Pells et al., 2016; Vertovec & Coen, 2002) and suggested by anecdotal evidence (Southern Poverty Law, 2019). Results from columns 3 and 4 in Table 1 support a causal relationship, going beyond a measure of association and providing estimates which remain consistent after many robustness checks. The throughout investigation of the causal link between the A8 migration shock and school bullying allows to overcome some level of biases in the

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results obtained when association rather than causation is scrutinized, at the same time showing a stronger effect exerted by the A8 migration shock. Therefore, evidence supports a "*defended school*" hypothesis for England.

The study for a channel for the transmission of the effects of the A8 migration shock has outlined that language barriers are relevant in moderating the shock. As summarized in Figure 5 and in Table 4, the wider the percentage change in language barriers experienced at school level, the stronger the effect of the cultural shock from A8 migration. Although preliminary, this evidence supports the relationship between extant exposure to low level of assimilation of cultural diversity in places and the effect of a cultural shock determined by the arrival of a new and unfamiliar cultural group. Areas with a relevant size of language barriers at school suffer from a lower assimilation of cultural diversity, which widens the effect of a cultural shock from migration. Distances among extant cultural groups due to linguistically unassimilated people hinders the local acculturation with respect to diversity. Since extant acculturation to cultural diversity eases the mitigation of a cultural shock due to newcomers, wherever this acculturation has not taken places, mitigation is prevented. Finally, the estimates of the considered cross-level interactions presented in Table 1 and 3 and summarized in Figure 4 suggest that local poverty promotes a solidarity effect among deprived pupils when coping with a shock, whereas spatial income polarization fosters the odds of school bullying. This finding provides the first spatially robust evidence at a fine-grained scale supporting inequality over poverty as positively correlated to school violence and it is consistent with existing contributions targeting the national and the cross-national level (Elgar et al., 2013; McCann, 2020; Wilkinson & Pickett, 2017).

## 7. CONCLUSIONS

To conclude, this paper has highlighted a non-negligible effect of a sudden and fast migration inflow on school violence for 15-year-old pupils, a school population segment

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that is more exposed to the external environment than younger pupils. Extant evidence, which considers the adult population only, details that the arrival of unfamiliar cultural groups triggers hostility among the receiving communities through the perception of threats to the sociocultural established outlook (Hainmueller & Hopkins, 2014). Results from this paper add a further step, providing causal evidence of the relationship between the exposure to a migration shock and school bullying in England. The "*defended school*" hypothesis appears relevant and the findings are consistent to the fact that cultural identity and social hierarchies do not intrude in people's life abruptly when reaching adulthood, rather they influence beliefs and behaviors through being and acting in a social environment (Vertovec & Coen, 2002). Therefore, as growing up implies being more exposed and active in the local social environment, it also determines increased influence of the environment itself on actions and perceptions.

The triggering effect exerted by migration inflows on school bullying outlined in this paper can be related to the thriving literature scrutinizing the geography of resentments (Rodríguez-Pose, 2018). Indeed, the places with higher bullying in 2014 are the ones voting Leave at the Brexit Referendum in 2016. This summary evidence corroborates that young people mimic adults' attitudes and behaviors. Further, according to a recent work, areas which voted Remain displayed the sharpest increase in adults' hate crimes after the Brexit Referendum (Albornoz, Bradley, & Sonderegger, 2020), probably due to the empowerment of latent haters in open-minded pro-European places. This opens to further research on bullying in England, when post-Brexit Referendum waves of the WAY survey will be released, to broaden the evidence-base on the relationship between the geography of school bullying and hate crimes committed by the adult population.

The current research provides support for the role of language barriers as a channel which fosters the effect of the migration shock, hence confirming that language barriers prevent a place to become familiar with cultural diversity. This evidence aligns with

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existing works suggesting that extant exposure to low level of assimilation of cultural diversity increases the impact of a cultural shock determined by the arrival of a new and unfamiliar cultural group (Hopkins, 2010; Newman, Hartman, & Taber, 2012). Since acculturation to diversity eases the mitigation of a cultural shock, wherever this acculturation has not taken places, mitigation is prevented.

The findings of the paper also align with extant contributions showing that the effects of migration on social tension are channeled by dynamic changes -*i.e.* exposure to a change in the local demographic composition and changes in the local language composition- rather than by static levels (i.a. Becker & Fetzer, 2017; Newman, 2013).

Another interesting finding refers to the economic dimension, since evidence from the paper depicts that income inequality rather than deprivation behaves a risk factor for bullying. This result adds a fine-grained spatial evidence to existing cross-country data on the positive relationship between income inequality and bullying, as well as on the relationship between inequality and discontent (McCann, 2020).

Overall, the analysis strongly suggests that that bullying-prevention programs should address the spatial dimension. This conclusion entails non-negligible policy implication, since bullying-prevention programs should consider spatial demographic changes when related to immigration of new cultural groups together with language barriers at school level. With respect to the latter, policy should aim at reducing them, so to favor the local assimilation of different cultures and improve the coping with new incoming culture. Finally, also the level of local spatial income polarization should be addressed.

Obviously, this study considers only England, therefore there are questions about generalization of results to other contexts. The results on the effect of spatial income polarization open up to further investigation on the role of spatial segregation, which is not analyzed here being beyond the scope of the present work. With respect to cultural variety of pupils in English schools, information is time-fragmented: The School Census data on languages spoken in schools are available for 2012 only and

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data about pupils' nationality/country of birth for 2017-2018 only and suspended afterwards. Thus, the measure for language barriers at school level amounts to a broad estimate of existing obstacles in communication among different cultures. Nonetheless, many research efforts are providing support for the role of language barriers in fostering cultural distance (i.a. Hainmueller & Hopkins, 2014), therefore further analysis is needed for a more refined scrutiny of their moderating role with respect to a cultural shock from migration. Another limitation of the present investigation is that risk factors belonging to the specific school attended by each individual who participated to the bullying survey are not considered. This limitation occurs because the WAY-2014 survey respondents are matched with the local authority they reside in and not with the school they attend, being the scope of the database the local level representation of bullying. If the future waves of the WAY-2014 survey will contain information on the respondents' attended school, further research could be performed adding the school-level data in the analysis.

***References***

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## *Endnotes*

[1] Polish represents by far the largest nationality among A8 migrants and in few years after 2004 they became the largest non-British nationality in the UK.

[2] 95% of respondents to the British Social Attitude Survey in 2014 thinks that to be "*truly British*" people have to speak English.

[3] England consists of 152 Upper-Tier Local Authorities: in the WAY-2014 two UTLAs are merged to the nearest neighbor due to small population (City of London with Hackney and Isles of Scilly with Cornwall). Therefore, survey results of the WAY-2014 refer to 150 UTLAs and the same holds for the analysis in this paper.

[4] The shares of pupils belonging to other ethnic groups have been considered, but they do not display significance at the same time not improving results fit.

[5] Other control variables that have been considered are juvenile crime, stock of human capital, religious outlook of places, adopted children, population density. However, they do not display significance at the same time not improving results fit.

[6] In the Appendix only the results for the spatial spillovers of the migration shock and the control variables are presented. Estimation results for the model specifications including also bullying in the neighboring UTLAs are available upon request.

[7] To further account for collinearity among control variables, estimation has been performed removing controls with VIF above 4.5 (unemployment and crime rate) and results do not change.

[8] Estimation results available upon request.

## Appendix

### 1. Descriptive Statistics

The WAY-2014 data from the UK NHS Digital are, up to now, the largest-scale database targeting bullying among pupils in a single country. The WAY-2014 is characterized by sufficient observations collected in each UTLA to achieve a +/-3% margin error at a 95% CI for youth in England aged 15 in each UTLA. A random sampling methodology was used in order to ensure that no bias was introduced into the sample selection and that the survey sample reflected the population. The 110,788 respondents to bullying-related questions amount to the 92% of total respondents, showing good internal consistency (α=0.90) and accounting for a weighted population of 520,221 pupils (Health and Social Care Information Centre of the UK Government, 2015b). England consists of 152 Upper-Tier Local Authorities: in the WAY-2014 two UTLAs are merged to the nearest neighbor due to small population (City of London with Hackney and Isles of Scilly with Cornwall). Therefore, survey results of the WAY-2014 refer to 150 UTLAs and the same holds for the analysis in this paper.

The WAY-2014 defines being bullied as *"...when another person, or a group of people, say or do nasty and unpleasant things to him or her. It is also bullying when a person is teased repeatedly in a way he or she does not like or when he or she is deliberately left out of things. Bullying may happen over the Internet or by text or phone messages. It is not bullying when a person is teased in a friendly and playful way*". On this definition, respondents rate six statements using a 5-points response scale ranging from 0 = "*I haven't been bullied this way in the past couple of months*" 1 = "*It has happened once or twice*", 2 = "*2 or 3 times a month*", 3 = "*2 or 3 times a week*", to 4 = "*Several times a week.*" The six statements worked as follows: "*I was called mean names, was made fun of, or teased in a hurtful way*"; "*I was hit, kicked, pushed, shoved around, or locked indoors*"; "*Other people left me out of things on purpose, excluded me from their group of friends, or completely ignored me*"; "*Other people told lies or spread false rumors about me and tried to make other people dislike me*"; "*Other people made fun of me because of my body weight*"; "*Other people made sexual jokes, comments, or gestures to me*" (Health and Social Care Information Centre of the UK Government, 2015a). To obtain a measure of experience of bullying, the analysis uses following indicator: if the sum of the number of traditional bullying items endorsed by each participant at greater than "*2 or 3 times a month*", then the pupils is a bully-victim (Przybylski & Bowes, 2017). Cyberbullying is not considered in the analysis. For each respondent, the

WAY-2014 database details the gender, the ethnicity, and the level of deprivation of the neighbourhood of residence[1] and the UTLA of residence at the time of the survey. The WAY-2014 data can be obtained through the UK Data Service according to a "*safeguarded*" policy, which requires a specific process of authentication and registration to access the data, since the data owner considers there to be a risk of disclosure. Figure 1 describes the observed spatial heterogeneity displayed by school bullying across the 150 English UTLAs.

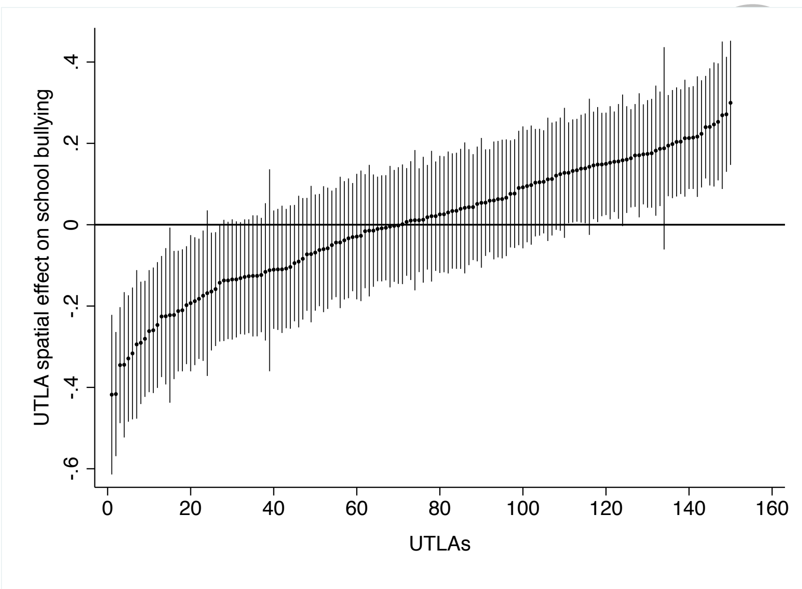



**Figure 1. Predicted UTLA effects on school bullying in each UTLA. It displays the ranking plot of estimated residuals for the 150 UTLAs. together with their 95% confidence intervals. The probability of being bullied for 15-years old is significantly above (below) average for a relevant of UTLAs, as outlined by the mass of confidence intervals which do not overlap the horizontal line at zero. 40 UTLAs have larger than average effects and 34 UTLAs have smaller than average effect. The relevance of the spatial dimension is also supported by: (i) loglikelihood test logit vs. ML logit: always supports ML logit; (ii) Wald statistic for estimated UTLA level variance against a chi-square distribution with 1 d.f. (taking p-value/2 since the distribution is one-sided). $H_0$: UTLA level variance = 0 is rejected** (Snjiders & Bosker, 2012); **(iii) MOR for the baseline ML logit = 1.053; (iv) including UTLA level variables explains 89.3% of the observed spatial heterogeneity in school bullying (Proportional Change of Variance of the baseline ML logit estimation of eq. (2) equals 89.3%, see also the notes of Table 4 in the main paper**

Table 1 shows the data sources for all the variables, Table 2 shows the descriptive statistics and Table 3 the correlation matrix.

[1] The neighbourhood of residency is identified through the postcode which refers to small area with an average of 15 properties.

Table 1:Data sources

| Variable | Source |
|---|---|
| **Level 1 (individual) Variables** | |
| Survey Weight | What About Youth (2016) UK National Health Service |
| Traditional bullying | What About Youth (2016) UK National Health Service |
| Belongs to non-white minority | What About Youth (2016) UK National Health Service |
| Male | What About Youth (2016) UK National Health Service |
| Lives deprived neighborhood | What About Youth (2016) UK National Health Service |
| **Level 2 (Local Authority) Variables** | |
| Split population | ONS 2011 Census |
| Same sex couples | ONS 2011 Census |
| Ethnic diversity Index | ONS 2011 Census |
| IMD average income score | UK Department of Communities and Local Governments. English Indices of Deprivation 2011 |
| IMD crime score | UK Department of Communities and Local Governments. English Indices of Deprivation 2011 |
| Unemployment | ONS 2011 Census |
| Income variation coefficient | UK Department of Communities and Local Governments. English Indices of Deprivation 2011 |
| Children looked after | 2010-11 Children in Need Census (CIN). UK Department of Education |
| Population size | ONS 2011 Census |
| A8 Migration Shock | Becker S, Fetzer T and Novy D (2017) |
| A8 Migrants' share in 2004 | Annual Population Survey – ONS (2017) |
| A8 Migrants' share in 2001 | ONS 2001 Census |
| Exposure to migration from ROW | Becker S, Fetzer T and Novy D (2017) |
| Rural | 2011 ONS Rural-Urban Classification (RUC11) |
| Secondary school: British white | UK Department of Education. School Census 2011 |
| Secondary school: % change EAL pupils | UK Department of Education. School Census |
| School: Language diversity | UK Department of Education. School Census 2012-2007 |

## Table 2: Descriptive statistics

| Variable | number of observations | mean | sd | min | max |
|---|---|---|---|---|---|
| **Level 1 (individual) variables** | | | | | |
| Survey Weight | 110,788 | 4.696 | 2.859 | 1.079 | 33.85 |
| Traditional bullying | 110,788 | 0.297 | 0.457 | 0 | 1 |
| Belongs to non-white minority | 110,788 | 0.23131 | 0.42167 | 0 | 1 |
| Male | 110,788 | 0.477037 | 0.499475 | 0 | 1 |
| Lives deprived neighbourhood | 110,788 | 0.42957 | 0.495017 | 0 | 1 |
| **Level 2 (Local Authority) variables** | | | | | |
| Split population (share) | 110,788 | 2.595 | 0.443 | 0.706 | 3.778 |
| Same sex couples (share) | 110,788 | 0.0966 | 0.071 | 0.0203 | 0.549 |
| Ethnic diversity Index (Simpson Index Inverse) | 110,788 | 6.478 | 9.731 | 0.332 | 54.61 |
| IMD average income score | 110,788 | 0.153 | 0.0492 | 0.052 | 0.276 |
| IMD crime score | 110,788 | 0.067 | 0.434 | -0.804 | 1.019 |
| Unemployment (share) | 110,788 | 5.528 | 3.455 | 0.037 | 12.002 |
| Income variation coefficient | 110,788 | 0. 519 | 0.158 | 0.128 | 1.067 |
| Children looked after (per 100k children) | 110,788 | 1.399 | 1.170 | 0.0315 | 5.378 |
| Population size (ln) | 110,788 | 1.172 | 0.601 | -0.984 | 2.684 |
| A8 Migration Shock | 110,788 | 0.171 | 0.116 | 0.0113 | 0.668 |
| A8 migrants' share in 2004 | 110,788 | 0.037 | 0.018 | 0 | 0.063 |
| Exposure to migration from ROW | 110,788 | 0.062 | 0.066 | -0.0005 | 0.3993 |
| Rural | 110,788 | 0.3022 | 0.4592 | 0 | 1 |
| Secondary school: British white (share) | 110,788 | 0.713 | 0.252 | 0.0475 | 0.966 |
| Secondary school: percentage change EAL pupils 2013-2007 | 110,788 | 1.448 | 0.423 | 0.296 | 3.117 |
| Secondary school: percentage change EAL pupils 2013-2007 | 110,788 | 2.585 | 3.189 | -8.59 | 15.78 |
| Secondary school: percentage change EAL pupils 2013-2008 | 110,788 | 2.723 | 2.656 | -4.8 | 15.6 |
| Secondary school: percentage change EAL pupils 2013-2009 | 110,788 | 2.198 | 2.327 | -5.2 | 12.5 |

Income deprivation is conveyed through the Income Deprivation Average Score*, i.e.* a population-weighted summary of the average level of income deprivation in the UTLA, through the proportion of UTLA population experiencing deprivation relating to low income(Department for Communities and Local Governments of the UK Government, 2015); if a UTLA scores 0,52, it means that 52% of the population is income deprived in that area. Spatial income polarization is given by the variation coefficient for the distribution of income across neighborhoods within the same UTLA[2] using data on income level at neighborhood-scale. The lower the coefficient, the more neighborhoods are homogenous in terms of income. Social frustration is measured through the number of children in need and the share of split population; social openness is proxied by the share of same sex couples. Other controls are population size and ethnic composition, crime, unemployment and rural/urban dichotomy. UTLA codes are used to match individual-level data and spatial level data.



[2] Subunits are given by Lower-Layer Super Output Areas (LSOAs): small areas designed to be of a similar population size, with an average of approximately 1,500 residents or 650 households. There are 32,844 LSOAs in England

## Table 3: Correlation matrix

| | A8 migration shock | British white share (school) | Ethnic diversity | Crime score | Pop size (ln) | Split population | Same sex couples | UTLA looked-after children | Unemployment | Income deprivation | Spatial Income polarization | EAL exposure (school) | Language diversity (school) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A8 migration shock | 1 | | | | | | | | | | | | |
| British white share (school) | -0,4046 | 1 | | | | | | | | | | | |
| Ethnic diversity | 0,4410 | -0,9161 | 1 | | | | | | | | | | |
| Crime score | 0,4703 | -0,6991 | 0,6171 | 1 | | | | | | | | | |
| Pop size (ln) | -0,1137 | 0,1481 | -0,1191 | -0,3025 | 1 | | | | | | | | |
| Split population | -0,1649 | 0,6791 | -0,641 | -0,2766 | 0,0422 | 1 | | | | | | | |
| Same sex couples | -0,1606 | -0,3917 | 0,3236 | 0,2168 | -0,0919 | -0,0445 | 1 | | | | | | |
| UTLA looked-after children | -0,0851 | 0,4279 | -0,3831 | -0,1829 | -0,0338 | 0,3752 | -0,1296 | 1 | | | | | |
| Unemployment | 0,4049 | -0,4198 | 0,3597 | 0,6911 | -0,6291 | -0,1405 | 0,0607 | -0,1871 | 1 | | | | |
| Income deprivation | 0,4340 | -0,3558 | 0,3056 | 0,692 | -0,3000 | 0,0283 | 0,1129 | -0,1018 | 0,823 | 1 | | | |
| Spatial Income polarization | -0,4895 | 0,4907 | -0,5063 | -0,6568 | 0,2539 | 0,0654 | -0,1976 | 0,1063 | -0,6381 | -0,8075 | 1 | | |
| EAL exposure (school) | 0,0512 | 0,3849 | -0,3408 | -0,1570 | -0,0703 | 0,2830 | -0,1750 | 0,4055 | -0,1019 | -0,1268 | 0,0998 | 1 | |
| Language diversity (school) | -0,0554 | -0.1971 | 0.1875 | 0,0756 | 0,1132 | -0,2590 | 0,1747 | -0,1069 | --0,1133 | -0,2255 | 0,1268 | -0,0309 | 1 |

## 2. Estimation Results and Robustness checks

### Table 4: Exposure to a cultural shock from migration and school bullying for the considered logit model specifications (ML, GEE, CF-TSRI ML)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | ML logit RI | ML logit RI *interactions* | GEE logit *interactions* | CF 2SRI 2nd stage GLM ML logit *interactions* | |
| | Odds ratio | Odds ratio | Odds ratio | Odds ratio | Coef. |
| **A8 Migration shock** | **1.237**$^{**}$ | **1.225**$^{**}$ | **1.226**$^{**}$ | **1.922**$^{***}$ | 0.654$^{***}$ |
| | **[1.061,1.441]** | **[1.047,1.432]** | **[1.049,1.433]** | | (0.180) |
| Belongs to Minority | | 0.755*** | 0.755$^{***}$ | 0.755$^{***}$ | -0.281$^{***}$ |
| | | [0.721,0.790] | [0.721,0.790] | | (0.0212) |
| British White in School | | 0.897 | 0.899 | 0.882 | -0.126 |
| | | [0.726,1.108] | [0.728,1.109] | | (0.0992) |
| Belongs to Minority*Brit | | 1.230$^{**}$ | 1.232$^{**}$ | 1.233$^{**}$ | 0.209$^{**}$ |
| White in School | | [1.050,1.441] | [1.052,1.443] | | (0.0735) |
| Lives in Deprived | | 1.153*** | 1.153$^{***}$ | 1.153$^{***}$ | 0.142$^{***}$ |
| Neighborhood | | [1.116,1.191] | [1.116,1.191] | | (0.0150) |
| UTLA Income | | 0.175*** | 0.173*** | 0.189$^{***}$ | -1.665$^{***}$ |
| Deprivation | | [0.063,0.486] | [0.0631,0.476] | | (0.330) |
| Deprived Neighborhood* | | 0.555* | 0.553* | 0.559$^{*}$ | -0.581$^{*}$ |
| UTLA IncomeDeprivation | | [0.293,1.053] | [0.292,1.045] | | (0.332) |
| CF Stage 1 residuals | | | | 0.577$^{**}$ | -0.550$^{**}$ |
| | | | | | (0.192) |
| *Individual level controls* | *YES* | *YES* | *YES* | *YES* | YES |
| *UTLA level controls* | *YES* | *YES* | *YES* | *YES* | YES |
| *DWH test (p-value)* | | | | | 0.047 |
| Log likelihood | -66120.259 | -66114.119 | | | -66111.602 |
| Observations | 110788 | 110788 | 110788 | 110788 | 110788 |
| Cluster | 150 | 150 | 150 | 150 | 150 |

*Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area

| | CF 2SRI:1st stage OLS |
|---|---|
| | coef |
| Shift share | -0.633*** |
| | (0.009) |
| Controls (all UTLA-level continuous covariates) | YES |
| F-test ex instrument | 15.58 |

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively; errors clustered at UTLA level; CF 2SRI is bootstrapped (1000 replications)*

Notes: The baseline ML logit specification is identified following a bottom-up approach: the model is developed stepwise, starting with a random intercept for each UTLA and subsequently adding predictors and random slopes. After each step, a log-likelihood ratio test gauges if the model constitutes a better fit to the data compared to classical logit, or a better fit compared to the previous step (Hox, 2010). The sample size is large, and the number of clusters exceeds 100, hence maximum likelihood estimation delivers accurate standard errors (Bryan & Jenkins, 2016). The Median Odd Ratios (MOR) is 1.0533, supporting the role of the spatial dimension (Austin & Merlo, 2017). The Proportional Change in Variance (PVC) equals 89.3%. The model appears not to suffer from severe multicollinearity (mean VIF = 3.85, EU 2004 migration accession VIF = 1.81). Following the bottom-up approach (Hox, 2010), other UTLA-level covariates have been assessed (juvenile crime, exposure to migration from other contexts, stock of human capital, religious outlook, adopted children, population density) showing both non-significance and no improvement in model fit. To control for potential concern about non-normally distributed residual errors, misspecification and outliers, the ML logit with RI is estimated both with cluster-robust standard errors and with White robust standard errors (Hox, 2010).

Table 4 shows the estimation results for the ML logit, the GEE logit and the CF-TSRI approach. The tables report odds ratios with their 95% confidence intervals being odds ratios a nonlinear transformation of the logit coefficients. Cross-level interactions are included even if there is no significant random slope for the individual-level covariate included in the interaction term, since estimation allows consistent and unbiased cross-level interactions(Rabe-Hesketh & Skrondal, 2012). Comparing column 1 with columns 2 and 3, it appears that the inclusion of meaningful cross-level interactions does not change the influence of the A8 migration shock on school bullying. CF-TSRI stage 1 estimates are reported in the bottom part of column 5. Estimations are performed using STATA 14. ML logit is estimated using melogit. GEE logit is estimated using xtgee. CF-TSRI is estimated using meglm and bootstrapping for 1000 replications to approximate the asymptotically correct standard errors (Terza, 2017).

Table 5 presents estimation results when exposure to migration from other contexts is considered.

**Table 5 Estimates from ML logit with exposure to migration from the Rest of the World (ROW)**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Measures of association (Odds ratio)** | ML logit RI *ROW exposure as control* | ML logit RI *ROW exposure as treatment* | ML logit RI *Asian exposure as treatment* | ML logit RI *African exposure as treatment* |
| **A8 Migration shock** | **1.237****<br>**[1.028,1.487]** | | | |
| Exposure to ROW migration 2011-2001 | 0.956<br>[0.670,1.364] | 0.958<br>[0.667,1.376] | | |
| Exposure to Asia migration 2011-2001 | | | 0.990<br>[0.973,1.008] | |
| | | | | 1.009<br>[0.995,1.024] |
| Individual level controls | YES | YES | YES | YES |
| UTLA level controls | YES | YES | YES | YES |
| Log likelihood | -66120.228 | -66122.732 | -66026.181 | -66115.088 |
| Observations | 110788 | 110788 | 110788 | 110788 |
| Cluster | 150 | 150 | 150 | 150 |

*Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively; errors clustered at UTLA leve*

Table 6 presents estimation results of the interaction of the A8 migration shock with local-level variables.

**Table 6: Estimates from ML logit with different interactions for the shock from migration**

| | (1) | (2) | (3) |
|---|---|---|---|
| **Measures of association (Odds ratio)** | ML logit RI | ML logit RI | ML logit RI |
| **A8 Migration shock** | **1.216*** | **1.198*** | **1.231**** |
| | **[0.985,1.503]** | **[0.989,1.451]** | **[1.040,1.458]** |
| Income Deprivation | 0.169*** | | |
| | [0.0617,0.463] | | |
| Income Deprivation* A8 Migration shock | 1.042 | | |
| | [0.0685,15.86] | | |
| Crime score | | 1.004 | |
| | | [0.928,1.086] | |
| Crime score* A8 Migration shock | | 1.071 | |
| | | [0.798,1.436] | |
| Ethnic diversity | | | 0.998 |
| | | | [0.993,1.003] |
| Ethnic diversity* A8 Migration shock | | | 0.999 |
| | | | [0.990,1.008] |
| Individual level controls | YES | YES | YES |
| UTLA level controls | YES | YES | YES |
| Log likelihood | -66115.776 | -66114.052 | -66114.105 |
| Observations | 110788 | 110788 | 89959 |
| Cluster | 150 | 150 | 150 |

*Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively; errors clustered at UTLA level;*

Table 7 outlines estimates of the effect of A8 migrants considered in levels rather than in dynamic change, both as a control variable and as main independent variable of interest.

**Table 7: Estimates from ML logit for the current share of Eastern Europeans**

| | (1) | (2) |
|---|---|---|
| **Measures of association (Odds ratio)** | ML logit RI | ML logit RI |
| **A8 Migration shock** | **1.239**** | |
| | **[1.030,1.491]** | |
| Local size of Eastern European pop | 0.00188 | 0.00086 |
| | [0.000,11.74] | [1.69e-07, 4.3677] |
| Local size of Eastern European pop *A8 Migration shock | 2.38470e+13 | |
| | [5.60e-28,1.02e+54] | |
| Individual level controls | YES | YES |
| UTLA level controls | YES | YES |
| Log likelihood | -65126.533 | -65128.733 |
| Observations | 110788 | 110788 |
| Cluster | 150 | 150 |

*Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively; errors clustered at UTLA level;*

Table 8 presents the estimates when only the UTLAs with the higher size of the A8 migration shock are considered.

[

**Table 8: Estimates from ML logit for the A8 Migration shock in the subset of UTLAs experiencing the strongest impact of the shock**

| | (1) |
|---|---|
| **Measures of association (Odds ratio)** | ML logit RI |
| **A8 Migration shock** | **1.334**** |
| | **[1.064,1.672]** |
| Ethnic diversity | 0.996 |
| | [0.992,1.002] |
| *Individual level controls* | *YES* |
| *UTLA level controls* | *YES* |
| Observations | 37801 |
| Clusters | 50 |

*Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, population size, unemployment, rural/urban area

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively; errors clustered at UTLA level;*

Table 9 shows estimates of causal evidence between A8 migration shock and school bullying under two sensitivity tests. First, choosing 2004 as the baseline year for the shift-share instrument (Table 9.a). Second, using the competing modelling strategy based on the Limited Information Maximum Likelihood Approach (Table 9.b).
Estimates in Table 9.a shows that the effect of the migration shock on bullying do not change when the baseline year for the shift-share instruments change from 2001 to 2004. Estimates from the reduced-form equation in Table 9.a support a positive and significant enclave effect of 2004 A8 migrants on future settlements (1st stage coefficient for the IV is positive). This finding are consistent with existing evidence showing that post-2004 A8 migrants have strong enclave ties (Okólski & Salt, 2014; Pollard, Latorre, & Sriskandarajah, 2008) and have different localization preferences compared to pre-2004 A8 migrants (Jaitman & Machin, 2013).

**Table 9: Sensitivity tests for the model estimates when endogeneity is addressed. Table 9.a: CF-TSRI when the shift-share instrument is designed with 2004 as baseline year. Table 9.b: Limited Information Maximum Likelihood estimation (Conditional-Mixed Process Approach** (Roodman, 2011)**)**

| Table 9.a | | | |
|---|---|---|---|
| CF-TSRI estimation with 2004 as baseline year for the shift-share instrument | | | |
| **Structural equation (logit)** | **Odds ratio** | **Reduced form equation (OLS)** | **coef** |
| A8 Migration shock | $1.823^{**}$ | Shift Share (2004 as baseline) | $0.650^{***}$ |
| | [1.176, 2.828] | | (0.013) |
| Belongs to Minority | $0.755^{***}$ | | |
| | [0.725, 0.786] | | |
| British White in School | 0.885 | | |
| | [0.706, 1.095] | | |
| Belongs to Minority * Brit white in school | $1.230^{**}$ | | |
| | [1.071, 1.412] | | |
| Lives in Deprived Neighbourhood | $1.153^{***}$ | | |
| | [1.119, 1.189] | | |
| UTLA Income Deprivation | $0.194^{***}$ | | |
| | [0.085, 0.442] | | |
| Deprived Neighbourhood * UTLA Income Deprivation | $0.551^{*}$ | | |
| | [0.293, 1.036] | | |
| *Individual level controls* | *YES* | | *YES* |
| *UTLA level controls* | *YES* | | *YES* |
| *Observations* | 110788 | | |
| F-stat ex instrument | | | 16.28 |

$^{***}$, $^{**}$ and $^{*}$ stand for statistical significance at 10, 5, and 1% levels, respectively; 95% confidence intervals in brackets; robust standard errors.
*Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area
Estimate for the effect of the migration shock on bullying are consistent with the one presented in the main manuscript. The shift-share approach with 2004 as baseline year delivers a positive and significant enclave effect (1st stage coefficient for the IV always positive). This finding supports that the A8 migrants after the EU Enlargement have strong enclave ties (Okólski & Salt, 2014; Pollard, Latorre, & Sriskandarajah, 2008)and have different localization preferences compared to 2001 A8 migrants (Jaitman & Machin, 2013).

| Table 9.b | | | |
|---|---|---|---|
| LIML estimation | | | |
| **Structural equation (logit)** | **Odds ratio** | **Reduced form equation (OLS)** | **coef** |
| A8 Migration shock | 1.484** | Shift Share (2001 as baseline) | -0.633** |
| | [1.049,2.098] | | (0.269) |
| Belongs to Minority | 0.848*** | | |
| | [0.825,0.871] | | |
| British White in School | 0.933 | | |
| | [0.817,1.067] | | |
| Belongs to Minority * Brit white | 1.118** | | |
| in school | [1.016,1.230] | | |
| Lives in Deprived Neighbourhood | 1.088*** | | |
| | [1.067,1.110] | | |
| UTLA Income Deprivation | 0.371** | | |
| | [0.190,0.726] | | |
| Deprived Neighbourhood * | 0.712* | | |
| UTLA Income Deprivation | [0.487,1.040] | | |
| *Individual level controls* | *YES* | *YES* | *YES* |
| *UTLA level controls* | *YES* | *YES* | *YES* |
| Observations | 110788 | | |

***, ** and * stand for statistical significance at 10, 5, and 1% levels, respectively; 95% confidence intervals in brackets; robust standard errors.
*Individual level controls:* gender, ethnicity, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area.

## Table 10: ML logit, GEE logit and CF-TSRI estimates removing the 14 biggest Metropolitan Boroughs°°

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ML logit RI *interactions* | GEE logit *interactions* | CF 2SRI $2^{nd}$ stage GLM ML logit *interactions* | |
| | Odds ratio | Odds ratio | Odds ratio | Coef. |
| **A8 Migration shock** | **1.255$^{**}$** | **1.253$^{**}$** | **1.616$^{**}$** | **0.480$^{**}$** |
| | **[1.039,1.516]** | **[1.036,1.515]** | | **(0.192)** |
| Belongs to Minority | 0.726$^{***}$ | 0.726$^{***}$ | 0.726$^{***}$ | -0.320$^{***}$ |
| | [0.687,0.766] | [0.687,0.766] | | (0.0258) |
| British White in School | 1.016 | 0.864 | 0.897 | -0.109 |
| | [0.694,1.486] | [0.595,1.253] | | (0.160) |
| Belongs to Minority*Brit White in School | 2.056$^{***}$ | 2.055$^{***}$ | 2.059$^{***}$ | 0.722$^{***}$ |
| | [1.568,2.695] | [1.567,2.694] | | (0.153) |
| Lives in Deprived Neighborhood | 1.177$^{***}$ | 1.176$^{***}$ | 1.175$^{***}$ | 0.161$^{***}$ |
| | [1.133,1,223] | [1.132,1.222] | | (0.0180) |
| UTLA Income Deprivation | 0.149$^{***}$ | 0.204$^{**}$ | 0.177$^{***}$ | -1.733$^{***}$ |
| | [0.0525,0.424] | [0.699,0.595] | | (0.375) |
| Deprived Neighborhood*UTLA Income Deprivation | 0.507$^{*}$ | 0.507$^{*}$ | 0.527$^{*}$ | -0.641$^{*}$ |
| | [0.231,1.112] | [0.231,1.111] | | (0.379) |
| CF Stage 1 residuals | | | 0.696$^{*}$ | -0.362$^{*}$ |
| | | | | (0.101) |
| *Individual level controls* | *YES* | *YES* | *YES* | *YES* |
| *UTLA level controls* | *YES* | *YES* | *YES* | *YES* |
| *DWH test (p-value)* | | | | 0.074 |
| Log likelihood | -48179.544 | | | |
| Observations | 79062 | 79062 | 79062 | 79062 |
| Cluster | 105 | 105 | 105 | 105 |

*Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area

| | CF 2SRI: $1^{st}$ stage OLS |
|---|---|
| | coef |
| Shift share (2001 as baseline) | -0.871$^{***}$ |
| | (0.010) |
| Controls (all UTLA-level continuous covariates) | YES |
| F-Stat ex instrument | 19.83 |

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively; errors clustered at UTLA level; CF 2SRI is bootstrapped (1000 replications);*

*°° London, Birmingham, Leeds; Sheffield, Bradford, Manchester, Liverpool, Bristol, Kirklees, Coventry, Leicester, Wakefield, Wigan, Wirral.* Results are confirmed also by removing only London and only the 6 biggest Metropolitan Boroughs (London, Birmingham, Leeds; Sheffield, Bradford, Manchester).

**Table 11: ML logit, GEE logit and CF-TSRI estimates accounting for spatial spillovers**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | ML logit RI *Interactions* | ML logit RI *Interactions* | GEE logit *interactions* | GEE logit *interactions* | CF 2SRI $2^{nd}$ stage GLM ML logit *Interactions* | | CF 2SRI $2^{nd}$ stage GLM ML logit *Interactions* | |
| | Odds ratio | Odds ratio | Odds ratio | Odds ratio | Odds ratio | Coef. | Odds ratio | Coef. |
| **A8 Migration shock** | **1.182**$^{**}$ | **1.191**$^{**}$ | **1.183**$^{**}$ | **1.192**$^{**}$ | **1.839**$^{**}$ | **0.609**$^{**}$ | **2.084**$^{**}$ | **0.734**$^{***}$ |
| | **[1.009,1.385]** | **[1.015,1.396]** | **[1.010,1.386]** | **[1.016,1.397]** | | **(0.225)** | | **(0.203)** |
| Belongs to Minority | 0.754$^{***}$ | 0.754$^{***}$ | 0.755$^{***}$ | 0.755$^{***}$ | 0.755$^{***}$ | -0.282$^{***}$ | 0.755$^{***}$ | -0.282$^{***}$ |
| | [0.721,0.790] | [0.721,0.790] | [0.721,0.790] | [0.721,0.790] | | (0.0213) | | (0.0201) |
| British White in School | 0.893 | 0.883 | 0.853 | 0.843$^{*}$ | 0.880 | -0.128 | 0.875 | -0.133 |
| | [0.724,1.102] | [0.718,1.087] | [0.695,1.047] | [0.688,1.033] | | (0.0948) | | (0.101) |
| Belongs to Minority*Brit | 1.229$^{**}$ | 1.230$^{**}$ | 1.231$^{**}$ | 1.232$^{**}$ | 1.229$^{**}$ | 0.206$^{**}$ | 1.229$^{**}$ | 0.206$^{**}$ |
| White in School | [1.049,1.440] | [1.051,1.441] | [1.051,1.442] | [1.052,1.444] | | (0.0670) | | (0.0776) |
| Lives in Deprived | 1.153$^{***}$ | 1.153$^{***}$ | 1.153$^{***}$ | 1.153$^{***}$ | 1.153$^{***}$ | 0.143$^{***}$ | 1.153$^{***}$ | 0.143$^{***}$ |
| Neighborhood | [1.116,1.192] | [1.116,1.192] | [1.116,1.192] | [1.116,1.191] | | (0.0172) | | (0.0163) |
| UTLA Income Deprivation | 0.185$^{**}$ | 0.177$^{***}$ | 0.235$^{**}$ | 0.224$^{**}$ | 0.193$^{***}$ | -1.645$^{***}$ | 0.177$^{***}$ | -1.732$^{***}$ |
| | [0.0676,0.507] | [0.0661,0.475] | [0.0838,0.660] | [0.0813,0.619] | | (0.386) | | (0.418) |
| Deprived | 0.562$^{*}$ | 0.568$^{*}$ | 0.560$^{*}$ | 0.565$^{*}$ | 0.555$^{*}$ | -0.588$^{*}$ | 0.555$^{*}$ | -0.588$^{*}$ |
| Neighborhood*UTLA Income Deprivation | [0.297,1.065] | [0.297,1.085] | [0.296,1.058] | [0.297,1.077] | | (0.331) | | (0.350) |
| Spatial spillovers of A8 | 1.185 | 1.211$^{*}$ | 1.187 | 1.214$^{*}$ | 1.020 | 0.0200 | 0.999 | -0.000952 |
| Migration shock | [0.953,1.474] | [0.968,1.515] | [0.954,1.479] | [0.968,1.522] | | (0.127) | | (0.126) |
| CF Stage 1 residuals | | | | | 0.604$^{**}$ | -0.504$^{**}$ | 0.529$^{**}$ | -0.638$^{**}$ |
| | | | | | | (0.239) | | (0.213) |
| Spatial spillovers of controls | *NO* | *YES* | *NO* | *YES* | *NO* | *NO* | *YES* | *YES* |
| *Individual level controls* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* |
| *UTLA level controls* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* |
| *DWH test (p-value)* | | | | | | 0.0348 | | 0.0027 |
| Observations | 110788 | 110788 | 110788 | 110788 | 110788 | 110788 | 110788 | 110788 |
| Cluster | 150 | 150 | 150 | 150 | 150 | 150 | 150 | 150 |

95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively; *Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.

*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area

| | CF 2SRI: 1st stage OLS | CF 2SRI: 1st stage OLS |
|---|---|---|
| | Coef | Coef |
| Shift-share (2001 as baseline) | -0.740*** | -0.780*** |
| | (0.0135) | (0.0137) |
| Controls (all UTLA-level continuous covariates) | YES | YES |
| F-stat ex instrument | 21.94 | 24.80 |

## Table 12a: ML logit, GEE logit and CF-TSRI estimates accounting for UTLAs heterogeneity in term of spatial size

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | ML logit RI<br>*Interactions*<br>*UTLA group A* | ML logit RI<br>*Interactions*<br>*UTLA group B* | GEE logit<br>*interactions*<br>*UTLA group A* | GEE logit<br>*interactions*<br>*UTLA group B* | CF 2SRI<br>2nd stage GLM ML logit<br>*Interactions*<br>*UTLA group A* | | CF 2SRI<br>2nd stage GLM ML logit<br>*Interactions*<br>*UTLA group B* | |
| | Odds ratio | Odds ratio | Odds ratio | Odds ratio | Odds ratio | Coef. | Odds ratio | Coef. |
| **A8 Migration shock** | **1.218$^{**}$** | **2.132$^{**}$** | **1.220$^{**}$** | **2.169$^{**}$** | **2.225$^{**}$** | **0.800$^{**}$** | **2.183$^{**}$** | **0.781$^{**}$** |
| | **[1.048,1.416]** | **[1.033,4.400]** | **[1.050,1.418]** | **[1.050,4.479]** | | **(0.281)** | | **(0.241)** |
| Belongs to Minority | 0.746$^{***}$ | 0.532$^{**}$ | 0.746$^{***}$ | 0.526$^{**}$ | 0.791$^{***}$ | -0.235$^{***}$ | 0.744$^{***}$ | -0.296$^{***}$ |
| | [0.709,0.785] | [0.310,0.912] | [0.709,0.785] | [0.307,0.899] | | (0.0428) | | (0.0226) |
| British White in School | 0.885 | 0.964 | 0.885 | 1.028 | 0.887 | -0.120 | 0.816$^{*}$ | -0.204$^{*}$ |
| | [0.716,1.093] | [0.102,9.097] | [0.717,1.093] | [0.108,9.799] | | (0.249) | | (0.117) |
| Belongs to Minority*Brit White in School | 1.185$^{*}$ | 12.96$^{*}$ | 1.186$^{**}$ | 13.95$^{*}$ | 1.448$^{*}$ | 0.370$^{*}$ | 1.193$^{**}$ | 0.176$^{**}$ |
| | [1.000,1.404] | [0.872,192.5] | [1.001,1.406] | [0.952,204.5] | | (0.190) | | (0.0791) |
| Lives in Deprived Neighborhood | 1.142$^{***}$ | 0.993 | 1.142$^{***}$ | 0.982 | 1.170$^{***}$ | 0.157$^{***}$ | | 0.143$^{***}$ |
| | [1.101,1.185] | [0.910,1.083] | [1.101,1.185] | [0.897,1.076] | | (0.034) | | (0.0172) |
| UTLA Income Deprivation | 0.188$^{**}$ | 0.00876$^{***}$ | 0.187$^{**}$ | 0.00848$^{***}$ | 0.0170$^{**}$ | -4.072$^{***}$ | 0.194$^{***}$ | -1.642$^{***}$ |
| | [0.0603,0.589] | [0.00109,0.0703] | [0.0604,0.579] | [0.00106,0.0679] | | (0.981) | | (0.472) |
| Deprived Neighborhood*UTLA Income Deprivation | 0.773 | 0.00279$^{***}$ | 0.766 | 0.00212$^{***}$ | 0.359$^{*}$ | -1.025$^{*}$ | 0.619 | -0.480 |
| | [0.392,1.527] | [0.000257,0.0302] | [0.389,1.509] | [0.000178,0.0252] | | (0.619) | | (0.395) |
| CF Stage 1 residuals | | | | | 0.475$^{**}$ | -0.744$^{**}$ | 0.513$^{*}$ | -0.668$^{**}$ |
| | | | | | | (0.353) | | (0.264) |
| *Individual level controls* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* |
| *UTLA level controls* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* |
| *DWH test (p-value)* | | | | | | 0.035 | | 0.0114 |
| Log likelihood | -52516.807 | -13580.039 | | | | | | |
| Observations | 88866 | 21922 | 88866 | 21922 | 88866 | 21922 | 88866 | 21922 |
| Cluster | 126 | 24 | 126 | 24 | 126 | 24 | 126 | 24 |

*Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area
UTLA belonging to group A and B are outlined in Figure Area is measured in logs of hectares

| | CF 2SRI: 1st stage OLS | CF 2SRI: 1st stage OLS |
|---|---|---|
| | Coef | Coef |
| Shift-share (2001 as baseline) | -0.610*** | -0.275*** |
| | (0.0309) | (0.016) |
| Controls (all UTLA-level continuous covariates) | YES | YES |
| F-stat ex instrument | 11.80 | 15.80 |

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively*

## Table 12b: ML logit, GEE logit and CF-TSRI estimates accounting for UTLAs heterogeneity in term of population size

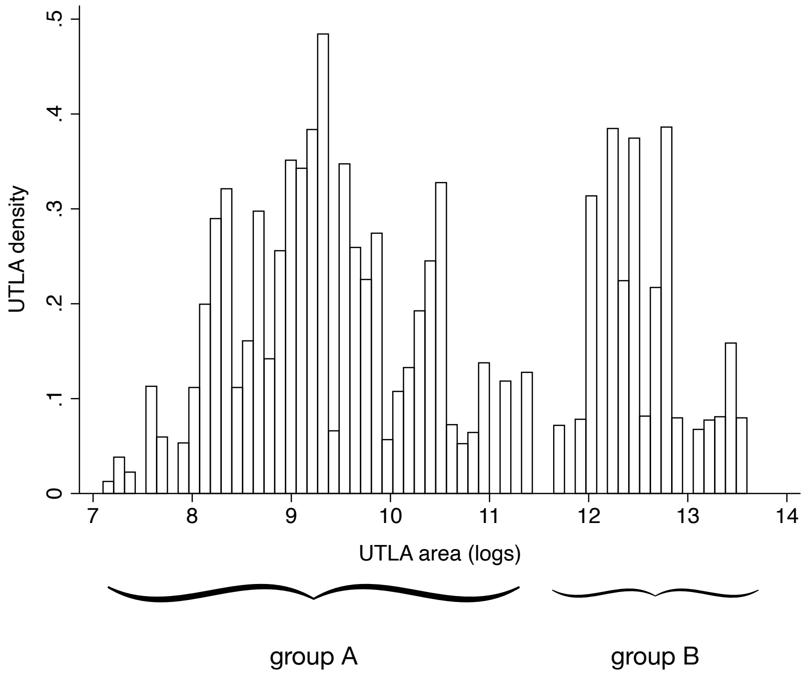
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | ML logit RI *Interactions UTLA pop< 200k* | ML logit RI *Interactions UTLA pop> 200k* | GEE logit *interactions UTLA pop< 200k* | GEE logit *interactions UTLA pop> 200k* | CF 2SRI $2^{nd}$ stage GLM ML logit *Interactions UTLA pop< 200k* | | CF 2SRI $2^{nd}$ stage GLM ML logit *Interactions UTLA pop< 200k* | |
| | Odds ratio | Odds ratio | Odds ratio | Odds ratio | Odds ratio | Coef. | Odds ratio | Coef. |
| **A8 Migration shock** | **1.395**$^{**}$ | **1.246**$^{**}$ | **1.390**$^{**}$ | **1.247**$^{**}$ | **2.225**$^{**}$ | **0.800**$^{**}$ | **2.183**$^{**}$ | **0.781**$^{**}$ |
| | **[1.047,1.857]** | **[1.006,1.543]** | **[1.045,1.849]** | **[1.006,1.545]** | | **(0.281)** | | **(0.241)** |
| Belongs to Minority | 0.792$^{***}$ | 0.744$^{**}$ | 0.792$^{***}$ | 0.744$^{***}$ | 0.791$^{***}$ | -0.235$^{***}$ | 0.744$^{***}$ | -0.296$^{***}$ |
| | [0.721,0.869] | [0.706,0.784] | [0.721,0.869] | [0.707,0.784] | | (0.0428) | | (0.0226) |
| British White in School | 0.969 | 0.860 | 0.885 | 0.826 | 0.887 | -0.120 | 0.816$^{*}$ | -0.204$^{*}$ |
| | [0.595,1.578] | [0.659,1.122] | [0.558,1.403] | [0.633,1.078] | | (0.249) | | (0.117) |
| Belongs to Minority*Brit White in School | 1.461$^{**}$ | 1.193$^{**}$ | 1.461$^{**}$ | 1.195$^{**}$ | 1.448$^{*}$ | 0.370$^{*}$ | 1.193$^{**}$ | 0.176$^{**}$ |
| | [1.040,2.051] | [1.007,1.414] | [1.040,2.052] | [1.008,1.416] | | (0.190) | | (0.0791) |
| Lives in Deprived Neighborhood | 1.171$^{***}$ | 1.153$^{**}$ | 1.171$^{***}$ | 1.152$^{***}$ | 1.170$^{***}$ | 0.157$^{***}$ | | 0.143$^{***}$ |
| | [1.080,1.269] | [1.112,1.195] | [1.080,1.269] | [1.112,1.195] | | (0.034) | | (0.0172) |
| UTLA Income Deprivation | 0.0130$^{***}$ | 0.248$^{**}$ | 0.0217$^{***}$ | 0.301$^{**}$ | 0.0170$^{**}$ | -4.072$^{***}$ | 0.194$^{***}$ | -1.642$^{***}$ |
| | [0.00152,0.111] | [0.0821,0.749] | [0.003,0.172] | [0.0935,0.968] | | (0.981) | | (0.472) |
| Deprived Neighborhood*UTLA Income Deprivation | 0.306$^{**}$ | 0.632 | 0.307$^{**}$ | 0.627 | 0.359$^{*}$ | -1.025$^{*}$ | 0.619 | -0.480 |
| | [0.105,0.891] | [0.291,1.374] | [0.106,10.888] | [0.289,1.361] | | (0.619) | | (0.395) |
| CF Stage 1 residuals | | | | | 0.475$^{**}$ | -0.744$^{**}$ | 0.513$^{*}$ | -0.668$^{**}$ |
| | | | | | | (0.353) | | (0.264) |
| *Individual level controls* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* |
| *UTLA level controls* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* | *YES* |
| *DWH test (p-value)* | | | | | | 0.035 | | 0.0114 |
| Log likelihood | -13815.985 | -52287.895 | | | | | | |
| Observations | 22804 | 87,984 | 22804 | 87,984 | 22804 | 22804 | 87,984 | 87,984 |
| Cluster | 40 | 110 | 40 | 110 | 40 | 40 | 110 | 110 |
| *Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency. | | | | | | | | |
| *UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area | | | | | | | | |
| | | | | | | CF 2SRI: $1^{st}$ stage OLS | | CF 2SRI: $1^{st}$ stage OLS |

| | Coef | Coef |
|---|---|---|
| Shift-share (2001 as baseline) | -0.610*** | -0.275*** |
| | (0.0309) | (0.016) |
| Controls (all UTLA-level continuous covariates) | YES | YES |
| F-stat ex instrument | 11.80 | 15.80 |

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively*

Figure 2 shows the density of UTLAs according to their area and the number of UTLAs belonging to group A and B for the estimations of Table 12.a

**Figure 2: Density of the 150 UTLAs according to their area (in logs). The density plot allows to identify two subsamples -group A and group B- which are used to assess the robustness of baseline estimates controlling for the effect of UTLAs spatial size. Results of estimation are summarized in Table 12.a**



## Table 13: ML logit, GEE logit and CF-TSRI estimates accounting for UTLAs distance from largest core urban centre in the region

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ML logit RI | GEE logit | CF 2SRI 2nd stage GLM ML logit | |
| | Odds ratio | Odds ratio | Odds ratio | Coef |
| **A8 Migration shock** | **1.224**** | **1.225**** | **1.819**** | **0.598**** |
| | **[1.046,1.432]** | **[1.047,1.434]** | | **(0.183)** |
| Belongs to Minority | 0.755*** | 0.755*** | 0.755*** | -0.281*** |
| | [0.721,0.790] | [0.721,0.790] | | (0.0204) |
| British White in School | 0.896 | 0.855 | 0.879 | -0.129 |
| | [0.725,1.108] | [0.696,1.052] | | (0.0966) |
| Belongs to Minority*Brit White in School | 1.230** | 1.232** | 1.229** | 0.207** |
| | [1.050,1.441] | [1.052,1.443] | | (0.0709) |
| Lives in Deprived Neighborhood | 1.153*** | 1.153*** | 1.154*** | 0.143*** |
| | [1.116,1.191] | [1.116,1.191] | | (0.0157) |
| UTLA Income Deprivation | 0.176*** | 0.226** | 0.196*** | -1.632*** |
| | [0.0632,0.491] | [0.0791,0.644] | | (0.364) |
| Deprived Neighborhood*UTLA Income Deprivation | 0.553* | 0.549* | 0.546* | -0.604* |
| | [0.291,1.052] | [0.289,1.043] | | (0.331) |
| Big city distance | 0.962 | 0.951 | 0.970 | -0.0303 |
| | [0.800,1.155] | [0.804,1.157] | | (0.0814) |
| CF Stage 1 residuals | | | 0.616** | -0.484** |
| | | | | (0.202) |
| *Individual level controls* | *YES* | *YES* | *YES* | *YES* |
| *UTLA level controls* | *YES* | *YES* | *YES* | *YES* |
| *DWH test (p-value)* | | | | 0.0164 |
| Log likelihood | -66114.045 | | | |
| Observations | 110788 | 110788 | 110788 | 110788 |
| Cluster | 150 | 110 | 110 | 110 |

*Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment, rural/urban area
*Big city distance* measure the distance between each UTLA and the closest largest core urban centre in the Region for each UTLA. Data on the largest core urban centres are from ONS (2019)

| | |
|---|---|
| Shift-share (2001 as baseline) | -0.662*** |
| | (0.013) |
| Controls (all UTLA-level continuous covariates) | *YES* |
| F-stat ex instrument | 19.87 |

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively;*

**Table 14: ML Logit on subsets of population on ethnicity**

| | (1) | (2) |
|---|---|---|
| **Measures of association (Odds ratio)** | UTLA with British white students > 50% of school population | UTLA with British white students < 50% of school population |
| **A8 Migration shock** | **1.249**** | **1.109** |
| | [1.041,1.499] | [0.829,1.4849] |
| *Individual level controls* | *YES* | *YES* |
| *UTLA level controls* | *YES* | *YES* |
| *Cross level interactions* | *YES* | *YES* |
| Log Likelihood | -54332.267 | -54332.267 |
| Observations | 89383 | 21405 |
| Cluster | 113 | 37 |

*Individual level controls*: gender, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively;* errors clustered at UTLA level

Table 15: CF-TSRI estimates with different timespans for exposure to language barriers

| | (1) | (2) | (3) |
|---|---|---|---|
| **Measures of association (Odds ratio)** | Language barriers 2013-2007 | Language barriers 2013-2008 | Language barriers 2013-2009 |
| Language Barriers Exposure | 0.966* | 0.978* | 0.966* |
| | [0.831,1.002] | [0.885,0.997] | [0.998,1.024] |
| **A8 Migration shock** | **2.104*** ** | **2.094*** ** | **2.087*** ** |
| | **[1.388,3.190]** | **[1.394,3.102]** | **[1.409,3.090]** |
| **Lang. Barriers Exposure * A8 Migration shock** | **1.093** ** | **1.038** ** | **1.293** ** |
| | **[1.011,1.067]** | **[1.013,1.184]** | **[1.012, 1.697]** |
| Stage 1 Residuals | 0.541** | 0.540** | 0.542** |
| | [0.348,0.843] | [0.337,0.812] | [0.343,0.856] |
| *Individual level controls* | *YES* | *YES* | *YES* |
| *UTLA level controls* | *YES* | *YES* | *YES* |
| *Cross level interactions* | *YES* | *NO* | *YES* |
| Log Likelihood | -66115.961 | -66115.998 | -66116.204 |
| Observations | 110788 | 110788 | 110788 |
| Cluster | 150 | 150 | 150 |

*Individual level controls*: gender, ethnicity, deprivation of neighbourhood of residency.
*UTLA level controls*: looked-after children, split population, same-sex couples, crime rate, ethnic composition, population size, unemployment

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively;* errors clustered at UTLA level

Table 16 shows that the ML logit converges for different scaled weights. Survey weights are rescaled to alleviate for potentially biased estimation according to the following strategies suggested in the literature $w_{ij}^{A} = w_{ij}\left({n_j}\middle/{\sum_i w_{ij}}\right)$ and $w_{ij}^{B} = w_{ij}\left({\sum_i w_{ij}}\middle/{\sum_i w_{ij}^2}\right)$. Given the large-enough number of clusters (greater than 50), convergence of estimation results allows to focus on unweighted multilevel specification (Asparouhov, 2006; Carle, 2009; Rabe-Hesketh & Skrondal, 2006). Table 15 displays estimates for the ML unconditional logit with different numbers of integration points for each weighting strategy. Estimates converge between the different weights for each considered number of integration points. 3 integration points are chosen as default value to speed up convergence.

**Table 16: ML unconditional logit estimates for different weights and different numbers of integration points**

| *a) Weight A* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | coeff<br>3 int points | coeff<br>5 int points | coeff<br>7 int points | coeff<br>15 int points |
| Intercept | -0.878*** | -0.878*** | -0.878*** | -0.878*** |
| | (0.0159) | (0.0161) | (0.0161) | (0.0161) |
| UTLA level intercept variance | 0.0309*** | 0.0309*** | 0.0309*** | 0.0309*** |
| | (0.00404) | (0.00411) | (0.00411) | (0.00411) |
| Observations | 110788 | 110788 | 110788 | 110788 |
| *b) Weight B* | | | | |
| | coeff<br>3 int points | coeff<br>5 int points | coeff<br>7 int points | coeff<br>15 int points |
| Intercept | -0.878*** | -0.878*** | -0.878*** | -0.878*** |
| | (0.0159) | (0.0161) | (0.0161) | (0.0161) |
| UTLA level intercept variance | 0.0304*** | 0.0304*** | 0.0304*** | 0.0304*** |
| | (0.00398) | (0.00404) | (0.00404) | (0.00404) |
| Observations | 110788 | 110788 | 110788 | 110788 |
| *c) Unweighted* | | | | |
| | coeff<br>3 int points | coeff<br>5 int points | coeff<br>7 int points | coeff<br>15 int points |
| Intercept | -0.870*** | -0.870*** | -0.870*** | -0.870*** |
| | (0.0152) | (0.0152) | (0.0152) | (0.0152) |
| UTLA level intercept variance | 0.0278*** | 0.0278*** | 0.0278*** | 0.0278*** |
| | (0.00410) | (0.00410) | (0.00410) | (0.00410) |
| Observations | 110788 | 110788 | 110788 | 110788 |

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively*

Table 17: Comparison of estimation results for the ML logit baseline model specification with 3 and 15 integration points for each weighting strategy

| | *Unweighted* | | *Weight A* | | *Weight B* | |
|---|---|---|---|---|---|---|
| **Measures of association (Odds ratio)** | 3 int points | 15 int points | 3 int points | 15 int points | 3 int points | 15 int points |
| *Individual level variables* | | | | | | |
| Belongs to non-white minority | 0.740*** | 0.737*** | 0.740*** | 0.740*** | 0.740*** | 0.740*** |
| | [0.706,0.775] | [0.710,0.765] | [0.707,0.776] | [0.707,0.776] | [0.706,0.775] | [0.706,0.775] |
| Male | 0.570*** | 0.570*** | 0.570*** | 0.570*** | 0.570*** | 0.570*** |
| | [0.554,0.586] | [0.555,0.585] | [0.554,0.585] | [0.554,0.585] | [0.554,0.586] | [0.554,0.586] |
| Lives in Deprived Neighborhood | 1.162*** | 1.150*** | 1.162*** | 1.162*** | 1.162*** | 1.162*** |
| | [1.124,1.202] | [1.116,1.186] | [1.124,1.202] | [1.124,1.202] | [1.124,1.202] | [1.124,1.202] |
| *UTLA level variables* | | | | | | |
| Income Deprivation | 0.167*** | 0.153*** | 0.166*** | 0.166*** | 0.167*** | 0.167*** |
| | [0.0617,0.454] | [0.0721,0.326] | [0.0608,0.451] | [0.0608,0.451] | [0.0617,0.454] | [0.0617,0.454] |
| **A8 Migration shock** | **1.237**** | **1.237**** | **1.237**** | **1.237**** | **1.236**** | **1.236**** |
| | **[1.061,1.446]** | **[1.028,1.487]** | **[1.057,1.446]** | **[1.057,1.446]** | **[1.057,1.446]** | **[1.057,1.446]** |
| Rural area | 1.045 | 1.051* | 1.046 | 1.046 | 1.045 | 1.045 |
| | [0.987,1.108] | [0.998,1.106] | [0.987,1.108] | [0.987,1.108] | [0.987,1.108] | [0.987,1.108] |
| Split population | 1.136*** | 1.142*** | 1.137*** | 1.137*** | 1.136*** | 1.136*** |
| | [1.061,1.216] | [1.075,1.212] | [1.062,1.218] | [1.062,1.218] | [1.061,1.216] | [1.061,1.216] |
| Same sex couples | 0.741** | 0.752* | 0.734** | 0.734** | 0.741** | 0.741** |
| | [0.573,0.958] | [0.558,1.015] | [0.565,0.955] | [0.565,0.955] | [0.573,0.958] | [0.573,0.958] |
| UTLA looked after children | 1.004*** | 1.005*** | 1.004*** | 1.004*** | 1.004*** | 1.004*** |
| | [1.003,1.006] | [1.003,1.006] | [1.003,1.006] | [1.003,1.006] | [1.003,1.006] | [1.003,1.006] |
| Unemployment | 1.002 | 1.004 | 1.002 | 1.002 | 1.002 | 1.002 |
| | [0.985,1.019] | [0.991,1.018] | [0.985,1.019] | [0.985,1.019] | [0.985,1.019] | [0.985,1.019] |
| Crime score | 0.995 | 1.008 | 0.994 | 0.994 | 0.995 | 0.995 |
| | [0.921,1.074] | [0.933,1.089] | [0.920,1.074] | [0.920,1.074] | [0.921,1.074] | [0.921,1.074] |
| Ethnic diversity | 0.996** | 0.996* | 0.996** | 0.996** | 0.996** | 0.996** |
| | [0.993,1.000] | [0.992,1.001] | [0.993,1.000] | [0.993,1.000] | [0.993,1.000] | [0.993,1.000] |
| Pop size (ln) | 0.999 | 1.007 | 1.000 | 1.000 | 0.999 | 0.999 |
| | [0.950,1.052] | [0.965,1.050] | [0.950,1.052] | [0.950,1.052] | [0.950,1.052] | [0.950,1.052] |
| Brit white share (school) | 0.871 | 0.871 | 0.895 | 0.895 | 0.896 | 0.896 |
| | [0.699,1.084] | [0.699,1.084] | [0.725,1.105] | [0.725,1.105] | [0.725,1.106] | [0.725,1.106] |
| Observations | 110788 | 110788 | 110788 | 110788 | 110788 | 110788 |
| Cluster | 150 | 150 | 150 | 150 | 150 | 150 |

95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively

Table 18: Detailed Estimates of ML logit with RI, GEE logit and CF-TSRI GLM logit

| | ML logit RI | GEE logit | CF-2SRI-Stage 2 |
|---|---|---|---|
| | Odds ratio | Odds ratio | Odds ratio |
| **A8 Migration shock** | **1.225**** | **1.226**** | **1.922***** |
| | **[1.047,1.432]** | **[1.049,1.433]** | **[1.352,2.733]** |
| Belongs to Minority | 0.755*** | 0.755*** | 0.755*** |
| | [0.721,0.790] | [0.721,0.790] | [0.724,0.787] |
| Brit white in school | 0.897 | 0.899 | 0.882 |
| | [0.726,1.108] | [0.728,1.109] | [0.726,1.071] |
| Belongs to Minority * Brit white | 1.230** | 1.232** | 1.233** |
| in school | [1.050,1.441] | [1.052,1.443] | [1.067,1.424] |
| Lives in Deprived Neighborhood | 1.153*** | 1.153*** | 1.153*** |
| | [1.116,1.191] | [1.116,1.191] | [1.120,1.188] |
| UTLA Income Deprivation | 0.175*** | 0.173*** | 0.189*** |
| | [0.0631,0.486] | [0.0631,0.476] | [0.0990,0.362] |
| Deprived Neighbourhood * | 0.555* | 0.553* | 0.559* |
| UTLA Income Deprivation | [0.293,1.053] | [0.292,1.045] | [0.292,1.071] |
| Male | 0.569*** | 0.570*** | 0.569*** |
| | [0.554,0.586] | [0.554,0.586] | [0.554,0.585] |
| Rural area | 1.058* | 1.057* | 1.055** |
| | [1.000,1.120] | [0.998,1.120] | [1.013,1.098] |
| Split population | 1.134*** | 1.136** | 1.105*** |
| | [1.059,1.214] | [1.062,1.214] | [1.052,1.162] |
| Same sex couples | 0.775* | 0.780* | 1.039 |
| | [0.591,1.016] | [0.598,1.018] | [0.764,1.413] |
| UTLA looked after children | 1.005*** | 1.005*** | 1.004*** |
| | [1.003,1.006] | [1.003,1.006] | [1.003,1.006] |
| Unemployment | 1.003 | 1.004 | 1.004 |
| | [0.987,1.020] | [0.987,1.021] | [0.993,1.014] |
| Crime score | 1.001 | 1.001 | 0.973 |
| | [0.926,1.083] | [0.926,1.083] | [0.909,1.041] |
| Ethnic diversity | 0.998 | 0.998 | 0.996* |
| | [0.994,1.002] | [0.994,1.002] | [0.991,1.000] |
| Pop size (ln) | 1.004 | 1.005 | 1.003 |
| | [0.955,1.056 | [0.956,1.057] | [0.971,1.036] |
| CF Stage 1 residuals | | | 0.577** |
| | | | [0.396,0.840] |
| Log likelihood | -66114.119 | | |
| Observations | 110788 | 110788 | 110788 |
| Cluster | 150 | 150 | 150 |
| | | | CF-2SRI-Stage 1 |
| | | | Coef |
| Shift-Share | | | -0.633*** |
| | | | (0.00965) |
| Brit white in school | | | 0.0569*** |
| | | | (0.00386) |
| UTLA Income Deprivation | | | 0.704*** |
| | | | (0.0159) |
| Rural area | | | -0.0132*** |
| | | | (0.000627) |
| Split population | | | 0.0330*** |
| | | | (0.00128) |
| Same sex couples | | | -0.539*** |
| | | | (0.00508) |
| UTLA looked after children | | | 0.000394*** |
| | | | (0.0000282) |
| Unemployment | | | -0.00407*** |
| | | | (0.000220) |
| Crime score | | | 0.0379*** |
| | | | (0.00126) |

| | |
|---|---|
| Ethnic diversity | 0.00734*** |
| | (0.0000999) |
| Pop size (ln) | 0.00136** |
| | (0.000670) |
| $R^2$ | 0.5428 |

*95% confidence intervals in brackets; ***,** and * stand for statistical significance at 10, 5, and 1% levels, respectively; errors clustered at UTLA level; CF-2SRI is bootstrapped (1000 replications); F-stat ex instrument: 15.58*

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