IZA Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 11073

Spatial-Ethnic Inequalities: The Role of Location in the Estimation of Ethnic Wage Differentials

Simonetta Longhi

OCTOBER 2017

DISCUSSION PAPER SERIES

IZA DP No. 11073

Spatial-Ethnic Inequalities: The Role of Location in the Estimation of Ethnic Wage Differentials

Simonetta Longhi
University of Reading and IZA

OCTOBER 2017

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Spatial-Ethnic Inequalities: The Role of Location in the Estimation of Ethnic Wage Differentials*

Analyses of ethnic and racial wage differentials neglect the fact that minorities cluster in urban and in more deprived areas. This paper estimates ethnic wage differentials by comparing minorities to the majority in the same local labour market and therefore facing similar socio-economic conditions. Location is important: in the UK ethnic wage differentials and their variation across areas are partly explained by job characteristics and especially occupation. Since minorities in some areas are worse off compared to minorities in other areas, there may be scope for policy to incentivise mobility of specific groups.

JEL Classification: J31, J71, R10, R23

Keywords: race, ethnicity, wage differentials, spatial location, unequal distribution, multilevel models

Corresponding author:
Simonetta Longhi
Department of Economics
University of Reading
Whiteknights
Reading RG6 6AA
United Kingdom
E-mail: s.longhi@reading.ac.uk

* I would like to thank Paul Clarke for useful discussion and comments, and participants to the Workshop on Spatial Dimensions of Inequalities (Mannheim, March 2017) and to the EALE conference (Saint Gallen, September 2017) for useful comments on previous versions of this paper.

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; these inequalities remain even after taking into account group differences in individual, household, and job characteristics (e.g. Longhi et al. 2013). The literature often refers to such wage differentials as "wage gaps". Despite extensive research, the origin of ethnic wage differentials is still not completely understood (Guryan and Charles 2013). A better understanding of the mechanism generating ethnic wage differentials is necessary to be able 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 geographical location.

There are relevant differences in socio-economic conditions and in immigration histories across Local Authority Districts in the UK, with some districts hosting much larger shares of minorities than others. Although residential segregation in the UK is not as prominent as in the US (Finney and Simpson 2009), ethnic minorities tend to concentrate in certain areas. Data from the 2011 census show that, although a large proportion of ethnic minorities live in London, different ethnic minorities tend to locate in different districts within London; for example Indians are more likely to live in the districts of Harrow and Hounslow, while Bangladeshis are more likely to live in Tower Hamlets and Newham. Black Africans concentrate in Southwark and Barking and Dagenham, while Black Caribbeans are more likely to live in Lewisham and Lambeth. A large proportion of Indians is also found in the East Midlands, for example Leicester, while Pakistanis are more likely to live in Yorkshire, for example Bradford, and in the South East, for example Slough.

Ethnic minorities tend to be overrepresented in more deprived and in more urbanised areas (Clark and Drinkwater 2002; Catney and Sabater 2015), characterised by different amenities, house prices, and different levels of wages on average. Hence, it would be inappropriate to compare an Indian person working in Leicester with a white British person working in London. It is the white British person working in Leicester that forms the appropriate comparison. In other words, the estimation of ethnic wage differentials should at least condition on average wages in the area. Yet, most of the literature estimating ethnic wage differentials has neglected inequalities in the geographical distribution of majority and minorities.

Since ethnic minorities are overrepresented in deprived areas with comparatively poorer employment prospects, ethnic wage differentials computed at the national level may be overestimated. On the other hand, the overrepresentation of ethnic minorities in urban areas, where wages are comparatively higher, may mean that wage gaps are underestimated. Over- and under-estimation are likely to compensate each other, and if one of the two prevails over the other is an empirical question. This paper fills this gap in the literature, being among the first to systematically analyse the effect of location and district of work on the estimates of ethnic wage differentials. In doing this, this paper investigates to what extent the location decision of minorities is optimal and whether there is room for policy intervention.

Including location in the analysis generates one additional complication: when we move away from a comparison between minority and majority groups at the national level, we are likely to find that ethnic wage gaps differ across areas. In principle, in the absence of mobility costs and other constraints, workers should locate across areas to maximise their lifetime wages given their skills and the location of jobs. An optimal choice of location should lead to ethnic wage differentials that are equal across areas. However, it is likely that that the choice of location is exogenous or predetermined, either because people have a low tendency to move, or because non-labour market aspects, such as proximity to family or co-ethnic friends, out-weight labour market aspects, such as the availability of good jobs, in the decision of where to locate. This may leave minorities in some areas worse-off (i.e. experiencing larger ethnic wage differentials) compared to minorities in other areas. If this is the case, there may be scope for policy to incentivise mobility of specific groups.

Although various studies estimate the impact of location on the probability of having a job or on wages (e.g. Hellerstein et al. 2008), this type of literature does not generally compare outcomes of ethnic minorities to those of natives, and even when such comparison is made, ethnic wage differentials are assumed to be the same across locations (see e.g. Tienda and Lii 1987; Cutler and Glaeser 1997, Edin et al. 2003, Damm 2009). The study which is closer to this paper is Black et al. (2013), who show that racial wage differentials vary across 14 US cities. However, Black et al. (2013) do not attempt to explain such variation.

This paper extends Black et al. (2013) in several ways. First of all, the analysis focuses on the UK and is not limited to cities and urban areas but also includes rural areas. Second, in line with Black et al. (2013) the estimated wage differentials are allowed to differ by district of work thus comparing wages of minority and majority workers who are in the same local labour market. In contrast to Black et al. (2013) this paper also investigates the relative importance of characteristics of individuals, jobs, and areas in the explanation of the variation of ethnic wage differentials across areas. This allows us to draw policy implications on possible ways to reduce ethnic wage differentials.

This paper also contributes to the literature by proposing econometric techniques rarely used for the analysis of ethnic wage differentials. Random effects multilevel models allow the estimation of ethnic wage differentials at the level of each local labour market and the analysis of the effects of individual, job and area characteristics on these differences. These methods have been used to analyse wages of racial minorities in the US by e.g. Parks (2012) and Shin and Liang (2014). However, as most of the US literature, Parks (2012) and Shin and Liang (2014) restrict their analysis only to metropolitan areas, while this paper includes all areas in the UK. 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 differentials across areas Parks (2012) focuses on the impact of characteristics on the level of wages rather than on the distribution of wage differentials across areas. Most analyses using multilevel models only focus on the estimated average wage differentials, this paper proposes a novel way to use the results of multilevel models by also focusing on how the estimates vary across areas and what might explain such variation.

The key finding is that ethnic wage differentials tend to be overestimated when computed without taking into account that minorities and majority concentrate in different local labour markets but underestimated when area dummies are included among the covariates. Ethnic wage differentials vary across districts in the UK and most of this variation seems to be explained by job characteristics, and especially occupation. Job characteristics explain between 1/2 and 2/3rd of ethnic wage differentials, while individual characteristics seem to have no – or sometimes the opposite – effect. Among the area characteristics, the proportion of co-ethnics in the area seems to be the only relevant one.

A critical issue in this analysis 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 differentials. There are various reasons to believe this is not a major issue in this analysis. First of all, the ethnic clusters in the UK 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 et al. 2014). In addition, residential mobility is relatively low. Data from the British Household Panel Survey and the UK Household Longitudinal Survey suggest that only 10% of the population changes residence in any given year (including very short move) and only about 10% of them report that the move was directly or indirectly related to the job. Second, recent evidence suggests that in the UK local labour markets are rather small geographically (Petrongolo and Manning 2017); since the areas analysed here are geographically relatively large, it is likely that minorities will move and cluster within areas but not across them (see also Dustmann and Preston 2001). Finally, various sensitivity analyses suggest that the results are robust to changes in the specification, thus suggesting that the choice of location is largely predetermined and there is room for policies to incentivise selected mobility.

2. Data and descriptive statistics

2.1. Individual data: the Labour Force Survey

The empirical analysis is based on the UK quarterly 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 labour market outcomes. Crucially, and in contrast with other surveys including only data on the place of residence, the LFS provides data on both the districts of residence and of work. Overall, the data identify 348 districts of work across the UK although for some analyses, because of data restrictions, the focus is on England and Wales only.

Because of its large sample size, the LFS is the only dataset that allows the analysis of 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 the rather heterogeneous group of "other whites" are excluded from the analysis. In addition, to avoid complications due to different labour 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 fourth quarter of 2015. 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 interview. To avoid having to deal with differential attrition across ethnic groups, the focus here is only on the first interview.

To analyse the impact that the characteristics of the area have on wages and on ethnic wage differentials, the models also include aggregate data from various other sources.

2.2. Aggregate data

The area characteristics included in this analysis are population density per hectare, the proportion of non-white British, the proportion of co-ethnics, and the percentage of people aged 16-64 who claim job seeker allowance. These are computed for each district in England and Wales using various data sources all available from the Office for National Statistics (ONS, at www.nomisweb.co.uk). Scotland and Northern Ireland are excluded due to issues of comparability across some of these datasets; this needs not be a problem since the vast majority of ethnic minorities live and work in England and Wales. All aggregate variables vary by calendar year (rather than quarter) and are computed based on the resident population in the district where the respondent works.

As already mentioned, ethnic minorities are more likely to concentrate in more urbanised and in more deprived areas, with fewer (good) job opportunities (Finney and Lymperopoulou 2014). Since wages tend on average to be higher in more urbanised areas (e.g. Wheaton and Lewis 2002), the models include a measure of population density to analyse to what extent urbanisation has an impact on ethnic wage differentials. Population density is computed by combining data on the geographical size of each district with population data for the census years (2001 and 2011). For the remaining years, population density is imputed using a shift-share approach combining census and LFS data as described in the Data Appendix.

Job opportunities in the district are measured using claimants of Job Seeker Allowance (unemployment benefits) in each district as a percentage of the population aged 16-64. These data are provided by the Department for Work and Pension and are available from ONS on a monthly basis from January 2001 to December 2015; the monthly percentages are averaged by calendar year.

There are various reasons why minorities tend to concentrate in some areas. 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 (Costa and Kahn 2003; Andersson et al. 2014). 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 and Miller 2005, Hellerstein et al. 2014). Living in areas with large communities of co-ethnics may reduce the costs 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 natives (Edin et al. 2003, Hatton and Leigh 2011). The literature on the importance of social networks suggests that networks of co-ethnics may increase the probability of finding a job via informal referrals (Bayer et al. 2008, Hellerstein et al. 2011) and may have a positive impact on wages (Edin et al. 2003, Damm 2009). On the other hand, the impact on labour market opportunities may be negative if the co-ethnic community has a high unemployment rate or concentrate in low pay jobs (Cutler and Glaeser 1997, Bentolila et al. 2010, Battu et al. 2011) and if natives are more likely than co-ethnics to have access to information on better jobs (Gorinas 2014).

The size of the co-ethnic community is measured here by the proportion of co-ethnics in the area. Since the impact may be non-linear, the models also include the square of this measure. The proportion of co-ethnics is computed by combining the 2001 and 2011 censuses for England and Wales with LFS data as described in the Data Appendix. This variable only applies to each of the minority groups analysed here and is zero for White British people (the majority group).

Besides the proportion of co-ethnics the models also include the proportion of non-White British people in the area and its square (see the Data Appendix). The literature suggests that because of competition over scarce resources between the majority and the minority group, 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 and Lii 1987). Some authors have found that 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 et al. 2012, Shin and Liang 2014). On the other hand, an increase in the size of the minority group will increase their bargaining power, as well as their political and economic influence which, in turn, will decrease discrimination (Tienda and Lii 1987). In this case the juxtaposition is between the majority (White British) and all minorities (non-White British) rather than each minority group separately. Hence, we also use the proportion of non-White British.

2.3. Descriptive statistics

There are clear differences among ethnic groups (see the Appendix, Table A1). First of all, minorities differ in terms of immigration: the proportion of second generations in the sample is highest for Black Caribbean men, 65.5% of whom were born in the UK. The proportion is much lower for the other ethnic minorities: 36% among Pakistani, almost 30% among Indian, 23% among Bangladeshi and only 14% among Black African men. Bangladeshis and Pakistanis are the youngest group on average (34-35 years of age) while for Black Caribbean men the average age is 41, the same as for White British.

There are also relevant differences in education, with Indians, Pakistanis and Black Africans more likely than White British to hold a university degree (or higher) qualifications. 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 Level 3 and Level 2 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; this is partly due to foreign qualifications that may not be recognised in the UK. This shows a polarisation of qualification levels among ethnic minorities which is not present for White British.

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. All ethnic minorities have fewer years of tenure in the job, are more likely to work part-time and in temporary jobs compared to White British. Pakistani and Bangladeshi employees are less likely to work in the public sector compared to White British, while Black African and Black Caribbean men are more likely.

Finally, there are differences in terms of area in which majority and minorities work. Black African, Black Caribbean and Bangladeshi men work in much more urbanised areas than the other groups and especially White British. For all minority groups the proportion of non-White British is around 30-40%; this is only about 16% for White British. The proportion of co-ethnics in the area of work is always low and ranges from 3% for Black Caribbeans to almost 7% for Indians (being 0 for White British).

3. Modelling strategy

3.1. Estimating ethnic wage differentials

Ethnic wage differentials measure differences in average wages of minority and majority groups (as in Table A1). When estimated within a regression framework where the dependent variable is the log of hourly wages, ethnic wage differentials are the estimated coefficients of the dummies for each ethnic minority group (β_1):

$$LnW_{iert} = \alpha + EM'_{iert}\beta_1 + T'_{iert}\beta_2 + \varepsilon_{iert} \quad (1)$$

where W_{iert} represents hourly wages of individual *i*, with ethnicity *e*, working in region *r* at time *t*. EM'_{iert} are the ethnic minority dummies and T'_{iert} are dummies for the year-quarter of the interview. The vector of coefficients β_1 is an estimate of the ethnic wage penalty and therefore measures the (unconditional) wage differentials, while the year-quarter dummies should control for differences in wages over time that are common to all ethnic groups.[1] Equation (1) is a Mincer regression where the only covariates are time and ethnicity dummies and is generally estimated using OLS.

As already mentioned, amenities and house prices vary across areas. These differences are of particular relevance when comparing wages of groups that are unequally distributed across areas. It is possible to partly take into account time-invariant differences across areas that may affect the level of local wages by including in the models a set of area dummies (R'_{iert}):

$$LnW_{iert} = \alpha + EM'_{iert}\beta_1 + T'_{iert}\beta_2 + R'_{iert}\beta_3 + \varepsilon_{iert} \quad (2)$$

Studies estimating ethnic wage differentials rarely include dummies for areas 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 (e.g. Longhi et al. 2013). Estimates including and excluding area dummies are rarely compared. Nevertheless, such comparison is informative. Hence, this paper compares the two versions of the model: the one including (equation 2) and the one excluding (equation 1) dummies for the district of work. Following Cameron and Miller (2015), in these models the standard errors are clustered by county.[2]

As pointed out by Black et al. (2013), area fixed effects can account for differences in amenities and house prices across areas only if preferences are homotetic, i.e. only if all ethnic groups have the same preferences. Although this may be the case for amenities such as weather or days of sunshine, minorities and majority may have different preferences in terms of, for example, presence of co-ethnics. In this case, random effect multilevel models should be preferred.

[1] It is plausible that ethnic wage differentials change over time. To avoid excessive complications due to small sample sizes for ethnic minorities, in this setting ethnic wage differentials are an average across the whole period. Sensitivity analyses restricted to shorter periods are discussed in Section 4.5.
[2] Models with standard errors computed using either district or government office regions clusters are not shown here for reasons of space but are available on request.

3.2. Area-specific ethnic wage differentials

Even when dummies for the district of work are included, the Mincer equation estimates one wage differential for each ethnic minority, which is an average of district-level ethnic differences in wages. The best method which can be used to estimate ethnic wage differentials at the district level is a random effects multilevel model. In a two-way multilevel random effects model, where individual observations *i* observed at time *t* are nested within districts *r*, equation (1) can be rewritten to include time-invariant district-specific intercepts (α_r) and slopes (β_{1er}):

$$LnW_{iert} = \alpha_r + EM'_{iert}\beta_{1er} + T'_{iert}\beta_2 + \varepsilon_{iert} \quad (3)$$

The district-specific intercepts capture differences in wages across areas that are due to structural factors (similarly to R'_{iert} in equation 2), while the district-specific slopes measure district-specific ethnic wage differentials. In this model ethnic wage differentials may vary by district, while the impact of the year-quarter dummies is assumed to be constant across districts. Hence:

$$\alpha_r = \alpha_{00} + u_{0r} \quad (4a)$$

$$\beta_{1er} = \beta_{10e} + u_{1er} \qquad \text{with } e = 1 \ldots 5 \quad (4b)$$

The subscript *e* refers to the five ethnic minority groups, α_{00} and β_{10e} are the district-invariant 'fixed effects' while u_{0r} and u_{1er} are random residual errors independent on ε_{iert} and with zero mean; u_{0r} and u_{1er} can be correlated (Hox 2002). Multilevel models including only random intercepts differ from OLS models with district dummies only by u_{0r}.

If location plays no role for ethnic wage differentials, the different slopes should be not statistically different from each other. However, ethnic wage differentials may vary across areas if, for example, ethnic differences in wages vary by education level and people with different levels of education work in different areas. Another reason why we may observe different slopes across areas is that ethnic wage differentials may vary by job type (e.g. public private) and there are systematic differences in types of jobs available across areas. In addition, wage differentials may differ across areas if the reaction of the majority towards the minority depends on the economic conditions of the local labour market (for example the level of local unemployment) or on the socio-demographic characteristics of the resident population (for example the proportion of minorities vs. majority). Finally, wage differentials may remain if people's location decisions are not optimal.

3.3. Effect of characteristics on ethnic wage differentials

The unconditional wage differentials give us an idea of how wages of ethnic minorities compare to those of white British people in each area. Although it is useful to identify whether ethnic wage differentials in some areas are larger than in others, it is also important to analyse whether the unconditional wage gaps result from differences between minorities and white British people in characteristics such as age, education, or type of job (Longhi 2017). Differences in characteristics can be modelled by including additional covariates:

$$LnW_{iert} = \alpha_r + EM'_{iert}\beta_{1er} + T'_{iert}\beta_2 + X'_{iert}\beta_3 + \varepsilon_{iert} \tag{5}$$

where X'_{iert} is a vector of individual, household, and job characteristics; these covariates are meant to control for differences in the distributions of the various groups and to partly control for factors that may influence the decision where to work. Hence, in this framework the ethnic minority dummies are an estimate of the wage penalty associated with each minority which is not explained by the other covariates included in the model (and are sometimes called conditional wage differentials). Equation (5) is essentially a Mincer equation, which is estimated using multilevel models instead of OLS.

Although in this model the individual, job and area characteristics do not have a direct impact on the district-level intercepts (α_r) and slopes (β_{1er}), they may have an indirect effect if they mediate the relationship between ethnicity and wages. Traditionally, the literature tends to find that ethnic wage differentials decrease after controlling for characteristics. If this is the case, we can expect all β_{1er} to move closer to zero after the inclusion of the covariates. By including the covariates in blocks (i.e. individual, job, or area characteristics), or one by one, we can compare their relative importance.

To analyse the relative importance of individual, job and area characteristics on the ethnic wage differentials and on their variation across areas random effects multilevel models are estimated using different specifications for X'_{iert}. First, X'_{iert} includes the individual characteristics traditionally included in the Mincer equation: dummies for the level of education to measure skills, age and its square to measure years of potential experience, dummies for those who are married or cohabiting, for the presence of dependent children, and a dummy for second generation ethnic minority (which is zero for white British people) to take into account that second generations should be more similar to White British people than immigrants are. Although not all these characteristics may affect differences in wage gaps across areas, they have all been shown to have a relevant impact on wages and should therefore be included in the models.

The second type of model only includes job characteristics in X'_{iert}: years of job tenure, dummies for part-time job, temporary job, public sector job, and for major occupation group. We expect the job characteristics to play a role since the location of types of firms and therefore jobs is likely to be uneven across areas. The third type of model includes in X'_{iert} only the area characteristics: population density, the proportion of non-white British people, the proportion of co-ethnics, the percentage of claimants of Job Seeker Allowance, and the squares of all four variables. This should measure differences across areas in the way minority and majority interact with each other. Hence, the covariates should partly correct for endogeneity and self-selection of people with different individual and household characteristics across districts. Controlling for job characteristics should partly account for the self-selection of firms and types of jobs. One final model includes all the covariates. Sensitivity models where the covariates are included one by one are discussed at the end of Section 4.2.[3]

After estimating the multilevel models it is interesting to analyse how district-level ethnic wage gaps vary across areas; perhaps surprisingly, this is rarely done in the literature. The analysis of the variability of the district-level ethnic wage gaps and how this changes when the different covariates are included in the models can give useful insights. If the difference in characteristics between minorities and the majority is the same across areas the variability of the coefficients β_{1er} should not be affected by the inclusion of the additional covariates. On the other hand, we would expect the inclusion of the additional covariates to reduce the spread of the β_{1er} coefficients across r if minorities are more dissimilar to the majority in some areas than in others. This may be the case, for example, if occupational segregation is more pronounced in certain districts than in others.

[3] Additional variables are available in the LFS such as religion and firm size. However, these have not been included due to data problems: some are not available over the whole period of analysis (e.g. religion), while others do not seem to have useful categories (e.g. firm size).

4. Results

4.1. Ethnic wage differentials

Estimates of ethnic wage differentials obtained using the various methods described in Sections 3.1 and 3.2 are shown in Table 1. Wage differentials estimated without dummies for district of work are in Column (1) and are consistent with previous research (e.g. Brynin and Güveli 2012): while Indian men appear to be paid slightly more on average than White British men, Black Caribbean men experience a wage gap of about 13% (for a coefficient of 0.120) while the wage differential for Black Africans is almost 18%. Wage differentials are much larger for Pakistani (31%) and Bangladeshi (56%). Perhaps surprisingly, the inclusion of dummies for the district of work, Column (2), substantially increases wage gaps for all ethnic minority groups, ranging now from more than 11% for Indians to more than 80% for Bangladeshis. This contrasts the finding for Black et al. (2013) for the US, where the gaps decrease after the inclusion of area dummies; this is probably because Black et al. (2013) focus only on metropolitan areas. The increase in the gaps following the inclusion of dummies for district of work suggests that ethnic minorities are more likely than White British people to work in districts that pay comparatively higher wages, and not taking this into account would partially hide ethnic wage differentials. This, however, does not answer the question of how wages of ethnic minorities compare to those of white British people working in the same district.

As discussed in Section 3.2, random effects multilevel models can be a useful alternative for the estimation of district-specific ethnic wage differentials; the results are shown in Columns (3) and (4) of Table 1. Column (3) shows the results of a multilevel model with random intercepts; this is comparable with the OLS model with dummies for district of work. The estimated differences in wages are similar to the OLS ones, although marginally smaller for all ethnic minorities. Average ethnic wage differentials reduce when estimated using a multilevel model with random slopes and intercepts as in Column (4). Here ethnic wage differentials are allowed to differ by district of work and therefore the comparison is between wages of minority and majority people who work in the same district. The wage differentials reported in Column (4) are an average across districts and are smaller than those estimated by all other models with the exception of OLS without district dummies. The results show no wage differentials for Indians on average but substantial gaps for all other minorities.

TABLE 1 ABOUT HERE

In summary, Table 1 suggests that ethnic wage differentials tend to be underestimated when district dummies are not included, but overestimated when such dummies are included. However, besides the average ethnic wage differentials, it is also interesting to analyse how the ethnic-specific slopes differ across areas.[4]

Figure 1 shows the distribution of the unconditional wage differentials (the random slopes) across areas by ethnic group. This confirms that Bangladeshi men experience the largest wage gaps on average, Indian experience no wage gaps on average, while the three remaining minorities have similar experiences. The new information conveyed by this figure is that, even without controlling for characteristics, wage gaps for each minority seem to be rather similar across areas, with the possible exception of Indians. For Indian workers ethnic wage differentials are on average zero but vary across districts more than for other minorities, with wage gaps in roughly half of the districts, and wage advantages in the remaining half: the average is less than 1% wage gap and the standard deviation 12.3%. For all other groups wage differentials are negative in almost all areas. For Bangladeshi men the estimated coefficients are about 54% at the 90th percentile and almost 63% at the 10th with a mean of 59% and a standard deviation of 4.5%. For Pakistani the estimated coefficients are about 21% at the 90th and 35% at the 10th percentile, with a mean of 27% standard deviation of 5.7%.

Wage differentials of Black Africans seem rather similar to those of Pakistani both in terms of size and variability, with estimated coefficients of 16% at the 90th and 34% at the 10th percentile. For Black Caribbean men the wage differential is on average similar to that of Black Africans but the variation across districts is much lower with coefficients of 19% at the 90th percentile and 29% at the 10th. For both Black African and Black Caribbean men the average is 24% with a standard deviation of 8.6% for Black African and of 4.6% for Black Caribbean men.

FIGURE 1 ABOUT HERE

[4] The LR test for random slopes 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.

4.2. Effect of characteristics on ethnic wage differentials

Is the variation in ethnic wage differentials across districts related to worker, job, or area characteristics? The results in Table 2 and Figure 2 suggest they are.

As discussed in Section 2.2, these results use data for England and Wales only. For comparison, the first column of Table 2 shows the results of a random effects model similar to the one in Column (4) of Table 1, but estimated on the restricted sample. The estimated ethnic wage differentials are slightly smaller for Pakistani and Bangladeshi men, and essentially the same for the remaining groups.

The model in column (2) of Table 2 includes the individual characteristics. The full set of results show the expected effects (see the Appendix, Table A2): wages increase non-linearly with age and with education; they are comparatively higher for second generations than for immigrants, for men who are married and for those with children. Column (2) of Table 2 also shows that for most ethnic minorities average wage differentials increase when we include the individual characteristics in the model; the only exception being Bangladeshis. This suggests that ethnic minorities have positive characteristics; for example, they are more likely than White British to have higher levels of education (Table A1). The larger ethnic wage differentials revealed when comparing minorities and majority with the same characteristics suggests that minorities experience lower returns to their positive individual characteristics. This may be due to incomplete information, for example if the quality of the school attended by minorities is lower than that of schools attended by the majority, but may also be due to e.g. (statistical) discrimination.

The model in Column (3) of Table 2 includes only the job characteristics. As expected, wages increase with years of job tenure, are comparatively lower for those working part-time and in temporary jobs, while they are higher for those working in the public sector. For all minorities ethnic wage differentials decrease substantially when job characteristics are included in the model: they halve for Pakistani and Bangladeshi, while they decrease by more than 2/3 for Black Africans. Hence, the main reason for ethnic wage differentials is the type of jobs that minorities have.

Figure 2 shows the distribution of ethnic wage differentials across areas, as estimated by the various models shown in Table 2. Besides decreasing average wage differentials, the inclusion of job characteristics in the models also decreases the variability of the wage differentials across areas compared to the models without covariates or only including individual characteristics (see also the Appendix, Table A3).

The model in Column (4) of Table 2 includes only the characteristics of the area. As expected, wages are comparatively higher in more densely populated areas and lower in areas with higher percentages of claimants of job seeker allowance; in both cases the effect seems to be linear. Wages are higher the higher the proportion of non-White British, although the relationship is non-linear; the positive impact of the proportion of non-White British starts to decline when it reaches 60%. A higher proportion of co-ethnics is associated with lower wages in a non-linear way.

When we take into account the characteristics of the area we see a wage advantage for Indian men, who are paid about 8% more than White British men working in similar areas. While wage gaps of Pakistani, Black African and Black Caribbean men decrease compared to the models with no covariates, there is only a small decrease in wage gaps for Bangladeshis. The variation in ethnic wage gaps across areas reduce compared to the models including no or only individual characteristics, but are still larger than the models including job characteristics. With only few exceptions (Black Caribbeans and Pakistanis in Model (3)), LR tests suggest that the ethnic wage gaps differ across areas, and these differences are statistically significant.

TABLE 2 ABOUT HERE

FIGURE 2 ABOUT HERE

The model in Column (5) of Table 2 includes all covariates. The coefficients of the individual, job and area characteristics tend to reduce. According to this model all ethnic minorities experience wage gaps; these are about 3% for Indians, around 13% for Black African, Black Caribbean and Pakistani men, while they are still about 37% for Bangladeshis. This is the model that also shows the smallest variability in the ethnic wage differentials across areas for Indians and Black Africans. For Pakistani, Bangladeshi and Black Caribbean men the model with the smallest variability is the one that only includes job characteristics.

The models in Table 2 only indicate the relative importance of job, area and individual characteristics in explaining ethnic wage differentials. Which, among the job and area characteristics plays the most relevant role? The results of models including only one covariate at a time are in Table A4 and are also summarised in Figures A1, A2 and A3 for individual, job and area characteristics respectively. Among the individual characteristics (Figure A1), the most important one seems to be qualifications. For Indian and Black African men this is the only variable that shift the distribution to the left, towards largest wage gaps. The pattern is similar for Pakistani men. This suggests that having comparatively higher levels of qualifications partly hides ethnic wage gaps, which appear when we compare men with the same qualification level. For Bangladeshi and Black Caribbean men the inclusion of qualifications in the model shows a decrease in the wage gaps, suggesting that these partly explain the gaps; for both groups this is the variable that shift the distribution closer to zero.

Among the job characteristics it is the inclusion of occupation that reduces the spread of the distribution for all groups (the LR test suggests that for Pakistanis, Bangladeshis and Black Caribbeans the random slopes are not statistically different across areas). With the exception of Indians, this is also the variable that shifts the distribution to the most right, i.e. towards smaller wage gaps, thus suggesting that for most ethnic minorities wage gaps are explained by the concentration of minorities in low-pay occupations. Among the area characteristics, it is the proportion of co-ethnics that differs from all other characteristics and for all minorities shifts the distribution to the right and tends to reduce its spread. This suggests that concentration has a negative impact, and that those who live in less concentrated areas may experience smaller wage gaps, consistent with that part of the literature focusing on the quality of networks.

Finally, to compare the relative importance of the three characteristics highlighted in the previous figures, Figure A4 compares wage gaps of models without covariates, including only qualification, occupation, or the proportion of co-ethnics. This confirms that occupation is the variable that most reduces the spread of the distribution and – for most groups – the average gaps. Although the importance of occupational concentration has already been highlighted in the literature (Elliot and Lindley 2008, Longhi et al. 2012), these new results highlight its prominence against all other characteristics in the explanation not only of wage gaps, but also of their variability across areas.

4.3. Discussion

In summary, unconditional ethnic wage differentials vary significantly across districts and do not seem to be related to individual or household characteristics of majority and minority workers in the district, with the possible exception of Bangladeshi. For Bangladeshi men ethnic wage gaps on average tend to decrease once we control for individual and household characteristics suggesting that their 'unfavourable' characteristics are partly responsible for the wage gaps they experience.

For all minorities ethnic wage gaps become less negative or more favourable when job characteristics are included in the models, confirming findings from the previous literature on the detrimental impact of occupational segregation (Elliot and Lindley 2008), suggesting that the problem may be access to good quality jobs. However, since this analysis compares majority and minority people working in the same area, we can also conclude that the issue of occupational segregation is not related to residential segregation but is more likely to be related to occupational closure or lack of career progression.

Similarly, wage gaps of all minority groups decrease – or their wage advantage increases – when we include the characteristics of the area. However, while for Indians the area characteristics seem to have the largest positive impact, for all other minorities the most important factors seem to be job characteristics. This is consistent with the idea that Indians tend to segregate in high-pay occupation, in contrast to the other minorities who are more likely to segregate in low-pay occupations.

Besides the average gap, the inclusion of covariates in the model also has an impact on the spread of the distribution, i.e. on the variation of the gaps across areas. The inclusion of the individual characteristics does not seem to have a large impact on the variation of the gaps across areas, compared to the other characteristics. For Pakistani the variability of the wage gaps seems to decrease with the inclusion of the individual characteristics, while for Bangladeshi the variability seems to increase. This may suggest that part of the differences across areas in wage gaps for Pakistani is due to the differences in their individual characteristics compared to White British working in the same area, while for Bangladeshi this is not the case.

For all minorities the inclusion of the job characteristics decreases the variability of the ethnic wage gaps; these are the variables that seem to have the largest impact. This suggests that even within districts it is the distribution of jobs between majority and minorities that is mostly responsible for the large ethnic wage differentials we observe. It is possible that ethnic wage differentials are larger in those areas where ‘good’ jobs are scarce and lower in those areas where ‘good’ jobs are more abundant. Given the relatively small sample size, it is not possible here to test whether this is the case. We can see, however, that in general the ethnic wage differentials correlate positively with the proportion of part-time workers in an area, with coefficients ranging between 0.22 for Indians to 0.43 for Black Africans. This is in line with the evidence that ethnic minorities are more likely to work part-time than White British and suggests larger gaps in areas with more part-time jobs. Although there seems to be no relevant correlation with the proportion of temporary and public sector jobs, the results also show that ethnic wage differentials seem to be smaller in those areas where there are larger proportion of people working in managerial and professional – or associate professional – occupations. This correlation is largest for Bangladeshis, Black Africans and Black Caribbeans, but slightly lower for Indians and Pakistanis. This too suggests that ethnic wage differentials are lower in those areas with a large availability of 'good' jobs.

4.4. Endogenous location of ethnic minorities

It is possible that the extent of ethnic wage differentials depends on where minorities locate, and the location of ethnic minorities may partly be driven by the level of wages in the area, or the perceived level of discrimination, which may in turn correlate with the wage gaps. The correlation between average wages in the area and the proportion of people of that minority in the area is 0.09 for Pakistanis (statistically significant only at 10%). For all other ethnic minorities the correlation is positive and statistically significant, being 0.26 for Indians, 0.36 for Bangladeshis, 0.42 for Black Caribbeans and 0.52 for Black Africans. Given that the number of observations ranges between 346-348, depending on the minority group, these correlations are not massive.

The correlation between the wage gaps (estimated based on Model 4, Table 1) and the proportion of each ethnic minority group is negative and statistically significant, being -0.27 for Bangladeshis, -0.30 for Black Caribbeans, -0.36 for Black Africans, -0.47 for Indians and -0.51 for Pakistanis. The number of observations here ranges from 181 for Bangladeshi to 296 for Indians.

This suggest that minorities tend to work in areas with comparatively higher wage levels on average, i.e. urban areas, confirming the idea that urbanisation is likely to be more important than deprivation. In addition, ethnic minorities seem to be concentrated in areas where the wage gaps are lower, thus suggesting that minorities who work in areas with smaller proportions of co-ethnics are more likely to suffer wage penalties compared to white British people working in the same area.

The crucial issue here is the extent to which residential choices of ethnic minorities are related to the types of jobs, the average wage level, or wage gaps, and whether this would affect our conclusions. Since the LFS is a rotating panel following individuals for up to five successive quarters, it is possible to identify (a small number of) workers who change their job within these five quarters. Among those, some keep working in the same district, while for a few the new job is in a different district (although they do not change residence).

Among White British about 67% of those who change job do not change district of work, while 33% do. These proportions do not seem to vary substantially by ethnicity: those most likely to change district of work are Indians and Black Africans (38% and 37% of those who change job also change district of work), while Pakistanis are the least likely (30%). It also seems that roughly half of those who change district of work find a job in an area with higher wage differentials for his/her minority, while half find a job in an area with lower wage differentials.

Up to now the analysis has been based on districts which are geographically relatively large: it is likely that minorities will move and cluster within districts but not across them (Dustmann and Preston 2001). However, since districts are administrative boundaries which tend on average to be smaller than travel-to-work areas (which are not available with these data), the main models have been re-estimated using counties. Counties are geographically larger than districts, there are about 50 in our analysis (where London is one single county). The average wage gaps in Table A5 of the Appendix are slightly lower than those in Table 2; nevertheless, the general pattern does not change. Average wage gaps disappear for most minorities when job characteristics are included in the models. When the area characteristics are included there is a wage advantage on average for Indians, no wage gaps for Pakistanis and smaller gaps for the other three minorities. The inclusion of job characteristics, in contrast, increases the average wage gaps for all groups except for Bangladeshis.

Following Cutler and Glaeser (1997), and more recently Hellerstein et al. (2014), the robustness of the results to endogeneity resulting from workers' residential choices is analysed by focusing on workers who were already living at their current address at least two years before starting the current job. The argument is that for these respondents the decision on where to live is likely to be independent on their current job. Because this reduces the number of observations available for analysis, these models are estimated at the county rather than the district level. Compared to the results in Table 2 (and Table A5) the results in Table A6 show slightly smaller wage gaps on average for Bangladeshi and slightly larger wage gaps on average for Pakistani. There are no wage gaps on average for the remaining minorities, although this may be the result of the reduced number of observations. The overall pattern described above, however, does not change.

As a final test we can compare models estimated including only workers who hold a university degree, or including only those who do not. Location is less likely to be endogenous for workers with lower levels of education, who tend to face geographically smaller labour markets (e.g. Nimczik 2016). The results are slightly stronger for those without a degree compared to those with a degree but still consistent with the ones discussed up to now.

4.5. Additional sensitivity analysis

The models focusing on the impact of the area characteristics may suffer from a potential issue since the area characteristics refer to the area where the individual works, but are computed based on the resident population. For some of these characteristics, such as the proportion of co-ethnics, besides the measure at the place of work, also the measure at the place of residence may play a role. Because of high correlation – more than 50% of respondents live and work in the same area – the inclusion of characteristics of both area of work and of residence is unlikely to produce useful insights. A suitable alternative, however, consists in re-estimating the models on the subset of people who work and live in the same area, where London is considered as one single area. The estimates, once again, can be done at the county rather than the district level. The results are in Table A7 and do not vary substantially from those in Table A5. Thus, our conclusions remain.

Finally, the analysis is based on a long period (2001-2015) and assumes that ethnic wage differentials have been stable over a period of 15 years. This is necessary to be able to have sample sizes large enough for the estimation of district-specific slopes. Sensitivity analyses using only the most recent years (2010-2015) are shown in the Appendix, Figure A5 and are consistent with the results based on the longer time period.

5. Summary and conclusions

This paper investigates ethnic wage differentials in the UK focusing on their spatial dimension. A large literature finds that in most developed countries ethnic and racial minorities receive on average lower wages than the white majority but generally does not take into account that ethnic minorities are more likely to cluster in urban and in more deprived areas. This paper argues that a proper analysis of ethnic wage differentials should compare wages of ethnic minorities to wages of white people working in the same local labour market and therefore facing similar socio-economic and labour market conditions. The results suggest that ethnic wage differentials tend to be overestimated when computed without taking into account that minorities and majority concentrate in different local labour markets. Ethnic wage differentials vary significantly across areas, even after accounting for individual, job, and area characteristics, thus suggesting that some minority workers fare worse – compared to the white British majority – compared to similar workers from the same minority because of their location.

Job characteristics, and especially occupation, explain a large part of ethnic wage differentials and of their variation across areas. The results tentatively suggest that even within the same area minorities concentrate in worse occupations, although ethnic wage differentials are smaller in areas with more abundance of 'good' jobs (e.g. in managerial and professional or associate professional occupations).

The results are robust to changes in the specifications and to possible endogeneity issues, thus suggesting that location plays a relevant role for ethnic wage differentials. The geographical location of minorities, with respect to labour market outcomes, is sub-optimal, leaving some minorities worse off than others. This suggests that there may be a role for policy to incentivise mobility of specific groups to reduce unequal outcomes.

References

Andersson, R., Musterd, S. and Galster, G.C. (2014) Neighbourhood Ethnic Composition and Employment Effects on Immigrant Incomes. *Journal of Ethnic and Migration Studies* 40(5): 710-736.

Battu, H., Seaman, P. and Zenou, Y. (2011) Job Contact Networks and the Ethnic Minorities. *Labour Economics* 18: 48-56.

Bayer, P., Ross, S.L. and Topa, G. (2008) Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes. *Journal of Political Economy* 116(6): 1150-1196.

Bentolila, S., Michelacci, C. and Suarez, J. (2010) Social Contacts and Occupational Choice. *Economica* 77(305): 20-45.

Black, D.A., Kolesnikova, N., Sanders, S.G. and Taylor, L.J. (2013) The Role of Location in Evaluating Racial Wage Disparity. *IZA Journal of Labor Economics* 2013, 2:2.

Brynin, M. and Güveli, A. (2012) Understanding the Ethnic Pay Gap in Britain. *Work, Employment and Society* 26(4): 574-587.

Cameron, A.C. and Miller, D.L. (2015) A Practitioner's Guide to Cluster-Robust Inference. *The Journal of Human Resources* 50(2): 317-372.

Castles, S., De Haas, H. and Miller, M.J. (2014) *The Age of Migration*. Basingstoke (UK), Palgrave Macmillan.

Catney, G. and Sabater, A. (2015) Ethnic Minority Disadvantage in the Labour Market. Participation, Skills and Geographical Inequalities, Joseph Rowntree Foundation Report - March 2015.

Chiswick, B.R. and Miller, P.W. (2005) Do Enclaves Matter in Immigrant Adjustment? *City and Community* 4(1): 5-35.

Clark, K. and Drinkwater, S. (2002) Enclaves, Neighbourhood Effects and Employment Outcomes: Ethnic Minorities in England and Wales. *Journal of Population Economics* 15(1): 5-29.

Costa, D.L. and Kahn, M.E. (2003) Civic Engagement and Community Heterogeneity: An Economist's Perspective. *Perspectives on Politics* 1(1): 103-111.

Cutler, D.M. and Glaeser, E.L. (1997) Are Gettos Good or Bad? *The Quarterly Journal of Economics* 112(3): 827-872.
Cutler, D.M., Glaeser, E.L. and Vigdor, J.L. (2008) When Are Gettos Bad? Lessons from Immigrant Segregation in the United States. *Journal of Urban Economics* 63: 759-774.
Damm, A.P. (2009) Ethnic Enclaves and Immigrant Labor Market Outcomes: Quasi-Experimental Evidence. *Journal of Labor Economics* 27(2): 281-314.
Dustmann, C. and Preston, I.P. (2001) Attitudes to Ethnic Minorities, Ethnic Context and Location Decisions. *The Economic Journal* 111(470): 353-373.
Edin, P.-A., Fredriksson, P. and Aslund, O. (2003) Ethnic Enclaves and the Economic Success of Immigrants: Evidence from a Natural Experiment. *The Quarterly Journal of Economics* 118(1): 329-357.
Elliot, R.J. and Lindley, J.K. (2008) Immigrant Wage Differentials, Ethnicity and Occupational Segregation. *Journal of the Royal Statistical Society - Series A* 171(3): 645-671.
Finney, N. and Lymperopoulou, K. (2014) Local Ethnic Inequalities, Runnymede Report.
Finney, N. and Simpson, L. (2009) *'Sleepwalking to Segregation'? Challenging Myths About Race and Migration*. Bristol, The Policy Press.
Gorinas, C. (2014) Ethnic Identity, Majority Norms, and the Native-Immigrant Employment Gap. *Journal of Population Economics* 27(1): 225-250.
Guryan, J. and Charles, K.K. (2013) Taste-Based or Statistical Discrimination: The Economics of Discrimination Returns to Its Roots. *The Economic Journal* 123(572): F417-F432.
Hatton, T.J. and Leigh, A. (2011) Immigrants Assimilate as Communities, Not Just as Individuals. *Journal of Population Economics* 24(2): 389-419.
Hellerstein, J.K., Kutzbach, M.J. and Neumark, D. (2014) Do Labor Market Networks Have an Important Spatial Dimension? *Journal of Urban Economics* 79: 39-58.
Hellerstein, J.K., McInerney, M. and Neumark, D. (2011) Neighbors and Coworkers: The Importance of Residential Labor Market Networks. *Journal of Labor Economics* 29(4): 659-695.
Hellerstein, J.K., Neumark, D. and McInerney, M. (2008) Spatial Mismatch or Racial Mismatch? *Journal of Urban Economics* 64(2): 464-479.
Hox, J. (2002) *Multilevel Analysis - Techniques and Applications*. Mahwah (NJ), Lawrence Erlbaurn Associates, Inc.
Johnson, K., Pais, J. and South, S.J. (2012) Minority Population Concentration and Earnings: Evidence from Fixed-Effects Models. *Social Forces* 91(1): 181-208.
Longhi, S. (2017) The Diversity of Racial Wage Differentials. *IZA World of Labor* Forthcoming.
Longhi, S., Nicoletti, C. and Platt, L. (2012) Occupation and Pay across the Generations: The Labour Market Experience of Four Ethno-Religious Groups in Britain. *Social Stratification: Trends and Processes*. Ed. by Lambert, P.S., Connelly, R., Blackburn, B. and Gayle, V., Ashgate: 151-165.
Longhi, S., Nicoletti, C. and Platt, L. (2013) Explained and Unexplained Wage Gaps across the Main Ethno-Religious Groups in Great Britain. *Oxford Economic Papers* 65(2): 471-493.
Nimczik, J.S. (2016) Job Mobility, Networks and Endogenous Labor Markets, Mimeo - conference paper.
Parks, V. (2012) The Uneven Geography of Racial and Ethnic Wage Inequality: Specifying Local Labor Market Effects. *Annals of the Association of American Geographers* 102(3): 700-725.

Petrongolo, B. and Manning, A. (2017) How Local Are Labor Markets? Evidence from a Spatial Job Search Model. *American Economic Review* 107(10): 2877-2907.
Shin, H.-j. and Liang, Z. (2014) Ethnic Labor Market Contexts and the Earnings of Asian Immigrants. *International Migration* 52(2): 140-157.
Tienda, M. and Lii, D.-T. (1987) Minority Concentration and Earnings Inequality: Blacks, Hispanics, and Asians Compared. *American Journal of Sociology* 93(1): 141-165.
Wheaton, W.C. and Lewis, M.J. (2002) Urban Wages and Labor Market Agglomeration. *Journal of Urban Economics* 51: 542-562.

Tables and Figures

Table 1: Average ethnic wage differentials at the national level

	(1) OLS	(2) OLS	(3) Multilevel	(4) Multilevel
Indian	0.023+	-0.105+	-0.102*	-0.006
	(0.009)	(0.040)	(0.009)	(0.018)
Pakistani	-0.272*	-0.328*	-0.326*	-0.274*
	(0.014)	(0.027)	(0.014)	(0.020)
Bangladeshi	-0.446*	-0.622*	-0.619*	-0.591*
	(0.022)	(0.056)	(0.021)	(0.026)
Black African	-0.167*	-0.339*	-0.335*	-0.245*
	(0.014)	(0.065)	(0.013)	(0.020)
Black Caribbean	-0.120*	-0.267*	-0.264*	-0.235*
	(0.017)	(0.038)	(0.016)	(0.020)
District of work dummies	no	yes	random intercept	random intercept and slope
LR test vs. linear model			15230*	15542*
LR test for random slopes				312*
Adjusted R2	0.043	0.133		
Observations	166,049	166,049	166,049	166,049

+ Significant at 5%, * Significant at 1%

Standard errors in parenthesis, those in Column (2) are clustered by county. Other explanatory variables: year-quarter of the interview.

Table 2: Importance of characteristics

	(1)	(2)	(3)	(4)	(5)
Indian	-0.005	-0.121*	-0.019	0.081*	-0.027+
	(0.018)	(0.016)	(0.011)	(0.017)	(0.013)
Pakistani	-0.253*	-0.309*	-0.128*	-0.150*	-0.127*
	(0.022)	(0.017)	(0.013)	(0.023)	(0.017)
Bangladeshi	-0.554*	-0.493*	-0.267*	-0.503*	-0.317*
	(0.029)	(0.026)	(0.023)	(0.030)	(0.023)
Black African	-0.249*	-0.331*	-0.064*	-0.174*	-0.121*
	(0.021)	(0.018)	(0.016)	(0.021)	(0.015)
Black Caribbean	-0.234*	-0.276*	-0.102*	-0.157*	-0.127*
	(0.022)	(0.020)	(0.016)	(0.023)	(0.018)
Individual characteristics	no	yes	no	no	yes
Job characteristics	no	no	yes	no	yes
Area characteristics	no	no	no	yes	yes
LR test for random slopes	246*	216*	108*	104*	67*
Observations	141,580	141,580	141,580	141,580	141,580

+ Significant at 5%, * Significant at 1%

Results of multilevel models with random intercept and random slope; standard errors in parenthesis

Other explanatory variables: year-quarter of the interview. The full set of results is in the Appendix, Table A2.

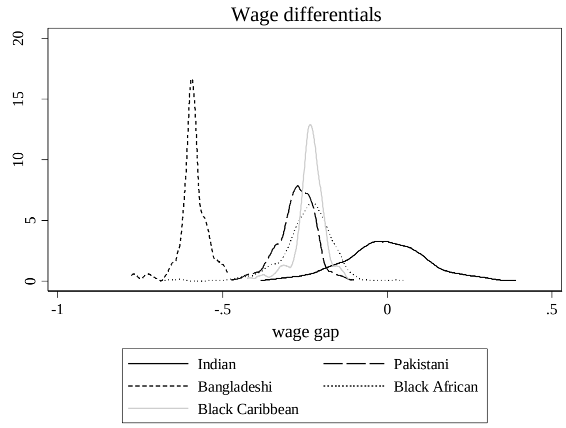


Figure 1: Distributions of unconditional ethnic wage differentials across areas
Derived from the model in Table 1, Column (4)

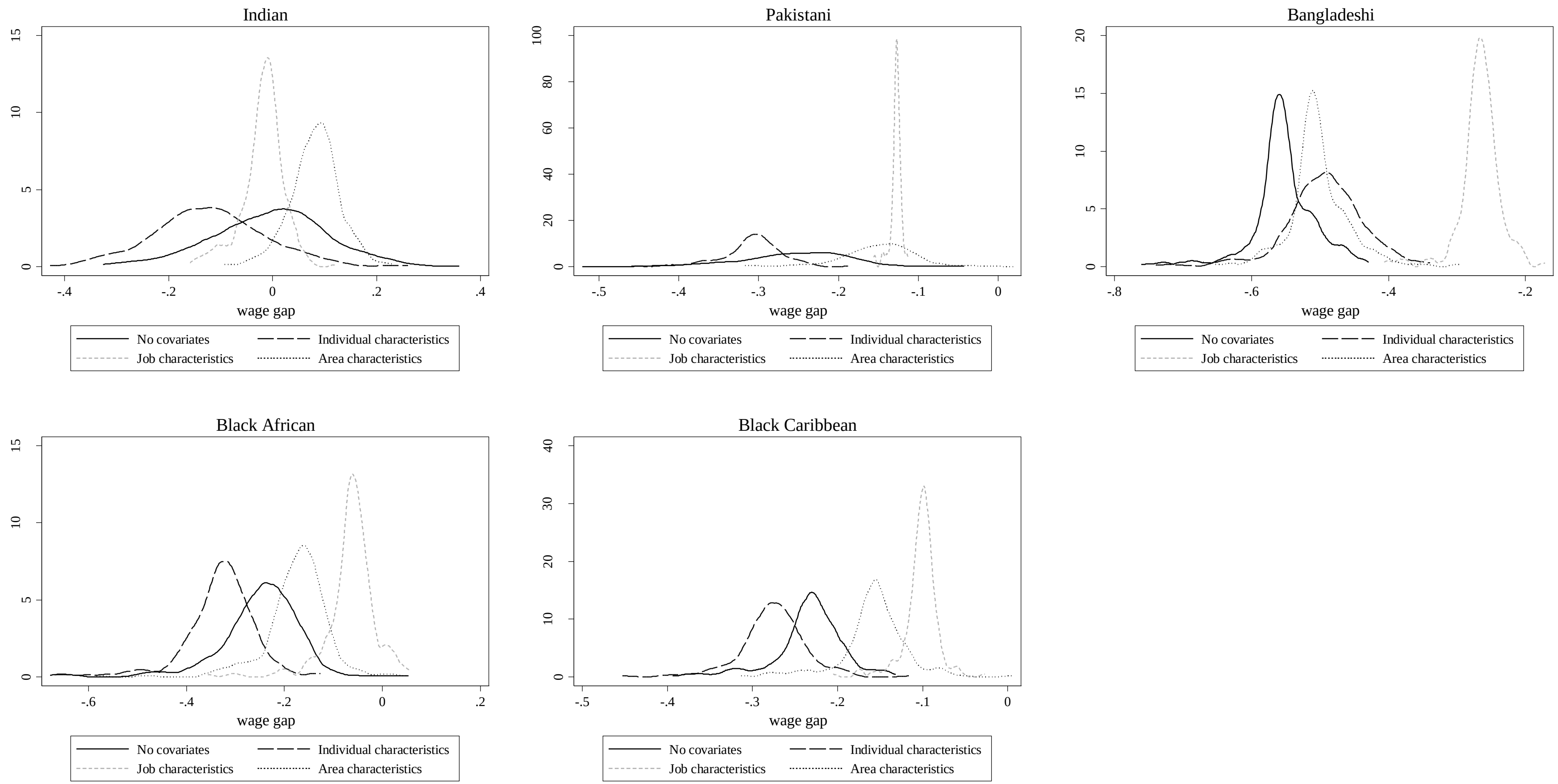


Figure 2: Distribution of ethnic wage differentials across districts of work by type of covariates
Derived from the models in Table 2; see also the Appendix, Table A3 for descriptive statistics

Data Appendix

Shift-share imputations

The 2001 and 2011 censuses provide information on the number of people from each ethnic group living in each district. For the intra-census years the total population, the non-White British population and populations belonging to each of the relevant ethnic minorities are imputed using a shift-share approach that combines data from the two censuses and from the LFS. From the two censuses we compute each variable at the district level (T_{ert}). From the LFS we compute each variable for each quarter at the national level using sample weights provided with the data to report the sample to the relevant population (see the Quarterly LFS User Guide, Volume 1). To increase sample size (the LFS is a rotating panel) and to decrease measurement errors the variables of interest are computed separately by quarter and then averaged across quarters for each calendar year.

We use the 2001 census as starting point and compute the figures for 2002-2010 using shift-share predictions based on a recursive estimation:

$$T^*_{rt} = T^*_{rt-1} * \left(1 + {(T_{LFS\_t} - T_{LFS\_t-1})}\Big/{T_{LFS_{t}-1}}\right) \tag{A1}$$

where T^*_{rt} is the variable of interest imputed for district *r* at time *t*. T^*_{rt-1} is the variable of interest computed from the census (when *t=2002* and *t-1=2001*) or computed for *t-1* using equation A1 when *t=2003-2010*. T_{LFS_t} and T_{LFS_t-1} are the variables of interest at the national level at times *t* and *t-1* computed from the LFS. We then use the 2011 as an additional starting point and derive the figures for 2012-2015 using equation A1 again (see also Table A). Hence, T^*_{rt} is estimated under the assumption that the growth rate of the variable of interest in district *r* is the same as the its growth rate at the national level.

Table A: Imputation of variables of interest

t	Source
2001	2001 census
2002	Equation A1
...	...
2010	Equation A1
2011	2011 census
2012	Equation A1
...	...
2015	Equation A1

Population density is then computed by dividing the total population by the area of each district (in Ha), while the proportion of non-White British is computed by dividing the number of non-White residents by the total population. Non-White people include all ethnic minority groups (both immigrants and second or further generations) as well as white immigrants. The proportion of co-ethnics is computed for each minority group by dividing the number of people belonging to that minority by the total population. The proportion are then matched to individual respondents by ethnicity and district. The proportion of co-ethnics applies only to the minority groups and is therefore zero for White British.

These variables are all computed based on the resident population and then combined with LFS data based on the district where the respondent works. Between the 2001 and the 2011 census some districts have been joined, while others have been divided into two or more smaller areas. Hence, for comparability for those districts that changed boundaries our analysis is based on the largest between the 2001 and the 2011 classifications.

Appendix -- Additional Tables and Figures

Table A1: Descriptive statistics by ethnic group

	White British	Indian	Pakistani	Bangladeshi	Black African	Black Caribbean
Observations	133,302	3,541	1,477	578	1,627	1,055
Second generation	--	0.299	0.360	0.230	0.141	0.655
Age	41	39	35	34	39	41
Married/cohabiting	0.724	0.756	0.760	0.706	0.677	0.599
Children	0.411	0.535	0.677	0.721	0.548	0.451
NVQ Level 4	0.342	0.529	0.423	0.351	0.534	0.272
NVQ Level 3	0.178	0.089	0.114	0.106	0.100	0.176
NVQ Level 2	0.235	0.097	0.100	0.116	0.098	0.239
Below NVQ 2	0.244	0.285	0.363	0.427	0.268	0.313
Hourly wages	13.92	14.76	10.87	9.29	11.43	12.47
Years job tenure	9.1	6.8	5.4	4.4	4.4	7.3
Part-time	0.095	0.104	0.209	0.389	0.176	0.133
Temporary job	0.041	0.072	0.062	0.081	0.112	0.057
Public sector	0.205	0.207	0.147	0.102	0.268	0.237
SOC2000-1	0.147	0.107	0.064	0.062	0.050	0.088
SOC2000-2	0.106	0.166	0.095	0.047	0.100	0.094
SOC2000-3	0.100	0.071	0.061	0.047	0.082	0.097
SOC2000-4	0.037	0.041	0.039	0.029	0.041	0.048
SOC2000-5	0.105	0.043	0.046	0.087	0.026	0.112
SOC2000-6	0.017	0.016	0.016	-	0.061	0.024
SOC2000-7	0.030	0.040	0.083	0.071	0.045	0.048
SOC2000-8	0.075	0.058	0.084	0.026	0.031	0.080
SOC2000-9	0.072	0.073	0.110	0.137	0.151	0.097
SOC2010-1	0.042	0.040	0.030	0.045	0.022	0.021
SOC2010-2	0.063	0.127	0.072	0.047	0.092	0.052
SOC2010-3	0.052	0.049	0.049	0.042	0.045	0.054
SOC2010-4	0.017	0.025	0.028	0.042	0.020	0.015
SOC2010-5	0.045	0.026	0.032	0.100	0.015	0.050
SOC2010-6	0.010	0.018	0.007	-	0.055	0.019
SOC2010-7	0.017	0.032	0.053	0.050	0.025	0.023
SOC2010-8	0.033	0.030	0.047	0.029	0.031	0.036
SOC2010-9	0.032	0.038	0.083	0.116	0.106	0.043
Pop. density (person per ha)	19	35	29	41	43	42
Prop. non-White British	0.165	0.356	0.312	0.364	0.371	0.366
Prop. co-ethnics	--	0.069	0.060	0.045	0.045	0.030
% JSA claimants	2.74	3.17	3.43	3.24	3.18	3.29

- not reported because of the small number of observations; -- zero by definition.

SOC2000: 1 Managers and Senior Officials (reference group); 2 Professional occupations; 3 Associate Professional and Technical; 4 Administrative and Secretarial; 5 Skilled Trades Occupations; 6 Personal Service Occupations; 7 Sales and Customer Service Occupations; 8 Process, Plant and Machine Operatives; 9 Elementary Occupations; SOC2010: 1 Managers, Directors And Senior Officials; 2 Professional Occupations; 3 Associate Professional And Technical Occupations; 4 Administrative And Secretarial Occupations; 5 Skilled Trades Occupations; 6 Caring, Leisure And Other Service Occupations; 7 Sales And Customer Service Occupations; 8 Process, Plant And Machine Operatives; 9 Elementary Occupations.

Table A2: Importance of characteristics, full results

	(1) No covariates	(2) Individual characteristics	(3) Job characteristics	(4) Area characteristics	(5) All covariates
Indian	-0.005	-0.121*	-0.019	0.081*	-0.027+
	(0.018)	(0.016)	(0.011)	(0.017)	(0.013)
Pakistani	-0.253*	-0.309*	-0.128*	-0.150*	-0.127*
	(0.022)	(0.017)	(0.013)	(0.023)	(0.017)
Bangladeshi	-0.554*	-0.493*	-0.267*	-0.503*	-0.317*
	(0.029)	(0.026)	(0.023)	(0.030)	(0.023)
Black African	-0.249*	-0.331*	-0.064*	-0.174*	-0.121*
	(0.021)	(0.018)	(0.016)	(0.021)	(0.015)
Black Caribbean	-0.234*	-0.276*	-0.102*	-0.157*	-0.127*
	(0.022)	(0.020)	(0.016)	(0.023)	(0.018)
Second generation		0.143*			0.081*
		(0.012)			(0.011)
Age		0.077*			0.052*
		(0.001)			(0.001)
Age square		-0.001*			-0.001*
		(0.000)			(0.000)
Married/cohabiting		0.132*			0.081*
		(0.003)			(0.003)
Children		0.046*			0.043*
		(0.003)			(0.003)
NVQ Level 3		-0.278*			-0.138*
		(0.004)			(0.004)
NVQ Level 2		-0.393*			-0.203*
		(0.004)			(0.004)
Below NVQ 2		-0.524*			-0.273*
		(0.004)			(0.004)
Years job tenure			0.010*		0.007*
			(0.000)		(0.000)
Part-time			-0.184*		-0.079*
			(0.004)		(0.005)
Temporary job			-0.107*		-0.062*
			(0.006)		(0.006)
Public sector			0.033*		-0.011*
			(0.003)		(0.003)
SOC2000-2			0.009		-0.014*
			(0.005)		(0.005)
SOC2000-3			-0.239*		-0.182*
			(0.005)		(0.005)
SOC2000-4			-0.532*		-0.405*
			(0.007)		(0.007)
SOC2000-5			-0.516*		-0.389*
			(0.005)		(0.005)
SOC2000-6			-0.682*		-0.570*
			(0.010)		(0.010)
SOC2000-7			-0.739*		-0.519*
			(0.008)		(0.008)
SOC2000-8			-0.592*		-0.480*
			(0.006)		(0.005)
SOC2000-9			-0.771*		-0.581*
			(0.006)		(0.006)

SOC2010-1			0.318*		0.250*
			(0.017)		(0.017)
SOC2010-2			0.361*		0.261*
			(0.017)		(0.017)
SOC2010-3			0.142*		0.118*
			(0.017)		(0.017)
SOC2010-4			-0.152*		-0.110*
			(0.018)		(0.018)
SOC2010-5			-0.180*		-0.111*
			(0.017)		(0.017)
SOC2010-6			-0.344*		-0.292*
			(0.020)		(0.020)
SOC2010-7			-0.345*		-0.225*
			(0.019)		(0.018)
SOC2010-8			-0.242*		-0.176*
			(0.017)		(0.017)
SOC2010-9			-0.416*		-0.295*
			(0.017)		(0.017)
Population density				0.003*	0.002*
				(0.001)	(0.001)
Population density square				-0.000	-0.000
				(0.000)	(0.000)
Prop. non-White British				0.821*	0.506*
				(0.094)	(0.068)
Pr. non-White British sq.				-0.660*	-0.436*
				(0.098)	(0.072)
Prop. co-ethnics				-3.901*	-2.088*
				(0.370)	(0.266)
Prop. co-ethnics square				9.529*	5.354*
				(1.463)	(1.065)
% JSA claimants				-0.032*	-0.019*
				(0.007)	(0.006)
% JSA claimants square				0.001	0.001
				(0.001)	(0.001)
Intercept	-	0.705*	2.492*	2.235*	1.374*
		(0.019)	(0.014)	(0.019)	(0.019)
Observations	141,589	141,589	141,589	141,580	141,580

+ Significant at 5%, * Significant at 1%
- not reported to avoid statistical disclosure
Results of multilevel models with random intercept and random slope; standard errors in parenthesis
Other explanatory variables: dummies for year and quarter of the interview;
Occupation dummies:
SOC2000: 1 Managers and Senior Officials (reference group); 2 Professional occupations; 3 Associate Professional and Technical; 4 Administrative and Secretarial; 5 Skilled Trades Occupations; 6 Personal Service Occupations; 7 Sales and Customer Service Occupations; 8 Process, Plant and Machine Operatives; 9 Elementary Occupations;
SOC2010: 1 Managers, Directors And Senior Officials; 2 Professional Occupations; 3 Associate Professional And Technical Occupations; 4 Administrative And Secretarial Occupations; 5 Skilled Trades Occupations; 6 Caring, Leisure And Other Service Occupations; 7 Sales And Customer Service Occupations; 8 Process, Plant And Machine Operatives; 9 Elementary Occupations.
Population density is measured in persons per hectare.

Table A3: Distribution of ethnic wage gaps across districts of work by type of covariates included in the models (derived from the models in Table 2)

	Variables	Number of districts	Mean	Min	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile	Max
Indian	No covariates	294	-0.005	-0.327	-0.148	-0.078	0.002	0.064	0.136	0.359
	Individual characteristics	294	-0.121	-0.428	-0.255	-0.193	-0.127	-0.054	0.023	0.260
	Job characteristics	294	-0.019	-0.159	-0.070	-0.035	-0.014	0.003	0.029	0.123
	Area characteristics	294	0.081	-0.093	0.020	0.054	0.083	0.109	0.140	0.231
	Individual, job and area	294	-0.027	-0.120	-0.056	-0.038	-0.027	-0.013	0.002	0.060
Pakistani	No covariates	214	-0.253	-0.521	-0.346	-0.289	-0.248	-0.207	-0.184	-0.042
	Individual characteristics	214	-0.309	-0.459	-0.361	-0.323	-0.305	-0.286	-0.264	-0.187
	Job characteristics	214	-0.128	-0.156	-0.134	-0.130	-0.127	-0.125	-0.122	-0.113
	Area characteristics	214	-0.150	-0.317	-0.202	-0.175	-0.147	-0.120	-0.104	0.018
	Individual, job and area	214	-0.127	-0.247	-0.160	-0.136	-0.126	-0.112	-0.098	-0.056
Bangladeshi	No covariates	165	-0.554	-0.761	-0.601	-0.569	-0.557	-0.529	-0.499	-0.429
	Individual characteristics	165	-0.493	-0.740	-0.550	-0.523	-0.495	-0.458	-0.418	-0.339
	Job characteristics	165	-0.267	-0.406	-0.294	-0.278	-0.265	-0.252	-0.235	-0.172
	Area characteristics	165	-0.503	-0.676	-0.552	-0.521	-0.508	-0.481	-0.452	-0.295
	Individual, job and area	165	-0.317	-0.526	-0.356	-0.338	-0.318	-0.294	-0.271	-0.125
Black African	No covariates	251	-0.249	-0.678	-0.343	-0.283	-0.240	-0.198	-0.166	0.053
	Individual characteristics	251	-0.331	-0.669	-0.403	-0.362	-0.324	-0.287	-0.259	-0.126
	Job characteristics	251	-0.064	-0.356	-0.112	-0.080	-0.060	-0.038	-0.011	0.058
	Area characteristics	294	-0.005	-0.327	-0.148	-0.078	0.002	0.064	0.136	0.359
	Individual, job and area	294	-0.019	-0.159	-0.070	-0.035	-0.014	0.003	0.029	0.123
Black Caribbean	No covariates	294	0.081	-0.093	0.020	0.054	0.083	0.109	0.140	0.231
	Individual characteristics	294	0.034	-0.065	0.013	0.027	0.035	0.043	0.053	0.105
	Job characteristics	294	-0.027	-0.120	-0.056	-0.038	-0.027	-0.013	0.002	0.060
	Area characteristics	214	-0.253	-0.521	-0.346	-0.289	-0.248	-0.207	-0.184	-0.042
	Individual, job and area	214	-0.128	-0.156	-0.134	-0.130	-0.127	-0.125	-0.122	-0.113

Table A4: Separate impact of covariates on ethnic wage differentials

Observations: 141,580	No covariates	Born abroad	Age (quadratic)	Marital status	Dependent children	Qualification
Indian	-0.005	-0.013	-0.007	-0.019	-0.021	-0.094*
	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)	(0.015)
Pakistani	-0.253*	-0.265*	-0.212*	-0.270*	-0.280*	-0.292*
	(0.022)	(0.022)	(0.020)	(0.021)	(0.022)	(0.019)
Bangladeshi	-0.554*	-0.561*	-0.505*	-0.555*	-0.595*	-0.502*
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.027)
Black African	-0.249*	-0.253*	-0.260*	-0.234*	-0.267*	-0.323*
	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)	(0.018)
Black Caribbean	-0.234*	-0.255*	-0.257*	-0.194*	-0.238*	-0.176*
	(0.022)	(0.024)	(0.020)	(0.021)	(0.022)	(0.020)

Observations: 141,580	Job tenure	Part-time	Temporary job	Public sector	Occupation	Population density (quadratic)	Proportion non-white British (quadratic)	Proportion co-ethnics (quadratic)	Proportion JSA claimants (quadratic)
Indian	0.046+	-0.004	0.012	-0.015	-0.052*	-0.005	-0.005	0.077*	-0.005
	(0.018)	(0.017)	(0.018)	(0.017)	(0.011)	(0.018)	(0.018)	(0.017)	(0.018)
Pakistani	-0.191*	-0.224*	-0.242*	-0.255*	-0.174*	-0.254*	-0.254*	-0.154*	-0.253*
	(0.022)	(0.019)	(0.022)	(0.021)	(0.013)	(0.022)	(0.022)	(0.022)	(0.022)
Bangladeshi	-0.475*	-0.419*	-0.547*	-0.532*	-0.355*	-0.558*	-0.558*	-0.501*	-0.554*
	(0.030)	(0.028)	(0.029)	(0.029)	(0.023)	(0.029)	(0.029)	(0.030)	(0.029)
Black African	-0.164*	-0.211*	-0.221*	-0.261*	-0.118*	-0.250*	-0.252*	-0.175*	-0.249*
	(0.021)	(0.021)	(0.021)	(0.021)	(0.016)	(0.021)	(0.021)	(0.021)	(0.021)
Black Caribbean	-0.196*	-0.211*	-0.230*	-0.237*	-0.123*	-0.236*	-0.237*	-0.158*	-0.234*
	(0.022)	(0.021)	(0.021)	(0.022)	(0.016)	(0.022)	(0.022)	(0.023)	(0.022)

+ Significant at 5%, * Significant at 1%

Results of multilevel models with random intercept and random slope; standard errors in parenthesis. Other explanatory variables: year-quarter of the interview.

Table A5: Importance of characteristics – County level

	(1)	(2)	(3)	(4)	(5)
Indian	0.037	-0.091*	0.009	0.161*	0.026
	(0.028)	(0.023)	(0.017)	(0.021)	(0.016)
Pakistani	-0.193*	-0.257*	-0.088*	-0.059	-0.061*
	(0.035)	(0.026)	(0.021)	(0.031)	(0.023)
Bangladeshi	-0.495*	-0.426*	-0.238*	-0.436*	-0.262*
	(0.040)	(0.035)	(0.026)	(0.035)	(0.021)
Black African	-0.206*	-0.286*	-0.028	-0.147*	-0.085*
	(0.029)	(0.025)	(0.022)	(0.020)	(0.017)
Black Caribbean	-0.194*	-0.260*	-0.075*	-0.120*	-0.099*
	(0.037)	(0.036)	(0.029)	(0.024)	(0.019)
Individual characteristics	no	yes	no	no	yes
Job characteristics	no	no	yes	no	yes
Area characteristics	no	no	no	yes	yes
Observations	133,312	133,312	133,312	133,312	133,312

+ Significant at 5%, * Significant at 1%
Results of multilevel models with random intercept and random slope; standard errors in parenthesis
Other explanatory variables: year-quarter of the interview; the individual, job and area characteristics are the same as in Table A2.

Table A6: Importance of characteristics – County level, including only those who lived at the current address at least two years before the current job started

	(1)	(2)	(3)	(4)	(5)
Indian	0.041	-0.150*	-0.028	0.221*	-0.026
	(0.043)	(0.036)	(0.029)	(0.041)	(0.034)
Pakistani	-0.252*	-0.316*	-0.131*	0.020	-0.083+
	(0.028)	(0.028)	(0.023)	(0.048)	(0.038)
Bangladeshi	-0.427*	-0.385*	-0.246*	-0.342*	-0.253*
	(0.054)	(0.048)	(0.035)	(0.047)	(0.036)
Black African	0.006	-0.207*	0.032	0.054	-0.084+
	(0.059)	(0.046)	(0.042)	(0.045)	(0.034)
Black Caribbean	-0.120	-0.264*	-0.050	-0.038	-0.123*
	(0.063)	(0.048)	(0.046)	(0.050)	(0.042)
Individual characteristics	no	yes	no	no	yes
Job characteristics	no	no	yes	no	yes
Area characteristics	no	no	no	yes	yes
Observations	39,185	39,185	39,185	39,185	39,185

+ Significant at 5%, * Significant at 1%
Results of multilevel models with random intercept and random slope; standard errors in parenthesis
Other explanatory variables: year-quarter of the interview; the individual, job and area characteristics are the same as in Table A2.

Table A7: Importance of characteristics – County level, including only those who work and live in the same district

	(1)	(2)	(3)	(4)	(5)
Indian	0.034	-0.108*	0.001	0.144*	0.002
	(0.029)	(0.025)	(0.020)	(0.026)	(0.023)
Pakistani	-0.149*	-0.206*	-0.061+	-0.024	-0.040
	(0.041)	(0.034)	(0.026)	(0.040)	(0.032)
Bangladeshi	-0.440*	-0.402*	-0.209*	-0.390*	-0.233*
	(0.043)	(0.036)	(0.028)	(0.032)	(0.027)
Black African	-0.204*	-0.260*	-0.014	-0.143*	-0.066*
	(0.034)	(0.032)	(0.028)	(0.026)	(0.024)
Black Caribbean	-0.174*	-0.245*	-0.087+	-0.104*	-0.131*
	(0.043)	(0.051)	(0.040)	(0.029)	(0.047)
Individual characteristics	no	yes	no	no	yes
Job characteristics	no	no	yes	no	yes
Area characteristics	no	no	no	yes	yes
Observations	73,369	73,369	73,369	73,369	73,369

+ Significant at 5%, * Significant at 1%
Results of multilevel models with random intercept and random slope; standard errors in parenthesis
Other explanatory variables: year-quarter of the interview; the individual, job and area characteristics are the same as in Table A2.

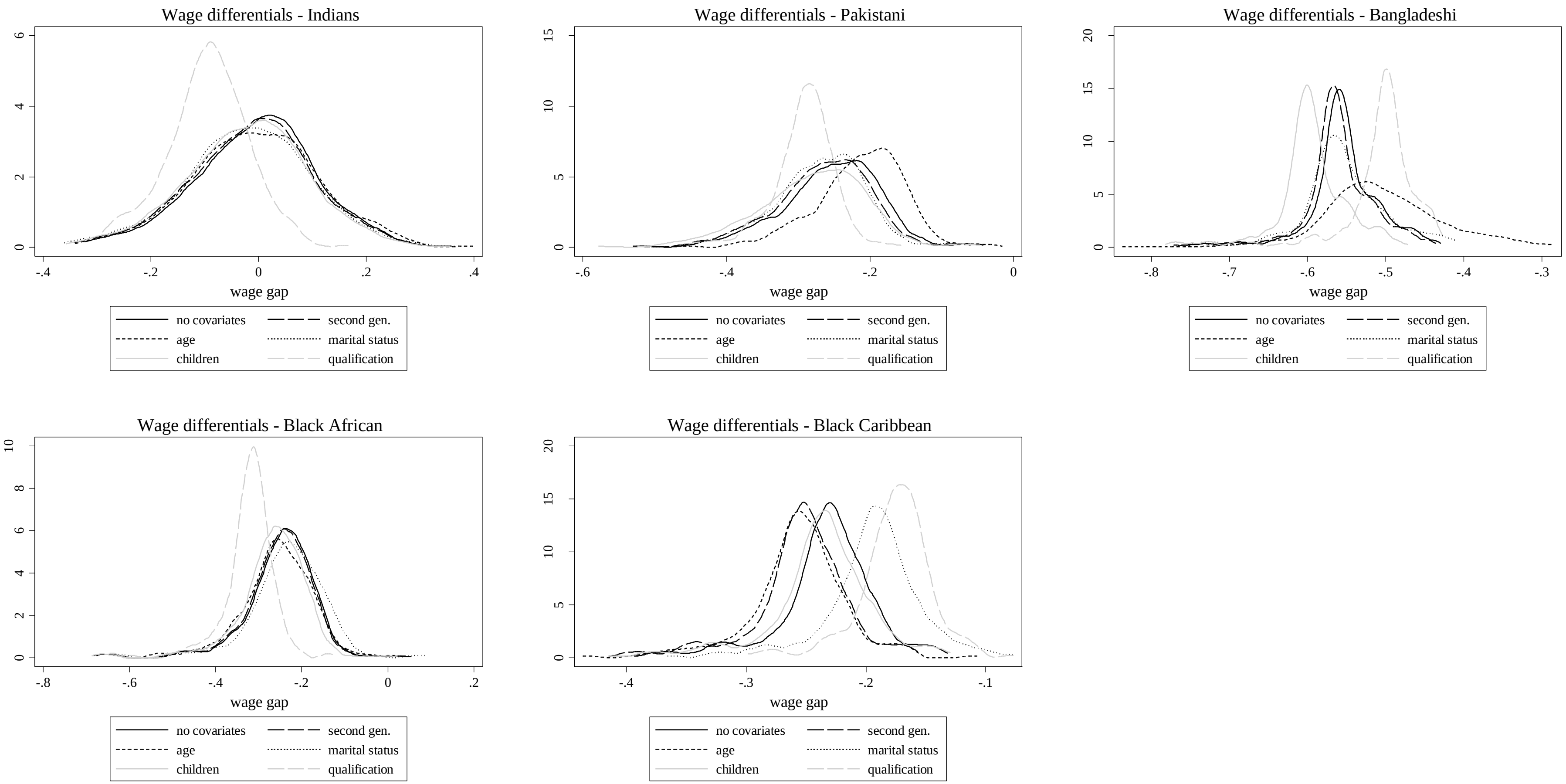


Figure A1: Distributions of ethnic wage differentials across areas by individual characteristics. Derived from the models in Table A4.

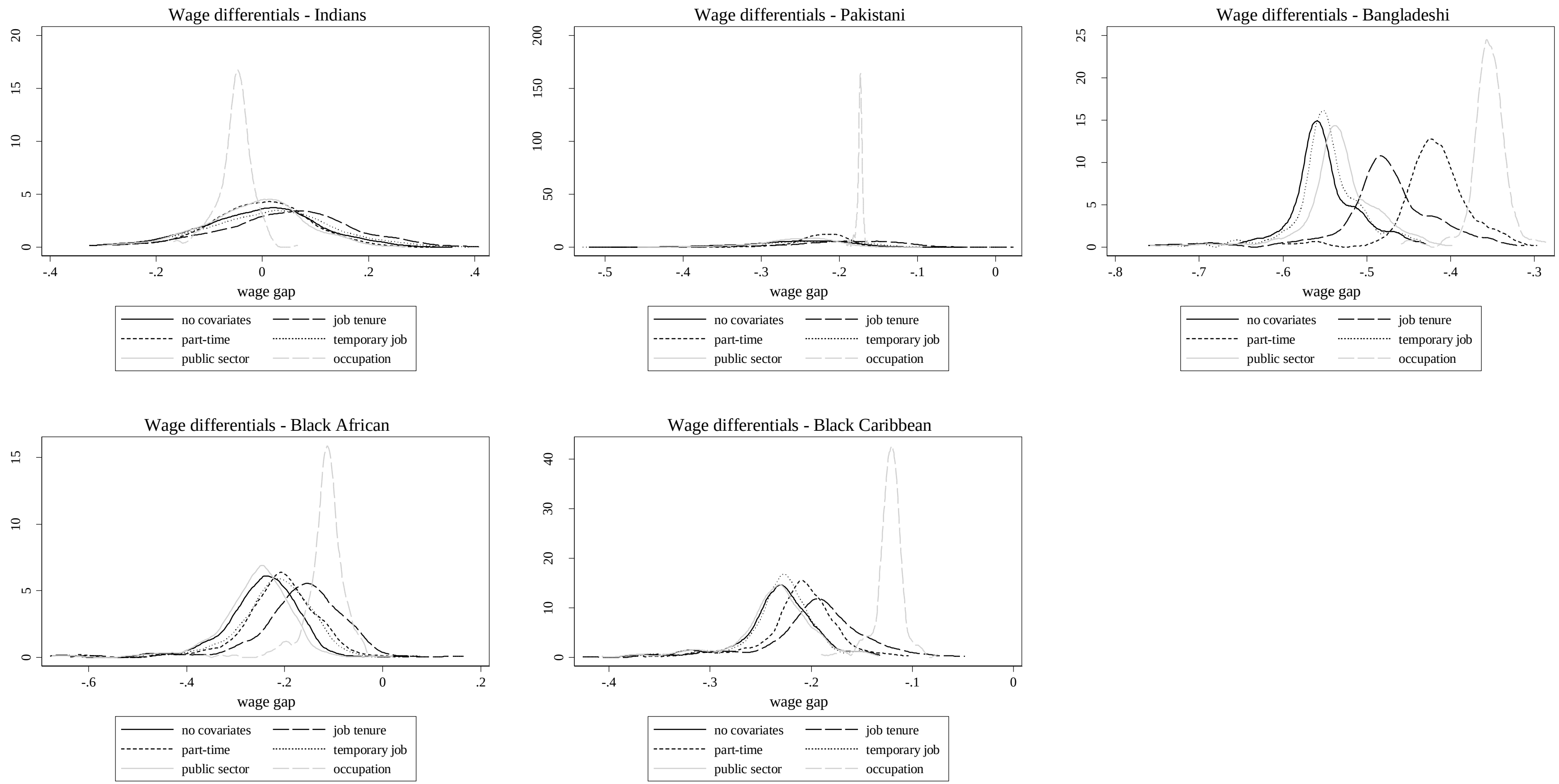


Figure A2: Distributions of ethnic wage differentials across areas by job characteristics. Derived from the models in Table A4.

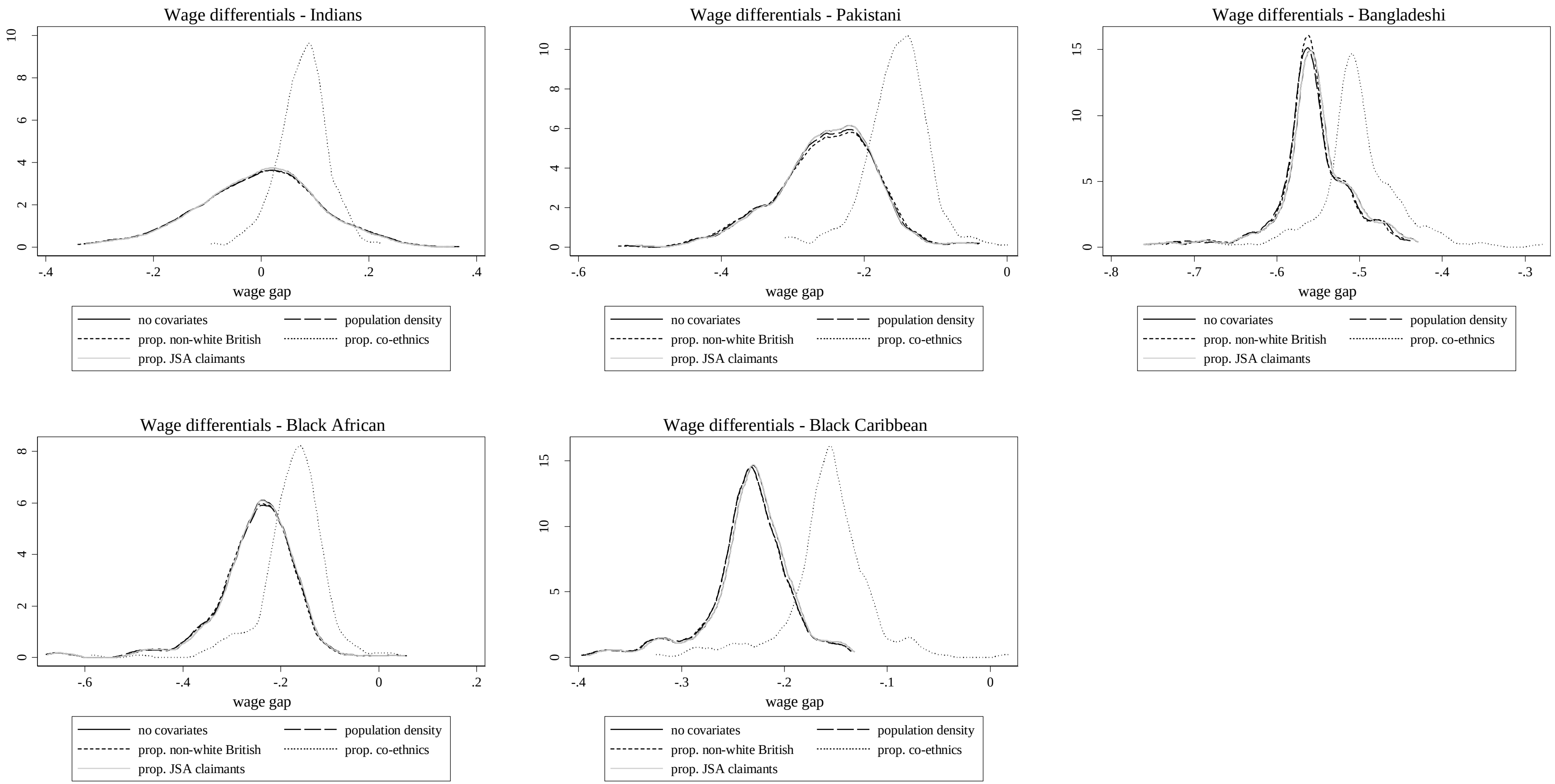


Figure A3: Distributions of ethnic wage differentials across areas by area characteristics. Derived from the models in Table A4.

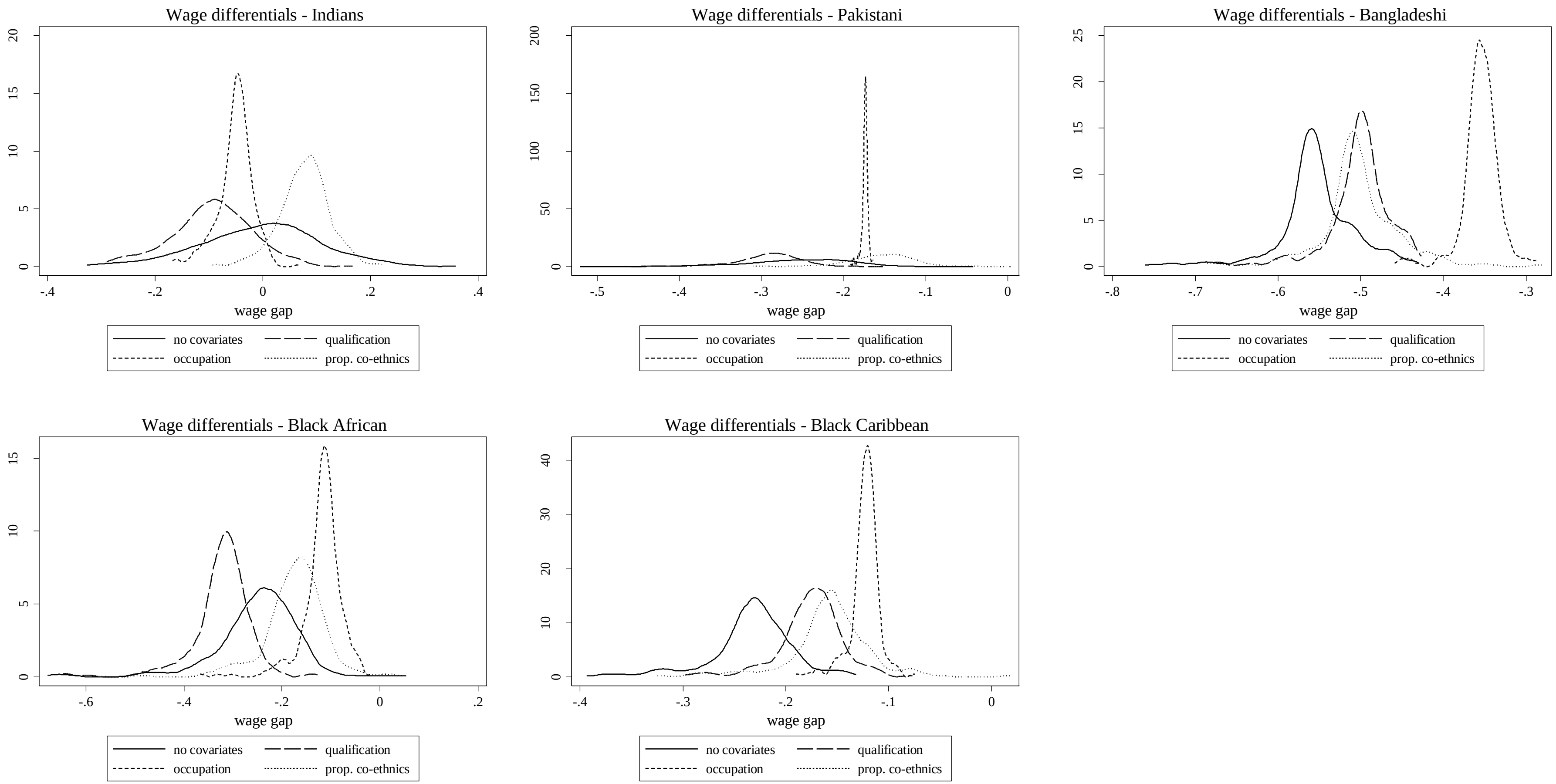
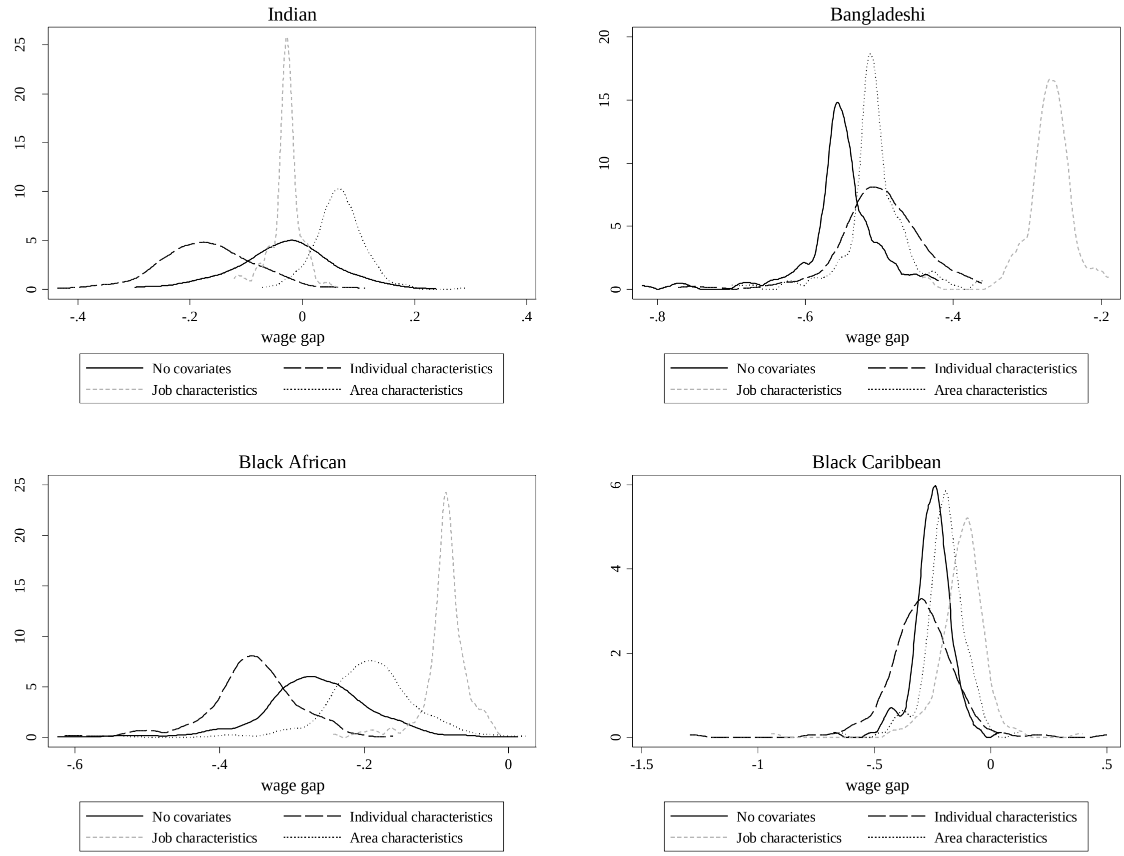


Figure A4: Distributions of ethnic wage differentials across areas for models including only qualification, occupation, or the proportion of co-ethnics. Derived from the models in Table A4.

Figure A5: Distribution of ethnic wage differentials across districts of work by type of covariates - 2010-2015



Regression results -- 2010-2015

	(1)	(2)	(3)	(4)	(5)
Indian	-0.032	-0.169*	-0.030+	0.066*	-0.053*
	(0.022)	(0.020)	(0.015)	(0.024)	(0.018)
Pakistani	-0.271*	-0.344*	-0.123*	-0.142*	-0.137*
	(0.025)	(0.020)	(0.018)	(0.029)	(0.022)
Bangladeshi	-0.551*	-0.501*	-0.271*	-0.507*	-0.323*
	(0.039)	(0.034)	(0.031)	(0.038)	(0.030)
Black African	-0.267*	-0.355*	-0.088*	-0.190*	-0.150*
	(0.027)	(0.023)	(0.020)	(0.029)	(0.021)
Black Caribbean	-0.251*	-0.299*	-0.125*	-0.198*	-0.171*
	(0.037)	(0.040)	(0.034)	(0.038)	(0.038)
Individual characteristics	no	yes	no	no	yes
Job characteristics	no	no	yes	no	yes
Area characteristics	no	no	no	yes	yes
Observations	55,327	55,327	55,327	55,327	55,327

+ Significant at 5%, * Significant at 1%

Results of multilevel models with random intercept and random slope; standard errors in parenthesis

Other explanatory variables: year-quarter of the interview. The full set of results is in the Appendix, Table A2.