

Article

Ethnicity pay gaps: 2019

Earnings and employment statistics for different ethnic groups, using regression analysis to provide more insight into factors that affect pay.

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1 . Main points

- The ethnicity pay gap between White and ethnic minority employees has narrowed to its smallest level since 2012 in England and Wales.
- Most of the minority ethnic groups analysed continue to earn less than White British employees but, in 2019, those in the Chinese, White Irish, White and Asian, and Indian ethnic groups all earned higher hourly pay than White British employees.
- The ethnicity pay gap is larger for men than women (though for most ethnic groups, men continue to earn more than women).
- The size of the ethnicity pay gap for those aged 30 years and over is larger than for those aged 16 to 29 years.
- The ethnicity pay gap differs across regions and is largest in London (23.8%) and smallest in Wales (1.4%).
- Adjusting for pay determining characteristics narrows the pay gap for many (though not all) ethnic groups, helping us to better understand differences in earnings.
- Adjusted pay gaps vary subnationally, with London often having wider pay gaps.

2 . Analysis of ethnicity pay gaps

This article presents analysis of ethnicity pay gaps. It builds on last year's [Ethnicity pay gaps in Great Britain: 2018](#) , updating it and considers a greater number of ethnic groups to provide greater detail.

The data analysed are from the Annual Population Survey 2012 to 2019 and each year covers January to December. All data were collected before the impact of the coronavirus (COVID-19) on the UK economy.

Definition of ethnicity pay gap

In this article, the headline measure for the ethnicity pay gap uses Annual Population Survey data and is calculated as the difference between the median hourly earnings of the reference group (White or White British) and other ethnic groups as a proportion of average hourly earnings of the reference group.

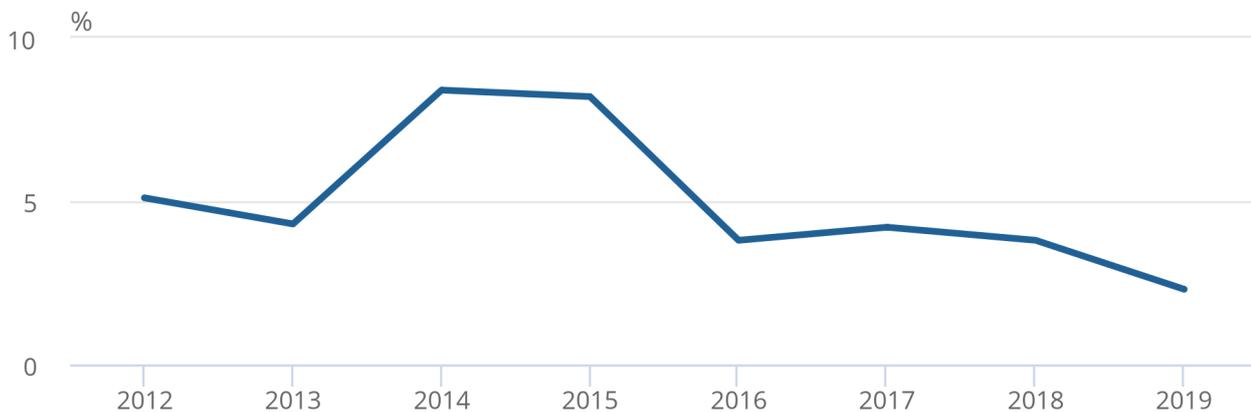
For example, a positive 5.0% ethnic pay gap between White British and Indian ethnic groups would denote that the median hourly earnings for employees of an Indian ethnicity are 5.0% less than median hourly earnings of White British employees. Conversely, a negative 5.0% pay gap would denote that employees of Indian ethnicity earn 5.0% more, on average, than White British employees. Using this terminology ensures consistency with existing analysis of different pay gaps.

Figure 1: The hourly median pay gap between White and the ethnic minority group has narrowed to the smallest since 2012

Pay gap between the White group and the ethnic minority group, England and Wales, 2012 to 2019

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Pay gap between the White group and the ethnic minority group, England and Wales, 2012 to 2019



Source: Office for National Statistics - Annual Population Survey (APS)

In 2019, the median hourly pay for those in the White ethnic group was £12.40 per hour compared with those in ethnic minority at £12.11 per hour – a pay gap of 2.3%, its narrowest level since 2012. The pay gap was at its largest in 2014, at 8.4%. This simple comparison between White and ethnic minority groups does, however, mask a wide variety of experiences among different ethnic minorities.

Figure 2: Within the ethnic minority group, the median hourly pay rate differs widely between different ethnic groups

Pay gap, 17 ethnic groups, England and Wales, 2012 to 2019

Notes:

1. While the 17-category ethnicity breakdown provides greater detail, this is at cost of relatively small sample sizes for some ethnic groups thereby resulting in volatility of some estimates between 2012 and 2019.
2. Due to small sample sizes, estimates for White and Black African, Black Other, and Arab ethnic groups should be treated with caution.

[Download the data](#)

Across 2012 to 2019, there was a negative pay gap for those of Chinese, White Irish, White and Asian, and Indian ethnicities. This means that they earn higher median hourly pay than those of White British ethnicity. Many other ethnic groups including Bangladeshi, Pakistani and Arab consistently earned less than those of White British ethnicity over the same time period.

Figure 3: Most minority ethnic groups earn less on average than White British people in 2019, though some groups earned more than their White British counterparts

Median hourly pay and pay gap, 17 ethnic groups, England and Wales, 2019

Notes:

1. Due to small sample sizes, estimates for White and Black African, Black Other, and Arab ethnic groups should be treated with caution.

[Download the data](#)

Focusing on 2019, the Bangladeshi (£10.58 per hour) and Pakistani (£10.55 per hour) ethnic groups had some of the widest positive pay gaps, respectively earning 15.3% and 15.5% less than White British employees (£12.49 per hour). Those found to earn more included: White Irish by 40.5% (£17.55 per hour), Chinese by 23.1% (£15.38 per hour) and Indian by 15.5% (£14.43 per hour).

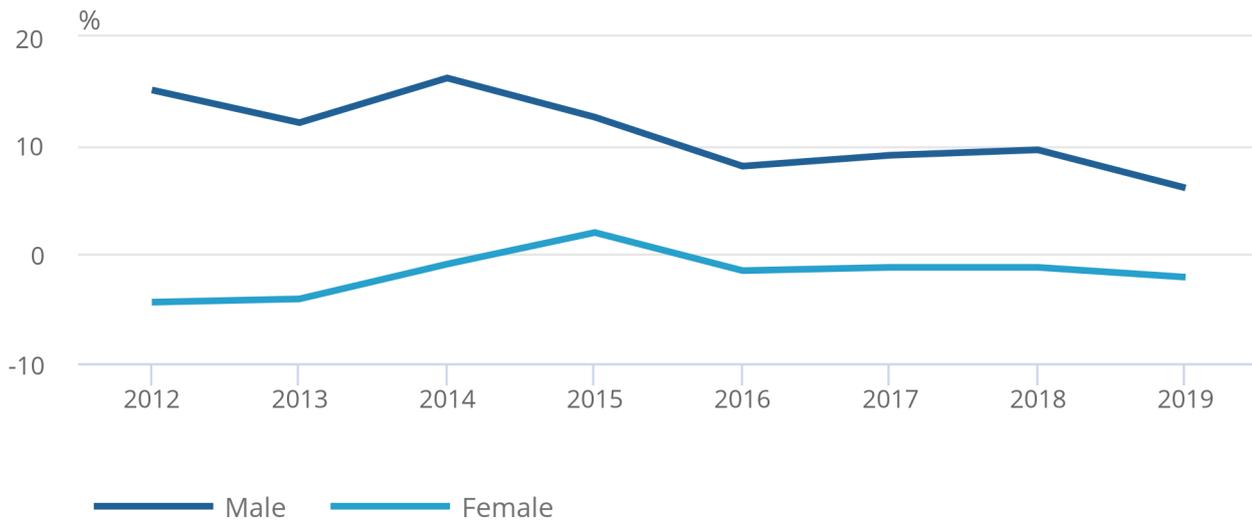
3 . Pay gaps by sex

Figure 4: For all years 2012 to 2019 the ethnicity pay gap is larger for men than for women

Pay gap between the White group and the ethnic minority group by sex, England and Wales, 2012 to 2019

Figure 4: For all years 2012 to 2019 the ethnicity pay gap is larger for men than for women

Pay gap between the White group and the ethnic minority group by sex, England and Wales, 2012 to 2019



Source: Office for National Statistics - Annual Population Survey (APS)

In 2019, ethnic minority men earned 6.1% less than White men whilst the hourly pay of ethnic minority women was 2.1% more than White women.

Figure 5: Men earned a higher hourly median wage than women in all but three ethnic groups in 2019

Median hourly pay, 17 ethnic groups by sex, England and Wales, 2019

[Download the data](#)

It is worth keeping in mind that, [overall, men tend to earn more than women](#) and that for those ethnicities where women earn more, it is only marginally more than men in the same ethnic group, and often less than men in other ethnic groups.

4 . Pay gaps by age

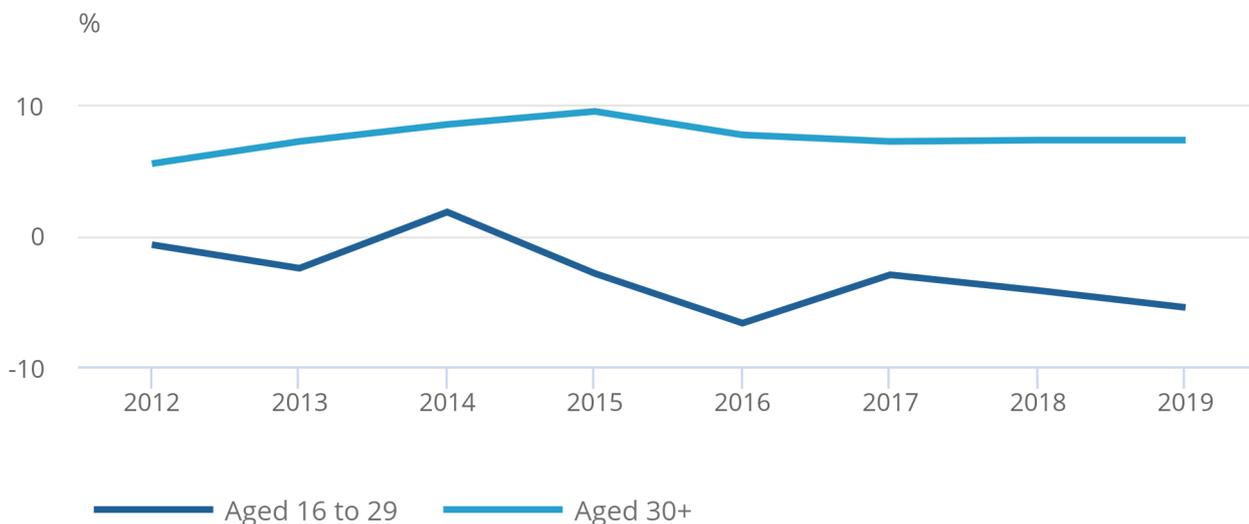
Ethnicity pay gaps differ by age group. The pay gap between the White group and the ethnic minority group is larger for those aged 30 years and over than for those aged 16 to 29 years. Among those aged 30 years and over, those in ethnic minority tend to earn less than those of White ethnicities. In contrast, those in the ethnic minority group aged 16 to 29 years tend to earn more than those of White ethnicities of the same age.

Figure 6: The pay gap between the White group and the ethnic minority group is larger for those aged 30 years and over than for those aged 16 to 29 years

Pay gap between the White group and the ethnic minority group by age group, England and Wales, 2012 to 2019

Figure 6: The pay gap between the White group and the ethnic minority group is larger for those aged 30 years and over than for those aged 16 to 29 years

Pay gap between the White group and the ethnic minority group by age group, England and Wales, 2012 to 2019



Source: Office for National Statistics - Annual Population Survey (APS)

Considering more granular ethnic groups, data suggest that while most minority groups aged 30 years and over earn less than their White British counterparts, many minority groups aged 16 to 29 years earn more than their White British counterparts. Those in the Arab ethnic group aged 16 to 29 years, for example, earn more than those White British aged 16 to 29 years (shown by a negative pay gap) whereas those Arab aged 30 years and over earn 10.9% less than their White British counterparts (shown by a positive pay gap).

Figure 7: Most ethnic minority groups aged 30 years and over tend to earn less than White British counterparts, many of those in ethnic minority groups aged 16 to 29 years earn more than White British

Median hourly pay and pay gap, 17 ethnic groups by age group, England and Wales, 2019

Note:

1. As noted in our report last year, there are several possible reasons why we see a widening of the pay gap between younger and older employees. These could include improved labour market outcomes for 2nd and 3rd generation migrants or alternatively, different rates of earnings progression between employees in different ethnic groups.

[Download the data](#)

5 . Pay gaps by region

Figure 8: The ethnicity pay gap is largest in London and smallest in Wales

Ethnicity pay gap between those White and those ethnic minority by region, Great Britain, 2019

[Download the data](#)

The ethnicity pay gap was largest in London at 23.8% in 2019 and smallest in Wales at 1.4%. There was a negative pay gap in the East of England region (negative 8.6%) meaning that, for that region, those ethnic minority earn a higher median hourly wage than those in the White ethnic group. The pay gaps by region and country have the possibility to be affected by employees who cross a boundary to another region or country to work. The pay they receive might be more representative of where they work rather than where they live.

6 . Modelling the factors that affect pay

For most ethnicities, the pay gaps narrow when adjusting for pay determining characteristics

The pay someone earns depends on multiple different factors, such as their occupation or where their job is in Great Britain (for example, those living in London sometimes have higher pay, which compensates for the higher cost of living in London).

If pay determining characteristics vary between ethnic groups, the pay gaps observed might result from differences in these characteristics, rather than because of ethnicity.

For example, earlier sections showed that the pay gap differed by age and sex. It is therefore necessary to isolate the effect that ethnicity has on pay, factoring out age, sex and other pay determining characteristics. We use regression to do this.

Regression is a statistical technique that allows us to model the relationship between the dependent variable (for example, hourly pay) and explanatory variables (ethnicity, occupation and so on).

In our analysis we model the logarithm of hourly pay against the following explanatory variables:

- ethnicity
- country of birth
- occupation
- highest qualification level
- age
- sex
- marital status
- working pattern
- disability status
- working in the public or private sector
- geography
- whether they have children or not

The model used to analyse pay on 2019 data is different from the model used to analyse [pay on 2018 data](#). The 2019 model includes more factors (marital status and whether they have children), which could affect pay to improve the fit of the model. Variables have been chosen as they are known to affect pay directly (occupation, for example) or indirectly (having a child might affect the choice of occupation). Using regression in this way allows us to estimate the effect of ethnicity, if all other characteristics were the same between the different groups of people.

In the [previous analysis](#) we used ordinary least squares regression (OLS) to estimate the percentage difference in pay, we have changed to using quantile regression instead (QR). Using OLS meant that we estimated pay gaps based on conditional means, while using QR we estimate pay gaps based on conditional medians. We can now compare more easily with the raw pay gaps discussed in the previous sections, which are also calculated from medians.

Even though medians are more robust to outliers than means, as a form of outlier treatment we have removed the top 1% and bottom 2% of the pay distribution from our data. Earnings data collected from the Annual Population Survey (APS) are known to be subject to greater recall error than data collected from the Annual Survey of Hours and Earnings (ASHE), a business survey. For more information about differences in earnings data captured between the APS and ASHE, please refer to Section 10: Data sources and quality.

Adjusting for pay determining characteristics influences the pay gaps observed, with a narrowing of pay gaps for most ethnicities. This suggests that differences in the average characteristics of different ethnic groups was influencing the unadjusted pay gap, often overstating the difference. There are, however, some ethnicities where these characteristics understated the extent that pay differed between the two groups.

The largest narrowing of the pay gap occurs for those whose ethnicity is White Irish. The extent of this reduction depends on whether they were born in the UK or not, with those not born in the UK having a 41.7 percentage point reduction in the pay gap between the unadjusted and adjusted figures. UK born have a 27.8 percentage point reduction. Both adjusted and unadjusted pay gaps show that White Irish employees earn more on average than White British employees.

Figure 9: The non-UK born White Irish pay gap narrows by 41.7 percentage points when adjusting for pay determining characteristics

Adjusted and unadjusted pay gap

[Download the data](#)

We can illustrate how modelling affects the pay gaps by focusing on certain characteristics and how they vary among different ethnic groups.

The pay someone receives differed by where in England and Wales they lived. If there was a different geographic distribution between the ethnic groups, the geographic difference in pay would contribute to the pay gaps. This model strips out the effect of geography by adjusting the pay to London levels (the reference category in the model).

The effect of the adjustment in pay gaps observed depends on the proportion of employees living in London. Of all White British employees, 9% live in London, the lowest proportion of all the ethnicities. Assuming that there is a “London premium”, the pay for White British employees is adjusted upwards more than that of the other ethnic minority groups, because fewer White British employees live there.

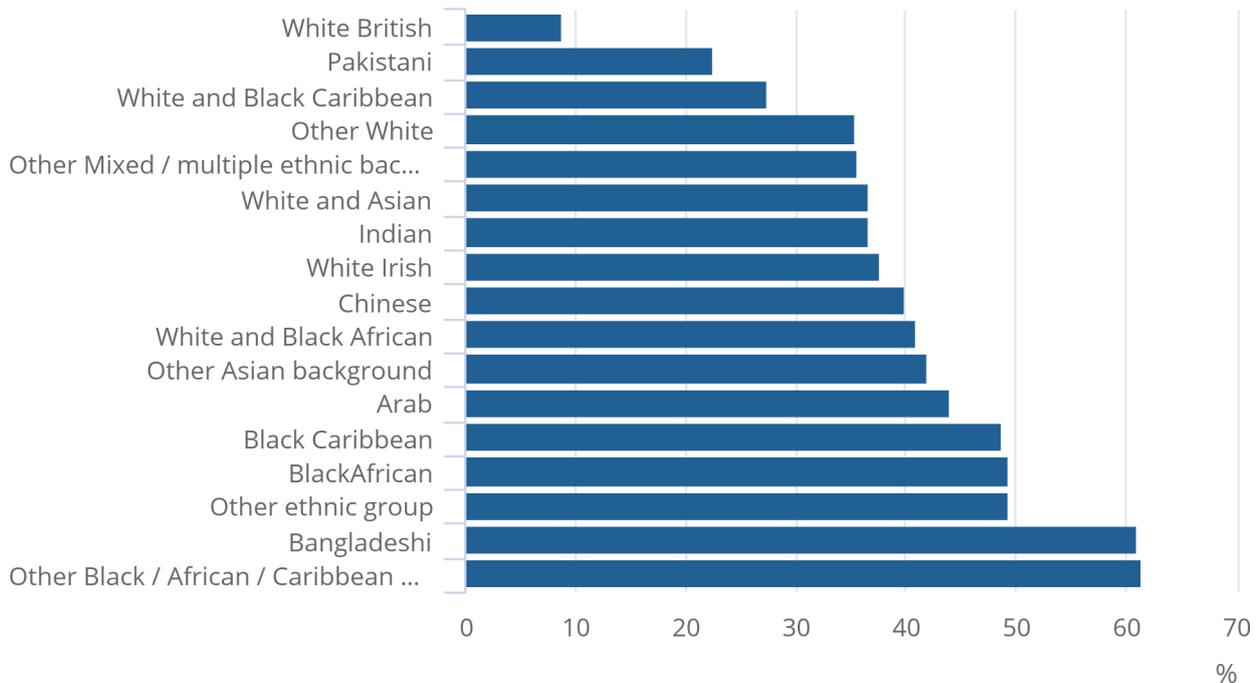
The removal of the effect of geography narrows some of the pay gaps as is the case for those of a White Irish ethnicity but widens others, for example, those of a Bangladeshi ethnicity.

Figure 10: White British employees are the least likely to live in London

Percentage of employees living in London by Ethnicity, England and Wales, 2019

Figure 10: White British employees are the least likely to live in London

Percentage of employees living in London by Ethnicity, England and Wales, 2019



Source: Office for National Statistics – Annual Population Survey

The highest qualifications an employee has gained is also a factor in the pay received. Those with a higher level of qualifications tend to have higher levels of pay (nearly half of those with a degree are in the top 25% of the pay distribution). The model adjusts to the level of pay of those with a degree or equivalent. Given that, after keeping all other factors constant, having a degree increases the pay on average by 18% compared with those with a GCSE, and 13% with those with an A Level, the adjustment would increase the median pays for those ethnic groups that are less likely to have a degree.

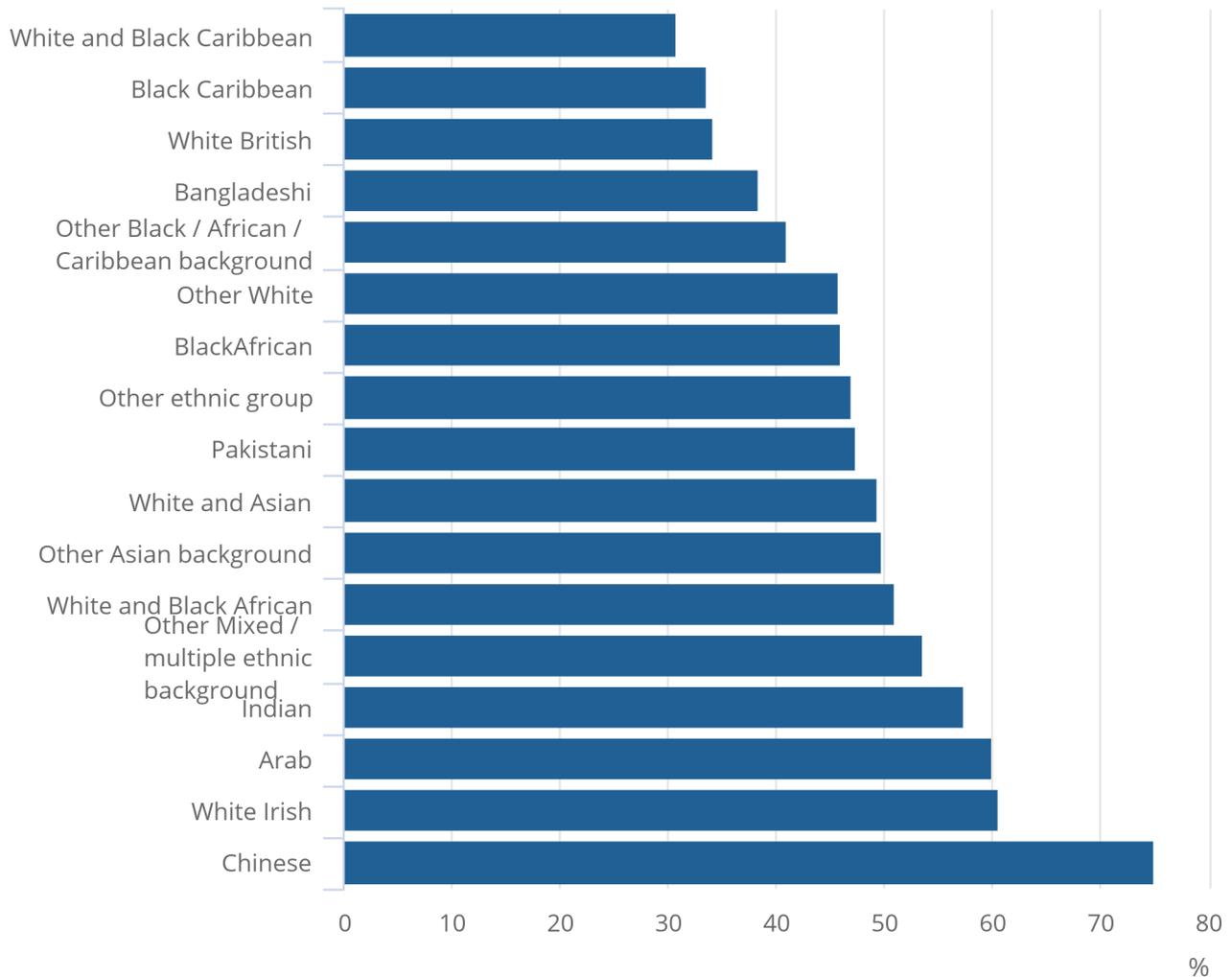
For instance, this adjustment for highest qualification gained, accounts for some of the difference in pay between Chinese employees and White British employees. More Chinese employees have a degree or equivalent (at 75%) than White British employees (at 34%), which means that the median pay for White British employees are more likely to be adjusted up more than for Chinese employees.

Figure 11: Chinese employees are the most likely to have a degree or equivalent

Percentage of employees who have a degree of equivalent by ethnicity, England and Wales, 2019

Figure 11: Chinese employees are the most likely to have a degree or equivalent

Percentage of employees who have a degree of equivalent by ethnicity, England and Wales, 2019



Source: Office for National Statistics – Annual Population Survey

Age affects the level of pay received. On average pay increases by 3% for each year older an employee is, which means that if the ethnic groups have different age profiles we might expect different median earnings levels.

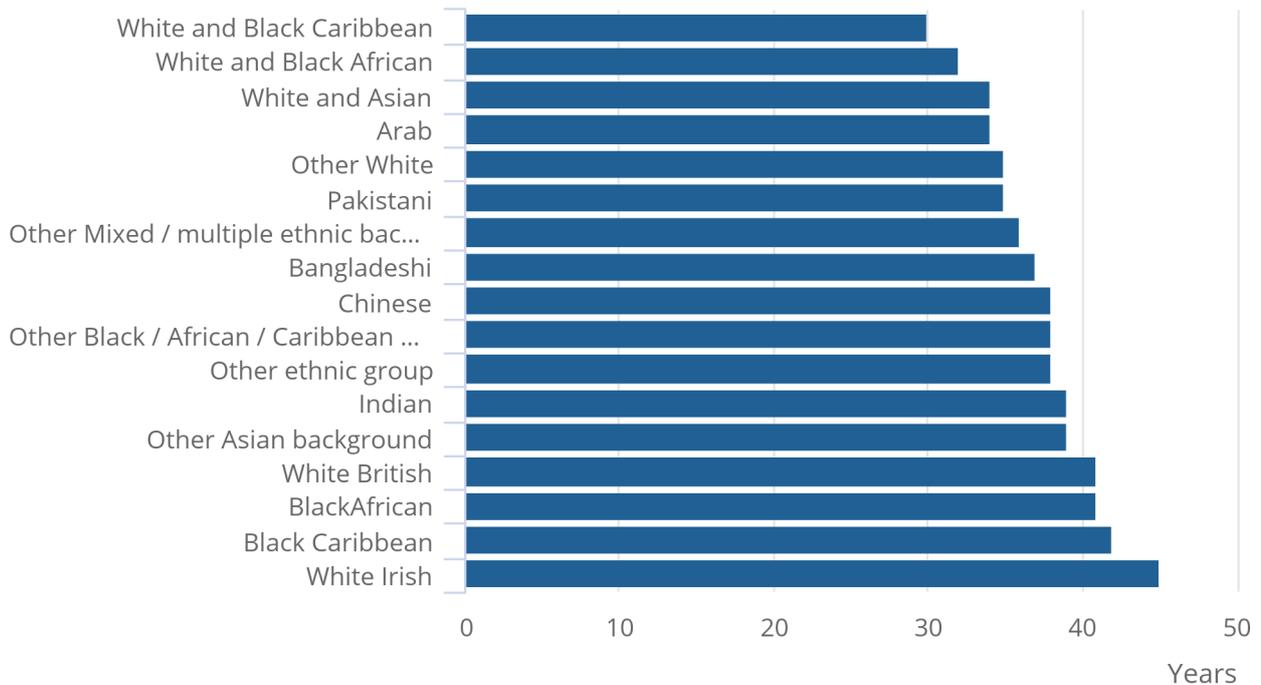
Figure 12 shows that employees of the mixed and multiple ethnicities had a lower median age than White British employees. For example, those in the White and Black Caribbean ethnic group had a median age of 30 years old, compared with 41 years old for White British employees. The adjustment for age strips out the effect, the gap for White and Black Caribbean employees narrows because of this.

Figure 12: Most ethnicities have a median age less than the median age for White British employees

Median age by ethnicity, England and Wales, 2019

Figure 12: Most ethnicities have a median age less than the median age for White British employees

Median age by ethnicity, England and Wales, 2019



Source: Office for National Statistics – Annual Population Survey

As referenced previously, the region in which an employee lives influences the adjusted pay gaps. We have therefore also modelled pay gaps within each of the regions and devolved nations of Great Britain and for the UK as a whole. Within each region, pay is compared against UK born employees in the White ethnic group.

Figure 13: Adjusted pay gaps differ by country and English region by country of birth

Adjusted pay gaps, 2019

Notes:

1. An aggregated set of ethnicities is used to improve the robustness and accuracy of the estimates, as the 17 category breakdown by Country of Birth and Region would lead to a low sample sizes and less accuracy. This breakdown also allows us to include Scotland in the comparison as the five categories are comparable between England, Scotland and Wales.
2. Northern Ireland has been excluded from the Subnational breakdown due to differences in the Ethnicity Classification for Northern Ireland, and what should the comparison group. Data for Northern Ireland is included in the calculation of the UK level adjusted pay gap.

[Download the data](#)

Looking across the regions and ethnic groups, we see that pay gaps tend to be wider for those who were born outside of the UK compared with those who are UK born. This is particularly the case for those in the Asian and Other ethnic groups, whereas the difference for those in the Black ethnic group is more modest.

We can also see that London often has wider adjusted pay gaps, with the widest adjusted pay gap being for those in the Other ethnic group who were not born in the UK, with employees in this group being paid 16.5% less than their White counterparts. Similarly, Scotland also tends to have wider pay gaps, where non-UK born employees in the Other ethnic group earned 20.5% less than their White counterparts.

Notes for: Modelling the factors that affect pay

1. The logarithm of x given a base b is y such that $b^y=x$, for example, the logarithm of base 3 of 9 is 2, as $3^2=9$. In our analysis we use natural logarithms, that is, the base is e . The logarithm of pay was used to stabilise the variance of the distribution and to improve the interpretability of the coefficients.
2. Unadjusted pay gap compares with the White British UK born employee group, which is different from the raw pay gap presented earlier, which compares within a characteristic, that is, minority ethnic non-UK born with White British non-UK born.

7 . Ethnicity breakdowns

The analysis in this article is mostly based around the 17-category ethnicity breakdown detailed in Table 1. This allows us to observe more detailed differences between ethnic groups than was presented in the previous analysis, which focused on a 10-category ethnicity breakdown.

This greater detail in terms of ethnic group, does, however, come with a trade-off. Responses to ethnicity questions differ between England and Wales, Scotland and Northern Ireland. Therefore, to use the more detailed ethnic groups the focus of this article is largely restricted to data on England and Wales. The greater level of detail coupled with more restricted geographic coverage may result in some small sample sizes for certain ethnic groups and which may result in greater volatility and uncertainty of some estimates.

Some of the main statistics presented in this article have also been made available for comparison in a more aggregated format in the [datasets](#), using the 10-category, 5-category and 2-category breakdowns, also detailed in Table 1. Table 1 presents the ethnicity breakdowns used in this article and accompanying datasets . Analysis of raw pay gaps considers these socio-demographic characteristics: sex, age group and geographical region.

Table 1: Ethnic group breakdowns and geographical coverage
2019

Geographic Coverage	England and Wales	Great Britain	UK	UK
Number of Categories	17	10	5	2
Ethnic Groups	White British	White British	White	White
	White Irish	White Other		
	White Other			
	White and Black Caribbean	Mixed/Multiple Ethnic Groups	Mixed/Multiple Ethnic Groups	Ethnic minority
	White and Black African			
	White and Asian			
	Other Mixed/Multiple groups			
	Indian	Indian	Asian	
	Pakistani	Pakistani		
	Bangladeshi	Bangladeshi		
	Chinese	Chinese		
	Asian Other	Asian Other		
	Black African	Black	Black	
	Black Caribbean			
	Black Other			
	Arab	Other ethnic group	Other ethnic group	
	Other ethnic group			

Source: Office for National Statistics – Annual Population Survey

Notes

1. For further information on the definition and presentation of ethnic groups and geographical coverage across the United Kingdom see [GSS Harmonised Principle for ethnic groupings].
2. Disaggregation into 17 ethnic groups results in greater uncertainty of estimates. Estimates for White and Black African, Black Other, and Arab ethnic groups should be treated with caution.

8 . Ethnicity pay gaps data

[Ethnicity pay gap reference tables](#)

Dataset | Released on 12 October 2020

Ethnicity pay gap estimates for 2018 across different ethnicity breakdowns using the Annual Population Survey.

9 . Data sources and quality

Data sources

Though this analysis makes use of the [Annual Population Survey \(APS\)](#) it should be noted that the primary source of data for earnings analysis in the UK is the [Annual Survey of Hours and Earnings \(ASHE\)](#). As a business survey, ASHE collects detailed information on the composition and distribution of earnings among employees, however, as a business survey, it collects only a limited range of personal characteristics regarding individual employees. This limits its usefulness in analysing earnings, for instance, by education and/or by different protected characteristics including ethnicity and disability.

As a result, the [Labour Force Survey \(LFS\)](#) (a quarterly version of the APS) is still heavily used as a source of data on earnings. Though it is accepted that the accuracy and detail of earnings information captured by the LFS falls short of that obtained by ASHE, the greater range of personal and household characteristics broaden its potential uses. However, one drawback of earnings analysis on the LFS is that the achieved sample is relatively small. This is because earnings questions are asked only to employees and only in 40% of the interviews carried out in each quarter.

Furthermore, earnings questions on the LFS are known to have poor response rates. The achieved sample for the LFS earnings questions is usually around 9,000, compared with approximately 150,000 respondents on ASHE. This limited sample size then restricts the extent to which you can perform multivariate analysis of earnings on the LFS, particularly where the variables of interest have many categories.

Therefore, for the analysis of earnings presented in this article, a new income weight has been calculated for the APS. The APS combines responses from the quarterly LFS and Annual Local Labour Force Surveys for England, Wales and Scotland. Though the APS has always collected information on earnings, until now there has never been an appropriate weight included for earnings analysis.

The income weight is calculated in a similar way to the LFS income weight. More information on this can be found in the Volume 6 LFS user guide. The main differences are that there are six calibration groups used to calculate the APS income weight, while for the LFS income weight there are four.

Finally, it should also be noted that, though the APS has a much-improved sample size compared with the LFS, it still suffers from some shortcomings when compared with ASHE. For instance, as a survey of businesses, ASHE is thought to capture more accurate earnings information as employers can consult payroll records when responding to the survey. In comparison, earnings information collected in the LFS and APS is self-reported and as such is likely to be subject to a higher degree of recall error.

Regression modelling

Model specification (variable name)

The variables included in the model are:

- log of hourly pay – log(hourpay)
- ethnicity – ethwe18/ethgbeul/ethukeul
- country of birth – cryox7
- sex
- occupation – sc10mmj
- highest qualification – hiqul15d
- age and age²
- region – govtof/nuts162
- marital status – marsta
- working pattern – ftpt
- disability status – disea
- sector of employment – sector
- dependent children – fdpch19

The variables for ethnicity depend on the level of disaggregation the analysis requires and the geography covered. For the UK, Great Britain and England and Wales level models the region variable uses the English regions and three nations. For models at the England, Wales, Scotland and English regions level, we have adjusted to the [Nomenclature of Territorial Units for Statistics: NUTS 2](#) level of geography.

Given that most of the variables are categorical variables, we have included them as dummy variables. We must exclude one of the levels to avoid perfect multi-collinearity. Collinearity is where one of the variables can be derived from the rest of the variables in the model. For example, if our categorical variable has three levels, A, B, and C, then if our model is:

$$y = \text{constant} + A + B + C$$

then A can be derived if B and C are set to zero. In this example A is our reference level.

The reference levels in our model are:

- ethnicity – White British (17 or 10 category models), White (5 or 2 category)
- country of birth – UK
- sex – male
- occupation – professional occupations
- qualification – degree or equivalent
- marital status – single
- working pattern – full- time
- disability status – not Equality Act disabled
- sector of employment – private sector
- dependent children – no

For region variable the reference level depends on the geography used:

- UK, Great Britain, England and Wales – London
- England – Tees Valley and Durham
- Wales – West Wales
- Scotland – North Eastern Scotland
- North East – Tees Valley and Durham
- North West – Cumbria
- Yorkshire and The Humber – East Yorkshire and Northern Lincolnshire
- East Midlands – Derbyshire and Nottinghamshire
- West Midlands – Herefordshire, Worcestershire and Warwickshire
- East of England – East Anglia
- London – Inner London – West
- South East – Berkshire, Buckinghamshire and Oxfordshire
- South West – Gloucestershire, Wiltshire and Bath and Bristol Area

Reference levels were selected if they satisfy one of two criteria, either they had the highest proportion of respondents in that category, for example, disability status and occupation, or they are natural choice that would aid interpretation, for example, marital status and qualification status.

The dependent variable is the log of hourly pay. This is because the distribution of pay is positively skewed, there is a higher density in the lower values of pay than in the higher values of pay. Taking the log of the hourly pay helps to make the distribution more symmetric and like a normal distribution so the assumptions used in regression are more valid. The rest of the variables in the model are the independent variables.

Both age and age squared are used in the model to approximate for a non-linear relationship between age and log(pay). A linear relationship between age and pay would infer that, for each year old a person gets, their pay would on average increase by the same amount. This is not the case in the APS data.

Some of the independent variables might interact with each other. Interaction means that effect of one variable is dependent on the values of a second variable. When this happens, we add a term to the model, where the two variables of interest are multiplied. For example, if variable x_1 interacts with variable x_2 then the model is as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \varepsilon$$

Adding interaction terms to a model drastically changes the interpretation of all the coefficients in the model. If we have no interaction, then β_1 would be interpreted as the unique effect that x_1 has on y . But with the interaction the effect that x_1 has on y is different dependent on the value of x_2 . The effect of x_1 is now not limited to β_1 but also depends on the values of β_3 and x_2 .

The effect of x_1 is represented by everything that is multiplied by x_1 in the model.

This is:

$$\beta_1 + \beta_3 x_2$$

β_1 is now interpreted as the effect of x_1 on y only when $x_2=0$

For our model we have interacted:

- sex with working pattern
- ethnicity with country of birth

This year we have updated the model estimation methodology to Quantile Regression (QR) rather than Ordinary Least Squares regression (OLS).

Ordinary Least Squares is a model of the form: $y = X\beta + E$

Whereas Quantile Regression is a model of the form:

$$Q_T(y) = X\beta_T + E$$

Q is the quantile function. A quantile q, for the probability T is a value such that:

$$P(y \leq q) = T$$

or:

$$Q(T) = q$$

The median is the quantile where T = 0.5 (or 50%).

Using QR means that we can talk about the effect a variable has on median pay, with OLS we can only talk about the effect in terms of means.

We need to take some care when interpreting the coefficients for each variable. As the dependent variable is log transformed, the coefficient is the effects on the log-scale of the variable. To interpret the coefficient in a meaningful way we take the exponential of the coefficient, which then can be interpreted as the percentage change in the level of median pay.

For example, if the estimate of the coefficient of x1 is 0.1 then the effect on pay is:
 $\exp(0.1) = 1.105$

which shows that each additional unit of x1 increase pay by 10.5% with all other variables held constant.

However, there are caveats that must be considered when interpreting estimates using the QR method. For example, predictor variables will have been excluded from the model because of their unavailability in the data, for example, family background. These excluded variables will influence the explanatory power of the model. It might be possible that the functional form of the model could be improved, for example, the relationship between log (hourly pay) and age, which would improve the accuracy of our estimates.

The outputs for each regression model are in the datasets .

Pay gaps methodology

Raw pay gaps

Raw pay gaps are calculated as follows:

$$\text{RawPayGap} = \frac{\text{median(White ethnicity)} - \text{median(EthnicGroup)}}{\text{median(White ethnicity)}} \times 100$$

Adjusted pay gap

Adjusted pay gaps are calculated as follows:

$$\text{AdjustedPayGap} = 100(1 - \exp(\beta_{eth} + \beta_{COB} + \beta_{eth \times COB}))$$

10 . Related Links

[Disability pay gaps in the UK: 2018](#)

Article | Released 2 December 2019 Earnings and employment for disabled and non-disabled people in the UK, raw disability pay gaps and factors that affect pay for disabled people.

[Gender pay gap in the UK: 2019](#)

Bulletin | Released 29 October 2019 Differences in pay between women and men by age, region, full-time and part-time, and occupation.