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Abstract

This paper analyzes ethnic wage gaps in Great Britain by comparing minorities to majority workers in the same local labor market and focuses on the variation of wage gaps across areas. As wage gaps vary across areas, using one single national measure may be misleading. Higher wage gaps across groups are associated with higher occupational segregation and ethnic diversity, while higher wage gaps within groups are associated with higher regional specialization and proportion of co-ethnics. Policies could help by improving job location and selection into occupations across groups.

Keywords: Race; ethnicity; wage gaps; geographical segregation; spatial location; local labor market; multilevel models

JEL Classification: J31; J71; R10; R23

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1. INTRODUCTION

Despite various equality and anti-discrimination legislations, in the UK, as in many other countries, ethnic and racial minorities receive on average lower wages than the (white British) majority. Although some groups are paid on average more than the majority, the literature often refers to such wage differentials as “wage gaps”.[1] Despite extensive research, the reasons for persisting ethnic wage gaps are still debated (Guryan & Charles, 2013). A better understanding of the mechanisms that create ethnic wage gaps is necessary to identify policies that may successfully reduce inequalities among ethnic groups, and that may have a positive impact on socio-economic integration and social cohesion. One important characteristic which has not been systematically taken into account in the literature is the geographical concentration of ethnic minorities in more urbanized and in more deprived areas. This is surprising given the increasing consensus on the importance of location for various socio-economic aspects of people’s lives.

A large part of the literature on ethnic and racial wage gaps focuses on discrimination. Starting from the theoretical models of taste-based (Becker, 1971) and statistical discrimination (Phelps, 1972), part of the empirical literature has tried to identify the effect of the various types of discrimination on ethnic and racial wage gaps (Guryan & Charles, 2013; Lang & Lehmann, 2012). Another part of the literature has instead focused on the impact of individual characteristics such as education, occupation, social class, etc. (Bjerk, 2007; Epstein, Gafni, & Siniver, 2015; Longhi, Nicoletti, & Platt, 2012). However, most of this literature has been largely non-spatial, estimating only one wage gap for the whole country, thus neglecting residential concentration.

Although residential concentration of ethnic minorities in the UK is not as prominent as in the US (Finney & Simpson, 2009), there are relevant differences in socio-economic conditions and in immigration histories across areas, with some hosting much larger shares of minorities than others. Data from the 2011 census for England and Wales show that, although a large proportion of ethnic minorities live in London, different ethnic minorities tend to locate in different areas within London. Indians also concentrate in cities located in the East Midlands of England, while Pakistanis also concentrate in cities in Yorkshire and in the South East of England. Ethnic minorities tend to be overrepresented in more deprived

[1] For precision, here the term “race” is used when the discussion focuses on the US, while the term “ethnicity” is used when the discussion focuses on UK or other European countries.

and in more urbanized areas (Catney & Sabater, 2015; Clark & Drinkwater, 2002), characterized by different job opportunities and different levels of wages on average. Hence, it would be inappropriate to compare an Indian person working in the city of Leicester with a white British person working in London. It is the white British person working in Leicester that forms the appropriate comparison. Yet, most of the literature on ethnic wage gaps does not take location into account.

A large literature, mostly focusing on the US, analyzes the effects of racial residential segregation across neighborhoods within cities on socio-economic outcomes of minorities. Studies have focused on outcomes such as assimilation and integration (Cutler, Glaeser, & Vigdor, 2008; Edin, Fredriksson, & Aslund, 2003; Hatton & Leigh, 2011), or the level of unemployment and wages of minorities (Bentolila, Michelacci, & Suarez, 2010; Cutler & Glaeser, 1997; Hellerstein, Neumark, & McInerney, 2008). This literature aims at explaining how residential location, lack of local jobs and restrictions to mobility and commuting results in worse employment and wage outcomes for blacks and minorities; in contrast, this paper analyzes whether there are differences in outcomes between minorities and the majority when we compare people living in the same area. In addition, because of data availability, this paper does not focus on residential segregation within cities, but on much larger geographical areas. This paper asks whether ethnic wage gaps vary across areas, and to what extent area-level differences in wage gaps are associated with the characteristics of the areas where majority and minority people live and work. In doing so, it explores various possible determinants of differences in wage gaps across areas.

This paper is closer to that strand of literature which analyzes racial wage gaps at the local level in the US. Parks (2012) and Shin and Liang (2014) use random effects multilevel models to estimate area-level racial wage gaps; however, Shin and Liang (2014) focus on wages of racial minorities without any comparison with wages of the white majority, while in her estimate of racial wage gaps across areas Parks (2012) focuses on the impact of characteristics on the level of wages rather than on the distribution of wage gaps across areas. More recently Ananat, Shihe and Ross (2018) find that larger city size and employment density are associated with larger racial wage gaps.

The aim of this paper is to compare wages of minority and majority workers in Great Britain who work in the same local labor market and therefore face the same socio-economic conditions (Northern Ireland is excluded because of data comparability issues). It combines the multilevel approach used by Parks (2012) and Shin and Liang (2014) with the two-step approach used by Ananat et al. (2018). The first step uses multilevel models to estimate area-level ethnic wage gaps, while the second step uses a macro-level model to analyze what factors may explain the variability of the ethnic wage gaps across areas. While Ananat et al. (2018) explain why wage gaps should be affected by city size and employment density, this paper extends this literature by comparing the relative importance of various factors, with the aim to shed light on the effects of occupational segregation and geographical concentration.

This paper contributes to the literature on ethnic wage gaps by including a spatial dimension and providing new evidence on the extent to which ethnic wage gaps vary across areas and what may explain such variation. From a policy perspective, the results suggest that using one single national measure for ethnic wage gaps may be misleading. Since wage gaps vary across areas, it is important to understand in which areas ethnic minorities face a smaller disadvantage compared to the majority. The results suggest that the size of ethnic wage gaps is partly hidden by the fact that minorities tend to concentrate in urban areas, characterized by comparatively higher wages. Occupational segregation and ethnic diversity are associated with larger wage gaps across minority groups, while differences in wage gaps across areas within ethnic groups are associated with higher regional specialization and proportion of co-ethnics. There may be a role for policies focusing on occupational segregation and promoting a more equal selection into occupations across different ethnic groups.

The paper proceeds as follows: Section 2 discusses the modelling strategy, the rationale for using multilevel models and the importance of comparing models with and without covariates. This section also discusses the theoretical and empirical background that motivates the choice of factors that may explain the variation of ethnic wage gaps across areas. Section 3 summarizes the data used in the analysis and provides descriptive statistics. Section 4 discusses the main results as well as their robustness. A critical issue is that of identification since the geographical location of ethnic minorities may be driven by the level of local wages and/or local ethnic wage gaps; however, considerations based on the previous literature and various sensitivity analyses (Section 4.4) confirm the robustness of the results. Finally, Section 5 summarizes and concludes with some implications for policy.

2. METHOD

2.1: Estimating ethnic wage gaps

Ethnic wage gaps measure differences in average wages between the majority and the various minority groups. In the UK, for example, UK-born men who identify themselves as Indian earn about the same as white British men, while UK-born men who identify themselves as Bangladeshi earn about 23 percent less (Longhi & Brynin, 2016). In the academic literature, ethnic wage gaps are often estimated in a regression where the dependent variable is the log of hourly wages, and the main explanatory variables are ethnicity dummies (Algan, Dustmann, Glitz, & Manning, 2010). The estimated coefficients of the ethnicity dummies, when no other covariates are included, are commonly interpreted as a measure of "raw" or "unconditional" ethnic wage gaps.

Ethnic minorities may have different characteristics (e.g. education) than the majority, and this may explain part of the wage gaps. It is straightforward to include in the regression covariates such as level of education or job characteristics that might affect wages and therefore explain ethnic wage gaps. Indeed, most of the academic literature always includes additional controls and does not report raw gaps (Aeberhardt, Coudin, & Rathelot, 2017; Algan et al., 2010). For policy, however, what is of interest are the raw gaps, and how they change when characteristics are taken into account. These characteristics can then be used as policy target in an attempt to reduce ethnic wage gaps. For these reasons, and in contrast with the previous literature, this paper starts with the estimation of raw wage gaps.

More formally, ethnic wage gaps are estimated using a regression model where the dependent variable is the log of hourly wages of individual *i*, with ethnicity *e*, working in area (local labor market) *r* at time *t* ($\ln W_{iert}$) and the explanatory variables of interest are dummies for the ethnicity of the respondent ($\mathbf{EM'}_{iert}$). The vector $\boldsymbol{\beta_1}$ measures the raw ethnic wage gaps for each ethnic minority:

$$\ln W_{iert} = \alpha + \mathbf{EM'}_{iert}\boldsymbol{\beta_1} + \mathbf{T'}_{iert}\boldsymbol{\beta_2} + \mathbf{R'}_{iert}\boldsymbol{\beta_3} + \varepsilon_{iert}. \quad (1)$$

Since the data used for this analysis cover various years, the model also includes dummies for the year-quarter of the interview ($\mathbf{T'}_{iert}$) to control for differences in wages over time that are common to all ethnic groups.[2] In line with the literature, Equation (1) is estimated using OLS.

Since ethnic minorities are overrepresented in deprived areas with comparatively poorer employment prospects, ethnic wage gaps computed at the national level may appear higher than ethnic wage gaps computed at the more appropriate local labor market level. On the other hand, because of the overrepresentation of ethnic minorities in urban areas, where wages are comparatively higher, ethnic wage gaps computed at the national level may appear smaller than those computed at the local level. Overall, whether ethnic wage gaps computed at the local level should be larger or smaller than the conventional measures computed at the national level is an open question.

The simplest way to take into account time-invariant differences across areas that may affect the level of local wages consists of including in the models a set of area dummies ($\mathbf{R}'_{iert}$). Perhaps surprisingly, studies estimating ethnic wage gaps rarely include such dummies and, when included, these are generally for rather large geographic areas, and often refer to the region of residence rather than the region of work (Longhi, Nicoletti, & Platt, 2013). In addition, estimates including and excluding area dummies are rarely compared. Nevertheless, such comparison is informative to distinguish between two opposite effects: because minorities tend to concentrate in more deprived areas, the inclusion of area dummies may decrease (explain) ethnic wage gaps; on the other hand, because minorities also tend to concentrate in more urbanized areas, the inclusion of area dummies may instead increase ethnic wage gaps. Which one of these two effects should prevail is an empirical question that is currently unanswered. It is to answer this question that this paper compares two versions of the model: one including and one excluding dummies for the area of work.

2.2: Area-specific ethnic wage gaps

Even when dummies for the area of work are included, Equation (1) estimates only one (national) wage gap for each ethnic minority group. To estimate ethnic wage gaps at the local labor market level this paper uses random effects multilevel models. In a two-way multilevel random effects model, where individuals are nested within areas, Equation (1) can be rewritten to include time-invariant area-specific intercepts ($\boldsymbol{\alpha}_r$) and 'slopes' ($\boldsymbol{\beta}_{\mathbf{1}er}$):

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[2] Although ethnic wage gaps may change over time, to avoid complications due to small sample sizes for ethnic minorities, the main models are computed for the whole period. Sensitivity analyses restricted to shorter periods are discussed in Section 4.3.

$$\ln W_{iert} = \boldsymbol{\alpha}_r + \mathbf{EM}'_{iert}\boldsymbol{\beta}_{\mathbf{1}er} + \mathbf{T}'_{iert}\boldsymbol{\beta}_{\mathbf{2}} + \varepsilon_{iert}. \qquad (2)$$

The area-specific intercepts ($\boldsymbol{\alpha}_r$) in Equation (2) capture differences in wages across local labor markets that are due to structural factors, similarly to $\mathbf{R}'_{iert}$ in Equation (1), while the area-specific slopes measure ethnic wage gaps for each local labor market. In this model ethnic wage gaps may vary across areas, while the impact of the year-quarter dummies is assumed to be constant across areas. Hence, $\alpha_r = \alpha_{00} + u_{0r}$ and $\beta_{1er} = \beta_{10e} + u_{1er}$ (with *e* = 1 ... 5) where the subscript *e* refers to the ethnic minority groups, α_{00} and β_{10e} are the area-invariant 'fixed effects' while u_{0r} and u_{1er} are random residual errors independent on ε_{iert} and with zero mean (Hox, 2002). Hence, factors that are controlled for in Equation (2) and are therefore picked up by the error term (ε_{iert}) should be independent on the factors that create regional differences in wages and in wage gaps.[3]

If location plays no role for ethnic wage gaps, the area-specific ethnic gaps ($\boldsymbol{\beta}_{\mathbf{1}er}$) should be not statistically different from each other across areas. However, if ethnic wage gaps vary across areas, it is interesting to graphically analyze their variation by plotting their distribution. Although this is rarely done in the literature, a density plot of the ethnic wage gaps can give useful insights on whether the wage gaps vary widely across areas within ethnic groups, or whether differences across ethnic groups are larger than differences within groups (across areas). The plot can also show whether there are overlaps across ethnic groups.

2.3: Effect of area characteristics on ethnic wage gaps

What explains the variation of ethnic wage gaps across areas? The literature has directly or indirectly suggested various possible factors, and we can measure their impact on the area-level wage gaps in a regression where the dependent variable is an estimate of the ethnic wage gap for ethnic group *e* in area *r* ($\widehat{\boldsymbol{\beta}}_{\mathbf{1}er}$, estimated from Equation (2)), and the explanatory variables are area-level characteristics, some of which may also vary across ethnic groups ($\mathbf{X}'_{er}$):

[3] The results indicate that these assumptions may not be too strong. In Table 1 treating α_r as area specific dummies (Column 2) or as random intercepts (Column 3) lead to very similar results. In addition, as discussed in Section 4.3, models including explanatory variables in equation (2), which may make the assumption of independence less strong, lead to similar conclusions as the models excluding them.

$$\widehat{\boldsymbol{\beta}}_{\mathbf{1}er} = \alpha_0 + \mathbf{X}'_{er}\boldsymbol{\beta}_{\mathbf{0}er} + \varepsilon_{er}. \tag{3}$$

Equation (3) is estimated by weighted least squares (with robust standard errors), where the weights are the inverse of the standard error of the estimate (of $\widehat{\boldsymbol{\beta}}_{\mathbf{1}er}$), so that more precise estimates are given higher weight than less precise ones. In addition, since most areas show wage gaps (i.e. negative values), for ease of interpretation the gaps have been reversed, so that higher values of the dependent variable reflect larger wage gaps.

As already mentioned, ethnic minorities are more likely to concentrate in more urbanized and in more deprived areas, with fewer (good) job opportunities (Finney & Lymperopoulou, 2014). Not only wages tend on average to be higher in more urbanized areas (Wheaton & Lewis, 2002; for the US, Ananat et al. (2018) find that the urban wage premium increases more slowly for blacks than for whites and that racial wage gaps increase with city size. To test if also in the UK ethnic wage gaps increase with urbanization, one of the explanatory variables included in $\mathbf{X}'_{er}$ is population density.

To measure job opportunities $\mathbf{X}'_{er}$ also includes the local unemployment rate. The 'wage curve' literature suggests a negative relationship between the local unemployment rate and local wages (Blanchflower & Oswald, 1995; Nijkamp & Poot, 2005) while 'correspondence studies' suggest the presence of discrimination in hiring of ethnic minorities (Zschirnt & Ruedin, 2016). If, for example because of stereotypes or statistical discrimination (Guryan & Charles, 2013), majority workers are preferred when unemployment rate is higher, those minority workers who do have a job are likely to be positively selected and may receive comparatively higher wages. In this case, we would expect local ethnic wage gaps to show a negative relationship with the local unemployment rate.

Local ethnic wage gaps may also be related to the demographic composition of the local population. Sociological theories suggest that because of competition over scarce resources between the majority and minority groups, an increase in the size of the minority group will be perceived as an economic and political threat by the majority group. The majority group will react with 'defensive discrimination' by preventing minorities from accessing resources (for example education) and high status (high wage) jobs (Tienda & Lii, 1987). Some authors have found that wage gaps are larger when minorities are in areas of high concentration, where the presence of minorities is more 'visible' and is more likely to be considered as a 'threat' by the majority group (Johnson, Pais, & South, 2012; Shin & Liang, 2014). As the size of the minority group increases, their bargaining power and their political and economic influence will increase as well, leading to decreasing discrimination (Tienda & Lii, 1987). We therefore expect the effect of the overall proportion of minorities, measured by the proportion of nonwhite British people in the area, to have an inverse U-shape: wage gaps will be larger with low and high proportions of nonwhite British.

A negative relationship between the proportion of nonwhite British and occupational segregation may also be the result of the relocation of jobs to new areas. The US, for example, has experienced employment decentralization from city centers to the suburbs at the same time when white people relocated from city centers to the suburbs. Since blacks remained segregated in the city center, this resulted in an increase in occupational segregation in those particular jobs that did not relocate (Boustan, 2012; Boustan & Margo, 2009). Although this process of relocation may not have been so prominent across areas in the UK, we may expect a negative relationship between occupational segregation and the proportion of nonwhite British if both jobs and white British, but not minorities, relocated to other areas.

From a different perspective, Roback (1982) relates wages to amenities and house prices. Workers who value diversity, e.g. because it translates into a wider variety of goods and services, may accept lower wages in areas that are more ethnically diverse and may require higher wages in areas without this type of amenity. This would lead to a negative effect of ethnic diversity on wages; the effect on wage gaps, however, would depend on the relative value that minorities and majority workers place on diversity. If there is no difference in the value that majority and minorities place on diversity, then ethnic diversity in the area may have no impact on wage gaps. However, if minority workers value diversity more than majority workers, wage gaps would be higher in areas that are more ethnically diverse.

According to the ethnic wage gap literature, occupation – and indirectly occupational segregation – explains a large part of the ethnic wage gaps (Elliot & Lindley, 2008; Longhi & Brynin, 2016). Given the unequal distribution of firms and jobs across areas, it is possible that the geographical concentration of minorities in areas characterized by low quality jobs – rather than discrimination due group competition suggested above – is the main contributor to occupational segregation and therefore ethnic wage gaps. Occupational segregation may result from residential segregation if minorities are more likely to live and work in areas that specialize in low quality (e.g. elementary) occupations while white British are more likely to live and work in areas that specialize in good quality (e.g. professional) occupations. Hence, there may be no occupational segregation within each area, but the combination of regional specialization and residential sorting may indirectly result in occupational segregation when the measure is computed at the national level. In this case it would not be occupational segregation that explains the ethnic wage gaps, but regional specialization in combination with geographical sorting. On the other hand, if occupational segregation varies across areas, we may expect a positive relationship between the ethnic wage gaps and the level of occupational segregation; the measure of regional specialization may or may not have an additional impact.

The last factor analyzed here relates to co-ethnic networks. Minorities may prefer to live in areas with high proportions of co-ethnics because this may make it easier to access ethnic goods and because they enjoy interaction with people with whom they share interests and cultural norms (Andersson, Musterd, & Galster, 2014; Costa & Kahn, 2003). Some authors suggest that the presence of co-ethnics may be considered an amenity and people belonging to a minority may be prepared to accept lower wages to be able to live and work in areas with a larger community of co-ethnic people (Chiswick & Miller, 2005; Hellerstein, Kutzbach, & Neumark, 2014). Living in areas with large communities of co-ethnics may reduce the cost of assimilation into the host society (Cutler et al., 2008) but also the incentive to integrate since this may reduce the need to interact with people from the majority (Edin et al., 2003; Hatton & Leigh, 2011). Networks of co-ethnics may increase the probability of finding a job via informal referrals (Bayer, Ross, & Topa, 2008; Hellerstein, McInerney, & Neumark, 2011) and may have a positive impact on wages (Damm, 2009; Edin et al., 2003). On the other hand, the impact on labor market opportunities may be negative if the co-ethnic community has a high unemployment rate or concentrates in low pay jobs (Battu, Seaman, & Zenou, 2011; Bentolila et al., 2010; Cutler & Glaeser, 1997) and if people from the majority are more likely than minorities to have access to information on better jobs (Gorinas, 2014). The expectation, therefore, is that the proportion of co-ethnics may affect wage gaps in a non-linear way, which may follow a U-shape form.

In summary, $\mathbf{X}'_{er}$ includes population density, the unemployment rate, the proportion of nonwhite British and its square, a measure of ethnic diversity, the proportion of co-ethnics and its square, as well as the measures of regional specialization and occupational segregation. These are discussed in details in the next Section.

To take into account that different types of jobs require different types of skills or human capital (some types of jobs, for example, require a degree), before estimating Equation (3) we first re-estimate Equation (2) after including a few additional explanatory variables: a series of dummies for educational qualifications, age and its square as a measure of potential labor market experience, and a dummy for minorities born in the country to control for experience and education acquired in the UK. This should partly account for differential occupational sorting of majority and minority workers (Aslund & Skans, 2010) and for the fact that minorities and majority working in the same area may still have different levels of human capital. This should also partly relax the assumption of independence between the random component of the area-specific ethnic wage gaps (u_{1er}) and the error term ε_{iert} in Equation (2). Controlling for human capital is also relevant since some of the explanatory variables used in Equation (3) reflect occupational segregation. However, the conclusions do not change if the models are estimated without including the human capital variables; this is discussed in Section 4.3.

Although the estimated ethnic wage gaps $\boldsymbol{\beta}_{\mathbf{1}er}$ differ between the models with and without covariates, we should not conclude that the coefficient estimated from a model without covariates is biased; rather, the ethnic wage gaps in the two models have different interpretations. As discussed in Section 2.1, the ethnic wage gaps estimated in a model without covariates measure the 'raw' gaps for the ethnic minority group (these are the figures generally userul for policy), while the wage gaps estimated in a model with covariates measure the 'adjusted' gaps where minority workers are compared to majority workers with similar characteristics (e.g. human capital).

3. DATA AND DESCRIPTIVE STATISTICS

3.1: Individual-level analysis

The empirical analysis is based on the UK Labour Force Survey (LFS), which is a quarterly household survey interviewing individuals living at private addresses in the UK. The LFS provides information on individual characteristics, including ethnicity, country of birth, and year of arrival in the UK, as well as information on labor market outcomes. Crucially, and in contrast with other surveys including only data on the place of residence, the LFS provides data on both the "Unitary Authority/Local Authority Districts" (areas) of residence and of work. Overall, the data identify 348 districts of work across Great Britain. Districts of work are used here as a proxy for local labor markets; Section 4.4 discusses the robustness of the results to this choice.

Because of its large sample size, the LFS is the only dataset that allows wage analysis for reasonably homogeneous ethnic groups (Longhi et al., 2013); the focus here is on the five largest ethnic minorities in the UK: Indian, Pakistani, Bangladeshi, Black African, and Black Caribbean, in comparison to White British people. All other ethnic minorities, including 'other whites' are excluded from the analysis. In addition, to avoid complications due to different labor market attachment of women belonging to the different ethnic groups, the focus here is on men only.

This paper pools data from the first quarter of 2001, the first full year when comparable data on the districts of residence and of work are available, up to the last quarter of 2017 (the most recent data available). Although the LFS has a rotating panel structure, where people are interviewed for up to five successive quarters, data on wages are only collected from the first and fifth interviews. To avoid having to deal with differential attrition across ethnic groups, the focus here is only on the first interview.

3.2: Aggregate-level analysis

As already mentioned, the factors that might explain the variation of the ethnic wage gaps across local labor markets are population density, the unemployment rate, the proportion of co-ethnics, the proportion of nonwhite British, and measures of regional specialization, occupational segregation and ethnic diversity. All these measures vary by area. Population density is computed by combining data on the geographical size of each district with data from the official population estimates produced by the UK Office for National Statistics for the period 2001-2017. All other measures are computed using the LFS, aggregating the data across different years and including all workers (without distinctions by gender nor ethnicity). All respondents in all waves have been included in the computation of the indices below, and each respondent has been weighted by the inverse of the number of times they appear in the data.[4] Hence, the size of the samples used to compute the indices is significantly larger than the size of the samples used in the wage regressions.

The unemployment rate is computed as the proportion of adult respondents (aged 16 or over) who are ILO unemployed over those who are active (i.e. employed, self-employed or unemployed). The proportion of nonwhite British is computed as the number of adults who

[4] As an alternative approach, the aggregate variables have been computed separately by quarter and then their quarterly values averaged over time. The results are consistent with the ones presented here.

do not identify themselves as white UK born British over the number of adults living in that area. The proportion of co-ethnics is computed as the number of adults with the same ethnicity as the respondent divided by the number of adults living in that area.

The measure of occupational segregation is computed using the dissimilarity index (Duncan & Duncan, 1955; Gorard & Taylor, 2002) where the proportion of majority workers employed in each occupation *o* over the total number of majority workers employed in any occupation ($EmplMaj_{or}/\sum_o EmplMaj_{or}$) is compared with the proportion of minority workers employed in each occupation *o* over the total number of minority workers employed in any occupation ($EmplEthnic_{or}/\sum_o EmplEthnic_{or}$):

$$D_{er} = 0.5 \sum_o |EmplMaj_{or}/\sum_o EmplMaj_{or} - EmplEthnic_{or}/\sum_o EmplEthnic_{or}|;$$

where $\sum_o$ indicates the sum across occupational groups; occupations are classified according to the one digit Standard Occupational Classification.[5] The index varies from zero, when the occupational distribution of ethnic minorities is the same as that of the majority, to one, which indicates complete segregation. The index is computed separately for each minority group, using the majority group as reference. It is worth noting that the index only indicates the presence of segregation, not whether minorities are segregated in good or bad jobs; minority segregation is generally towards the bottom of the occupational distribution (Demireva, 2011; Elliot & Lindley, 2008; Longhi & Brynin, 2016).

The measure of regional specialization is computed using the Krugman index (Krugman, 1991) where the proportion of workers employed in a certain occupation in a certain area *r* ($Empl_{or}/\sum_o Empl_{or}$) is compared with the proportion of workers employed in a certain occupation at the national level ($\sum_r Empl_{or} / \sum_r \sum_o Empl_{or}$):

$$S_r = \sum_o |Empl_{or}/\sum_o Empl_{or} - \sum_r Empl_{or} / \sum_r \sum_o Empl_{or}|;$$

where $\sum_r$ indicates the sum across areas. A value of zero indicates that the occupational distribution within the area is the same as the distribution at the national level, while higher values indicate higher levels of specialization in one or few occupations. The index is

[5] For simplicity we ignore changes in the Standard Occupational Classification over time. The results do not change if the analysis is based on a shorter period of time, when the Standard Occupational Classification has not changed (Section 4.3).

computed for occupations – instead of industries – since occupations are a better indicator of types of jobs than industries are.

Finally, ethnic diversity in the area is measured by the index of fractionalization (Alesina, Devleeschauwer, Easterly, Kurlat, & Wacziarg, 2003):

$$F_r = 1 - \sum_e (Ehnicity_{er} / \sum_e Ehnicity_{er})^2;$$

where $\sum_e$ indicates the sum across ethnic groups (this includes all ethnic groups analyzed here, including White British, with the addition of a residual group of "other" ethnicity). The index ranges between zero and one and measures the probability that two people randomly drawn from the population belong to the same group. Higher values indicate higher levels of ethnic diversity.

3.3: Descriptive statistics

There are clear differences among ethnic groups (Table 1). In terms of earnings, all ethnic minorities receive on average lower hourly wages than White British, with the only exception of Indians, who receive higher wages on average. Minorities also differ in terms of educational qualifications: Indian, Pakistani and Black African men are more likely than White British men to hold a university degree or higher level qualification (NVQ Level 4). Bangladeshis have similar proportions of people with the highest level of qualification than White British, while for Black Caribbean men the proportion is much lower. For middle-level qualifications Black Caribbean men have similar proportions than White British while all other minority groups have lower proportions. However, all minorities are more likely than White British to hold the lowest qualification levels (Below NVQ 2); this is partly due to foreign qualifications that may not be recognized in the UK. This shows a polarization of qualification levels among ethnic minorities which is not present for White British.

Bangladeshis and Pakistanis are the youngest group on average (34-35 years of age) while for Black Caribbean men the average age is 41, similar to White British. In terms of immigration, the proportion of second generations in the sample is highest for Black Caribbean men, 65 percent of whom were born in the UK, while it is much lower for the other ethnic minorities: 38 percent among Pakistani, 31 percent among Indian, 24 percent among Bangladeshi and only 14 percent among Black African men.

TABLE 1 ABOUT HERE

The aggregate variables have been computed by area and exclude white British, and Table 1 shows averages across areas where the different minorities work. Occupational segregation is largest for Bangladeshis and smallest for Indians; while all minorities experience similar levels of regional specialization, this is slightly higher for Indians and Blacks, and slightly lower for Bangladeshis. Ethnic diversity, population density and the proportion of nonwhite British are slightly higher for Bangladeshis and Pakistanis compared to the other groups.

4. EMPIRICAL FINDINGS

4.1: Ethnic wage gaps

Estimates of ethnic wage gaps obtained using the various methods described in Sections 2.1 and 2.2 are shown in Table 2. Wage gaps estimated without dummies for area of work are in Column (1) and are consistent with previous research: while Indian men appear to be paid slightly more on average than White British men, Black Caribbean men experience a wage gap of about 11 percent (for a coefficient of -0.120) while the wage gap for Black Africans is about 15 percent. Wage gaps are much larger for Pakistani (about 23 percent) and Bangladeshi (35 percent) men. Perhaps surprisingly, the inclusion of dummies for the area of work, Column (2), substantially increases wage gaps for all ethnic minority groups, ranging now from about 9 percent for Indians to more than 46 percent for Bangladeshis. This suggests that ethnic minorities are more likely than White British people to work in high-density areas that pay comparatively higher wages, and not taking this into account would partially hide the real ethnic wage gaps. This, however, does not answer the question of how wages of ethnic minorities compare to those of white British people in the same local labor market.

The results of the random effects multilevel models are in Columns (3) and (4) of Table 2. Column (3) shows the results of a multilevel model with random intercepts but gaps that do not vary across areas; this is comparable to the OLS model with dummies for area of work. The estimated differences in wages are similar to the OLS ones, although marginally smaller for all ethnic minorities. Average ethnic wage gaps reduce when the estimated gaps are allowed to vary across areas as in Column (4); here the comparison is between wages of minorities and majority working in the same local labor market. The wage gaps reported in Column (4) represent the fixed component ($\boldsymbol{\beta}_{10e}$, see Section 2.2) and are smaller than those estimated by all other models with the exception of OLS without area dummies. The results show no wage gaps for Indians on average but substantial gaps for all other minorities.

TABLE 2 ABOUT HERE

Since the ones reported in Column (4) represent only the fixed component, some areas may have much lower ethnic wage gaps than others. Hence, it is also interesting to analyze how the ethnic wage gaps vary across areas.[6]

Figure 1 shows the (smoothed) distribution of the unconditional area-specific wage gaps by ethnic group. The horizontal axis shows the wage gaps (when negative) or wage advantages (when positive, and minorities are paid more than the majority). The vertical axis shows the density of each distribution, i.e. the number of areas with that wage gap. This confirms that Bangladeshi men experience the largest wage gaps on average, Indians experience no wage gaps on average, while the three remaining minorities have similar experiences in terms of wage gaps. The new information conveyed by this figure is the variation of the wage gaps across groups and across areas. For Indians ethnic wage gaps vary across areas more than for other minorities, with wage gaps in roughly half of the areas, and wage advantages in the remaining half. For all other groups wage gaps are negative in almost all areas.

FIGURE 1 ABOUT HERE

While there is substantial overlap of wage gaps for Pakistani, Black African and Black Caribbean men, ethnic wage gaps for Indians tend to be closer to zero, while those for Bangladeshis are much farther away from zero. It could be argued that wage gaps differ more across groups than across areas within groups. It is worth noticing, however, that to obtain more precise estimates of the area-specific ethnic wage gaps multilevel models 'shrink' less accurate coefficients back to the mean (Hox, 2002). This may reduce the variability of the area-specific gaps shown in Figure 1 and of the dependent variables in the

[6] The Likelihood Ratio test in Column (4) of Table 1 suggests that ethnic wage differentials vary significantly across areas; this is true jointly and separately for each ethnic minority – the additional ethnic-specific tests are not shown here but available on request.

aggregate models, thus potentially reducing the explanatory power of the explanatory variables. The estimates shown, therefore, are likely to be conservative.

4.2: Effect of area characteristics on ethnic wage gaps

As discussed in Section 2.3, to take into account that different types of jobs require different skills, a set of models similar to the ones in Table 2 has been re-estimated after including a set of variables aiming at measuring skills or human capital. The results are in Table A1 and Figure A1 and are consistent with the ones in Table 2, although with small variations. As expected, and in line with the literature (Longhi & Brynin, 2016) after controlling for human capital the wage gaps for Indians become negative. The variation in ethnic wage gaps across areas becomes lower for Pakistanis, suggesting that part of the differences in wage gaps across areas is due to sorting across areas by skills. The reverse is true for Bangladeshi, while there seem to be no major difference for the other ethnic minorities.

The aggregate models (Equation (3)) use as dependent variable the area-specific ethnic wage gaps estimated from the model in Column (4) of Table A1; the results are in Table 3, which shows two different versions of the model, one excluding (Column (1)) and one including (Column (2)) dummies for ethnic groups. While the first model explains differences across ethnic groups, the second model explains differences within ethnic groups. Hence, the comparison of the coefficients of the two models is informative. The large increase in the adjusted R2 when the ethnic dummies are included is in line with the previous tentative conclusion that ethnic wage gaps differ across ethnic minorities more than they differ across areas within ethnic minorities. The positive message here is that the place where minorities live and work does not seem to massively affect their outcomes in comparison to White British people. Hence, if there is an area effect on wages, this seems similar for minorities and White British workers.

All coefficients in Table 3 are in line with the expectations discussed in Section 2.3. Column (1) of Table 3 suggests that wage gaps tend to be larger in areas characterized by more occupational segregation and in areas that are more ethnically diverse. However, while these factors seem important in explaining differences in wage gaps across minority groups, they do not seem to explain the variation of the ethnic wage gaps within groups across areas. In contrast, regional specialization and the proportion of nonwhite British do not seem to play a role in explaining ethnic wage gaps across groups. The coefficient of regional specialization becomes statistically significant at 10 percent in Column (2), thus suggesting that the spatial distribution of jobs might play a role in explaining differences in ethnic wage gaps across regions within groups more than the proportion of nonwhite British (and group competition theories).

The proportion of co-ethnic is associated with lower ethnic wage gaps in a non-linear way in the first model, while in the second model it is associated with higher wage gaps. Those groups who live in areas with higher proportions of co-ethnics, e.g. Indians, tend to have lower ethnic gaps than those groups who live in areas with lower proportions of co-ethnics (e.g. Bangladeshis, see Table 1). Within ethnic minorities, however, those who work in areas with higher proportions of co-ethics, relatively to other workers of the same group, do experience higher wage gaps, consistent with a negative effect of (poor) social networks.

The unemployment rate is statistically significant at the 10 percent level in the second model, consistent with the idea that, within ethnic groups, those minorities who do have a job in high unemployment areas are positively selected and therefore experience lower wage gaps compared to White British workers. The analysis of the probability of having a job would be an interesting further direction for research.

Finally, the models do not show any statistically significant impact of population density. These results are not necessarily inconsistent with Ananat et al. (2018) since, besides looking at a different country and types of minorities, they focus on city size and employment instead of population density.

TABLE 3 ABOUT HERE

4.3: Robustness tests

The choice of the variables indicating human capital is somehow arbitrary and, due to missing values, it also reduces sample sizes (Table 1). Hence, to check the robustness of the results, the aggregate models have also been estimated without including any covariate in the individual-level model (i.e. the model used is the one in Column (4) of Table 2). The results of the aggregate models are in the first column of Tables A2 (for the models without ethnic dummies) and A3 (for the models with ethnic dummies) and the main conclusions do not change. The coefficients become slightly larger since they also pick up differences in e.g. education across areas and ethnic groups.

The current analysis is based on a long period (2001-2017) and assumes that ethnic wage gaps have been stable for a long time. This is to have larger sample sizes. A sensitivity analysis using only the most recent years (2010-2017) is in the Appendix, in Columns (2) of Tables A2 and A3; the conclusions from Table 3 do not change.

4.4: Endogenous location of ethnic minorities

An important issue is the extent to which residential choices of ethnic minorities are driven by exogenous factors such as family ties instead of being driven by the types of jobs, the average wage level, or wage gaps in an area. In the UK, the ethnic clusters date back to various post-war waves of immigration and developed often in relation to housing and manufacturing job availability at the time of entry in the country (Castles, De Haas, & Miller, 2014); with the declining of manufacturing, labor market conditions have changed significantly over time but the residential clusters have remained stable. Residential mobility in the UK is low: data from the British Household Panel Survey and the UK Household Longitudinal Survey suggest that only 10 percent of the population changes residence in any given year (including short distance moves) and only about 10 percent of movers (i.e. 1 percent of the total) report that the move was directly or indirectly related to a job. This suggests that the choice of location is more likely to be driven by factors such as proximity to family or friends than by labor market considerations. In line with this, a recent UK study by Petrongolo and Manning (2017) suggests that unemployed people, and especially low-skill workers, tend to search across short distances, thus confirming that geographical mobility is unlikely to be a relevant factor in this analysis.

As an additional robustness test, the models have been re-estimated using a different geographical definition of local labor markets. UK districts are administrative boundaries which are sometimes smaller than travel-to-work areas (which are not available with these data); since issues of endogeneity should be reduced when using larger geographical areas, the main models have also been re-estimated using counties. Counties are geographically larger than districts, there are about 50 for this analysis (London is used as one single county). The results, not shown here but available on request, are in line with those in Table 3 although some coefficients lose statistical significance, possibly due to the smaller number of areas.

To further analyze the robustness of the results to endogeneity resulting from workers' residential choices, following Cutler and Glaeser (1997), and more recently Hellerstein et al. (2014), the models have also been re-estimated focusing only on workers who were already living at their current address at least two years before starting the current job. For these respondents the decision on where to live is likely to be predetermined and therefore unrelated to their current job.[7] The results are in Columns (3) of Tables A2 and A3, and the main conclusions do not change.

Location is less likely to be endogenous for workers with lower levels of education, who tend to face geographically smaller labor markets (Nimczik, 2016; Petrongolo & Manning, 2017). Hence, an additional robustness test compares models estimated including either only workers who hold a university degree, or including only those who do not. The results are in Tables A2 and A3, Columns (4) for graduates and Columns (5) for non-graduates. Occupational segregation is associated with higher wage gaps for non-graduates, but not for graduates, while the proportion of co-ethnics seems to affect both (Table A2). Within ethnic groups, a higher proportion of co-ethnics is associated with higher wage gaps for graduates but not for non-graduates, consistent with the idea that low quality social networks may lead to e.g. over-qualification.

5. CONCLUSIONS

This paper has investigated ethnic wage gaps in Great Britain by taking into account the different geographical concentration of minorities and majority. The aim was to provide an account of ethnic wage gaps by comparing minorities to the majority working in the same local labor market. The results suggest that, when computed at the national level, the size of ethnic wage gaps is partly hidden by the fact that minorities tend to concentrate in urban areas, characterized by comparatively higher wages. In addition, ethnic wage gaps vary across areas. For example, while the average wage gap at the national level for Indians appears very small, there seem to be large differences across areas: while in some areas Indians experience wage gaps, in others they experience wage advantages. All other minority groups seem to experience wage gaps in all areas, although the gaps seem larger in some areas than in others. Wage gaps differ more across minority groups than within groups across areas. The first tentative conclusion is that the place where minorities live and work may not massively affect their outcomes in comparison to White British people.

Why do ethnic wage gaps differ across areas for people belonging to the same minority? This paper has discussed various possible explanations and found that more

[7] The LFS does not follow people if they move residence, but only ask a few question about how long people have lived at the same address before entering the survey.

occupational segregation and ethnic diversity are associated with larger wage gaps across minority groups, but do not seem to explain the variation of the ethnic wage gaps within groups across areas. Within groups, ethnic wage gaps are larger in areas characterized by higher regional specialization and proportion of co-ethnics; these results are consistent with a negative effect of (poor) social networks and point to the importance of the spatial distribution of jobs. Policies aimed at improving the types of jobs available in areas where minorities concentrate may play a small part in reducing the variation of ethnic wage gaps across areas within groups. There also seems to be a role for policies focusing on occupational segregation and promoting a more equal selection into occupations across different ethnic groups. However, more research is needed to explain the determinants of occupational segregation, how and why it differs across areas and ethnic groups, also in relation to (un-)employment.

Finally, the aim of this paper was to identify factors that may drive inequalities within areas by analyzing differences in ethnic wage gaps – rather than in the level of wages – across areas. It still is possible that areas with low inequality between minorities and the majority are also characterized by lower levels of wages on average and that minority workers in areas with low inequalities compared to the majority are still worse off e.g. in terms of wage levels than minority workers in areas with higher inequalities compared to the majority. The analysis of the association between wage gaps and the level of wages is also left for future research.

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Population estimates are available from the Office for National Statistics (www.ons.gov.uk).

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Tables and Figures

TABLE 1: Descriptive statistics by ethnic group

	White British	Indian	Pakistani	Bangladeshi	Black African	Black Caribbean
Individual-level models:						
- Obs. max (no covariates)	173,360	4,683	2,029	840	2,167	1,459
- Obs. min (with covariates)	149,883	4,113	1,717	690	1,932	1,206
Hourly wages	14.27	15.32	11.29	9.66	11.73	12.63
NVQ Level 4 (degree)	.354	.556	.447	.384	.563	0.295
NVQ Level 3	.183	.092	.114	.113	.104	.180
NVQ Level 2	.237	.097	.107	.120	.098	.244
Below NVQ 2	.226	.255	.333	.383	.235	.281
First generation	--	.692	.624	.757	.861	.345
Second generation	--	.308	.376	.243	.139	.655
Age	41	39	35	34	39	41
Aggregate variables						
Occupational segregation		.272	.297	.335	.305	.295
Regional specialization		.184	.179	.173	.183	.181
Ethnic diversity		.282	.298	.310	.285	.283
Pop. density (person per ha)		14.3	15.9	18.2	14.8	15.2
Prop. nonwhite British		.188	.200	.206	.189	.186
Prop. co-ethnics		.017	.013	.007	.012	.007
Unemployment rate		.056	.057	.058	.056	.055

-- zero by definition

TABLE 2: Average unconditional ethnic wage gaps at the national level

	(1) OLS	(2) OLS	(3) Multilevel	(4) Multilevel
Indian	0.032*	-0.096+	-0.093*	-0.001
	(0.009)	(0.039)	(0.009)	(0.017)
Pakistani	-0.265*	-0.324*	-0.322*	-0.268*
	(0.013)	(0.030)	(0.013)	(0.019)
Bangladeshi	-0.432*	-0.610*	-0.607*	-0.578*
	(0.021)	(0.060)	(0.020)	(0.024)
Black African	-0.167*	-0.336*	-0.332*	-0.241*
	(0.013)	(0.067)	(0.012)	(0.019)
Black Caribbean	-0.120*	-0.272*	-0.268*	-0.239*
	(0.016)	(0.038)	(0.015)	(0.019)
Area of work dummies	no	yes		
Gaps by	ethnicity	ethnicity	ethnicity	area and ethnicity
LR test vs. linear model			16962*	17327*
LR test for area-specific gaps				365*
Adjusted R2	.049	.138		
Observations	184,538	184,538	184,538	184,538

+ Significant at 5 percent, * Significant at 1 percent
Standard errors in parenthesis, those in Column (2) are clustered by county. Other explanatory variables: year-quarter of the interview.

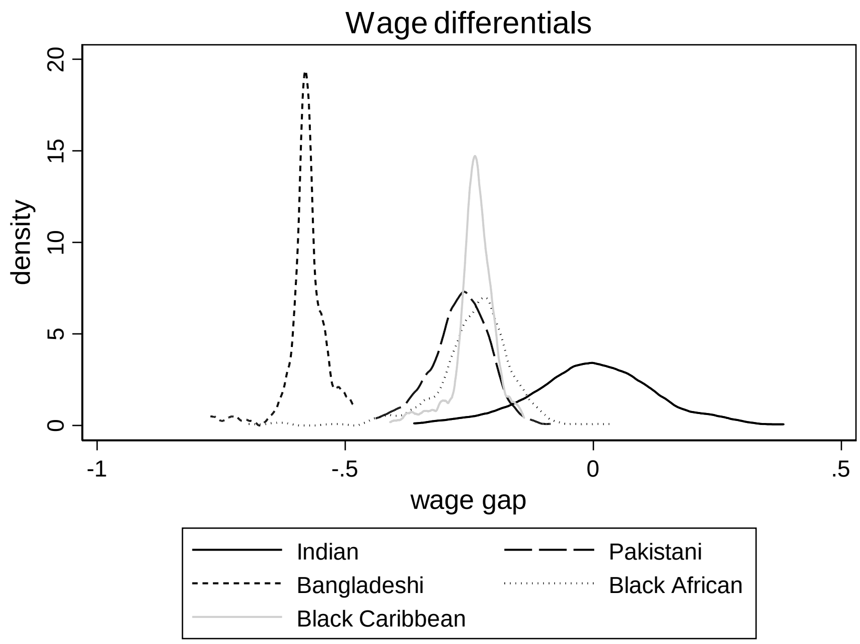

FIGURE 1: Distributions of unconditional ethnic wage gaps across areas
Derived from the model in Table 2, Column (4)

TABLE 3: Determinants of ethnic wage gaps across areas

	(1)	(2)
Regional specialization	-0.009	0.059
	(0.056)	(0.031)
Occupational segregation	0.285*	-0.042
	(0.060)	(0.032)
Ethnic diversity	0.871*	-0.214
	(0.334)	(0.161)
Proportion non White British	-0.841	0.465
	(0.644)	(0.314)
Prop. nonwhite British square	0.440	-0.238
	(0.409)	(0.213)
Proportion of co-ethnics	-2.551*	0.531*
	(0.341)	(0.181)
Proportion of co-ethnics square	10.326*	-0.095
	(1.860)	(0.700)
Population density	-0.000	-0.000
	(0.000)	(0.000)
Unemployment rate	-0.120	-0.255
	(0.304)	(0.151)
Intercept	0.093*	0.091*
	(0.028)	(0.013)
Dummies for ethnicity	No	Yes
Adjusted R2	.125	.783
Observations	1,120	1,120

+ Significant at 5 percent, * Significant at 1 percent

Robust standard errors in parenthesis, dependent variable: estimated ethnic wage gaps by areas (reverse-coded: higher values identify larger gaps); the models are weighted by the inverse of the standard error of the estimated the wage gaps.

Appendix -- Additional Tables and Figures

TABLE A1: Average ethnic wage gaps at the national level conditional on human capital

	(1) OLS	(2) OLS	(3) Multilevel	(4) Multilevel
Indian	-0.069*	-0.161*	-0.158*	-0.105*
	(0.009)	(0.031)	(0.009)	(0.015)
Pakistani	-0.261*	-0.303*	-0.301*	-0.279*
	(0.013)	(0.041)	(0.013)	(0.017)
Bangladeshi	-0.354*	-0.497*	-0.494*	-0.478*
	(0.020)	(0.051)	(0.019)	(0.023)
Black African	-0.284*	-0.401*	-0.397*	-0.332*
	(0.012)	(0.060)	(0.011)	(0.017)
Black Caribbean	-0.180*	-0.301*	-0.297*	-0.291*
	(0.016)	(0.037)	(0.016)	(0.019)
Area of work dummies	no	yes		
Gaps by	ethnicity	ethnicity	ethnicity	area and ethnicity
LR test vs. linear model			11897*	12138*
LR test for area-specific gaps				241*
Adjusted R2	.314	.368		
Observations	159,541	159,541	159,541	159,541

+ Significant at 5%, * Significant at 1%

Standard errors in parenthesis, those in Column (2) are clustered by county. Other explanatory variables: age and its square, dummies for qualification, a dummy for born abroad, and dummies for year-quarter of the interview.

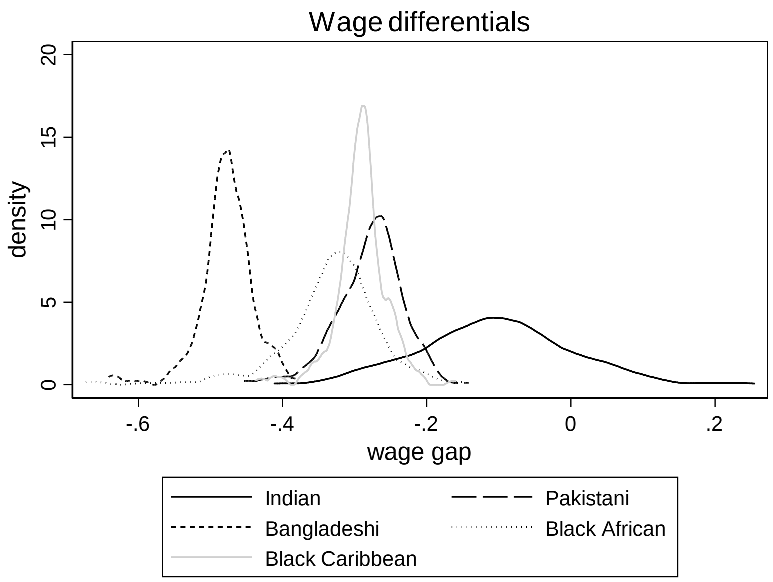

FIGURE A1: Distributions of ethnic wage gaps across areas conditional on human capital
Derived from the model in Table A1, Column (4)

TABLE A2: Determinants of ethnic wage gaps across areas -- sensitivity -- models without dummies for ethnicity

	(1) No controls for skills	(2) Shorter time	(3) Lived at address more than 2 years before job started	(4) Only graduates	(5) Only non graduates
Regional specialization	-0.045	-0.073	0.035	0.019	-0.017
	(0.075)	(0.059)	(0.049)	(0.074)	(0.058)
Occupational segregation	0.477*	0.411*	0.279*	0.118	0.419*
	(0.081)	(0.060)	(0.049)	(0.076)	(0.060)
Ethnic diversity	1.254*	0.448	0.343	0.316	0.586
	(0.471)	(0.286)	(0.255)	(0.399)	(0.314)
Proportion nonwhite British	-1.178	-0.197	-0.315	0.094	-0.615
	(0.899)	(0.556)	(0.495)	(0.762)	(0.600)
Prop. nonwhite British square	0.580	0.080	0.255	-0.126	0.349
	(0.569)	(0.352)	(0.315)	(0.483)	(0.380)
Proportion of co-ethnics	-3.449*	-2.321*	-1.468*	-1.765*	-2.119*
	(0.481)	(0.281)	(0.226)	(0.491)	(0.273)
Proportion of co-ethnics square	14.403*	8.820*	5.370*	7.388+	8.496*
	(2.633)	(1.278)	(0.827)	(2.964)	(1.211)
Population density	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment rate	-0.356	0.370	0.102	-0.084	0.482
	(0.410)	(0.263)	(0.253)	(0.352)	(0.304)
Intercept	-0.043	0.092*	0.124*	0.123*	0.085*
	(0.036)	(0.025)	(0.022)	(0.032)	(0.027)
Adjusted R2	.141	.157	.135	.073	.134
Observations	1,147	893	683	875	872

+ Significant at 5 percent, * Significant at 1 percent

Robust standard errors in parenthesis, dependent variable: estimated ethnic wage gaps by areas (reverse-coded: higher values identify larger gaps); the models are weighted by the inverse of the standard error of the estimated the wage gaps.

TABLE A3: Determinants of ethnic wage gaps across areas -- sensitivity -- models with dummies for ethnicity

	(1) No controls for skills	(2) Shorter time	(3) Lived at address more than 2 years before job started	(4) Only graduates	(5) Only non graduates
Regional specialization	0.088+	0.021	0.089*	0.070	0.045
	(0.035)	(0.038)	(0.033)	(0.040)	(0.031)
Occupational segregation	-0.052	0.038	0.045	-0.033	0.007
	(0.034)	(0.040)	(0.028)	(0.036)	(0.030)
Ethnic diversity	-0.500+	-0.270	-0.231	-0.311	-0.169
	(0.194)	(0.154)	(0.173)	(0.196)	(0.159)
Proportion nonwhite British	1.028*	0.533	0.405	0.659	0.360
	(0.379)	(0.298)	(0.335)	(0.379)	(0.310)
Prop. nonwhite British square	-0.593+	-0.268	-0.151	-0.373	-0.221
	(0.258)	(0.195)	(0.216)	(0.258)	(0.205)
Proportion of co-ethnics	1.285*	0.165	0.279	0.502+	0.196
	(0.218)	(0.183)	(0.172)	(0.241)	(0.158)
Proportion of co-ethnics square	-1.934+	0.954	-0.187	-0.045	0.885
	(0.863)	(0.663)	(0.586)	(1.136)	(0.572)
Population density	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment rate	-0.424+	-0.012	-0.045	-0.291	0.065
	(0.172)	(0.145)	(0.157)	(0.172)	(0.140)
Intercept	-0.014	0.120*	0.136*	0.080*	0.119*
	(0.015)	(0.015)	(0.013)	(0.015)	(0.013)
Adjusted R2	.860	.731	.692	.779	.802
Observations	1,147	893	683	875	872

+ Significant at 5 percent, * Significant at 1 percent

Robust standard errors in parenthesis, dependent variable: estimated ethnic wage gaps by areas (reverse-coded: higher values identify larger gaps); the models are weighted by the inverse of the standard error of the estimated the wage gaps. All models include dummies for ethnic groups.