The impact of the NMW/NLW on employment retention and wage progression by Ethnicity, Disability and Gender

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Executive Summary

Lower average rates of employment and higher average rates of low wage employment among ethnic minorities and people with disabilities suggest that these groups might be at greater risk of negative employment effects from minimum wage increases. Conversely, in the absence of negative effects on employment, they have the most to gain in terms of higher wages. This means that studying these groups is likely to be particularly informative.

In this research, we analyse a decade of UK household survey data (2009-2019) from the Annual Population Survey and Understanding Society to provide new estimates of minimum wage coverage by ethnicity, disability and intersections between ethnicity and gender, and disability and gender. These estimates are based on three wage measures: directly reported wage rates (a subsample of employees who are paid an hourly rate), derived wage rates based on reported earnings and working hours, and imputed wage rates which combine information on directly reported wages with imputed values for employees where this information is missing. The derived wage measure is known to suffer from measurement error and the directly reported wage is only available for a sub-set of employees who are paid an hourly rate. Minimum wage coverage rates measure the proportion of employees whose hourly rate of pay is at or below the minimum wage rate. Estimated minimum wage coverage rates based on the imputed wage measure are close to estimates using data from the Annual Survey of Hours and Earnings (ASHE), which are considerably lower than rates based on derived or directly reported wage measures. Among working age employees aged 25 and over, key findings on minimum wage coverage are that:

- Minimum wage coverage rates are higher among employees with disabilities relative to their non-disabled peers and highest among disabled female employees.
- Coverage rates are considerably higher among women, even to the extent that minimum wage coverage rates among non-disabled female employees are higher than among disabled male employees.
- Minimum wage coverage rates among disabled employees vary by types of functional impairment. Coverage rates are highest for disabled male and female employees reporting that they are impaired in terms of recognising when in physical danger, followed by communication or speech impairments.
- For all types of impairment, disabled female employees have higher rates of minimum wage coverage relative to their male peers.
- Over the last decade, minimum wage coverage rates increased for employees with and without disabilities but increases were greater for disabled employees (in absolute and percentage terms). In particular, rates increased after the introduction of the National Living Wage (NLW) but since then coverage rates declined and for some groups returned to rates estimated just prior to the NLW.
- Minimum wage coverage rates are higher among Black, Asian and Minority Ethnic (BAME) employees relative to non-BAME employees. They are higher for BAME women than for

BAME men but the BAME gap in coverage rates is higher among men than for women due to very low rates of minimum wage coverage among non-BAME men.

- There is considerable heterogeneity in minimum wage coverage rates between ethnic minority groups, with higher rates of coverage among Bangladeshi and Pakistani employees while coverage rates for Indian employees are similar to white employees.
- Following the introduction of the NLW, there were large increases in minimum wage coverage rates among ethnic minorities, although rates declined after 2017 and some estimates suggest they have returned to rates observed prior to the NLW.

We estimate the impact of the introduction of the NLW on employment retention, along ethnicity, disability and gender dimensions using a triple difference-in-differences model. Key findings are:

- The introduction of the NLW did not lead to negative effects on employment retention for employees with disabilities or disabled employees reporting at least one functional impairment.
- There are also no statistically significant negative effects on employment retention for BAME employees or for Pakistani-Bangladeshi employees.
- In contrast, the introduction of the NLW appears to have led to a reduction in employment retention among Indian men. This suggests that while, on average, Indian men are less likely to be disadvantaged in the labour market, as they enjoy high rates of employment and relatively high average wage rates, those employed in minimum wage jobs prior to the NLW were less likely to be in paid work one year later.

In relation to annual wage progression for individuals in minimum wage employment, we find that after the introduction of the NLW:

- There were statistically significant falls in upward mobility (models based on all three wage measures) and, conversely, statistically significant increases in minimum wage employees becoming stuck in minimum wage jobs, from one year to the next. These results appear to be driven by changes in progression for male employees.
- For employees with disabilities, there was no statistically significant change in progression to higher wage employment or becoming stuck in minimum wage employment in models based on the directly reported or imputed wage measures.
- For models based on the derived wage measure, there was a statistically significant increase in the predicted probability of disabled employees remaining in minimum wage employment and a fall in progressing to higher wage employment in 2017.
- For disabled employees reporting at least one functional impairment, none of the changes in wage progression over the decade appear to be due to the introduction of the NLW.
- For the direct and imputed wage measures, there was no statistically significant change in annual transitions for minimum wage BAME employees either in terms of remaining stuck in minimum wage employment or progressing to higher wage employment.
- For the derived wage measure, we estimate a statistically significant fall in the predicted probability of upward mobility and an increase in remaining stuck in minimum wage employment for minimum wage BAME employees.

The analysis in this paper shows that it is important to look beneath broad categories of disability and ethnicity, highlighting differences in minimum wage coverage by ethnic minority groups and for disabled people, between different types of impairment. Overall, the results show that

increases in minimum wage rates over the last decade have been largely beneficial for people with disabilities and for ethnic minorities. Increases in minimum wage rates have led to higher rates of pay without appearing to harm employment prospects. The main exceptions to this otherwise positive picture are found among groups of workers less likely to be working in minimum wage jobs. Indian men experienced a fall in employment retention following the introduction of the NLW and men working in minimum wage employment were less likely to progress to higher wage employment and more likely to be stuck in minimum wage employment. Finally, the results show some variation in findings depending on the wage measure. The most commonly used wage measure in household survey data is the derived wage measure but measurement error in this variable can bias findings due to misclassification of minimum wage employees.

1. Introduction

People with disabilities and ethnic minorities have relatively low employment rates and relatively high rates of minimum wage coverage. This less advantaged labour market position has the potential to make these groups particularly exposed when minimum wage rates increase. Conversely, if rates of employment are not harmed, they have the most to gain in terms of higher earnings. Given their position, the Low Pay Commission (LPC) has monitored employment for both groups ever since the introduction of the National Minimum Wage (NMW) in 1999. This aggregate-level tracking exercise has not revealed any obvious signs that minimum wage upratings have damaged their employment (see, for example, LPC, 2020). However, broad categorisations can hide heterogeneous effects between sub-groups and simple monitoring of employment rates is not sufficient to estimate impact.

National level research on disability and ethnicity needs to be conducted using household survey data as individual level information on disability and ethnicity is not available in administrative data sources such as the Annual Survey of Hours and Earnings (ASHE)[1]. Improvements to large scale household survey datasets (such as booster samples for minority groups) and advances in variable definition, have allowed researchers to look beneath broad classifications of ethnicity and disability. However, it is well-documented that derived wage information available from household surveys contains measurement error and leads to upward bias in estimates of the proportion of employees earning at or below minimum wage rates (Skinner et al., 2002). We build on previous research (Skinner et al., 2002; Beissel-Durrant and Skinner, 2003; Avram and Harkness, 2020) to impute wage rates for survey respondents with missing directly reported hourly wage rates. This method allows us to provide new estimates of minimum wage coverage by ethnicity and disability status and estimate heterogeneous impacts of minimum wage upratings on employment retention and wage progression.

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[1] Strictly speaking ASHE data are collected from a survey of employers, but the data they report on earnings and employment are based on administrative (payroll) records.

2. Context

Low Pay Commission reports have previously highlighted relatively high rates of minimum wage coverage among people with disabilities and ethnic minorities (see, for example, LPC, 2001; LPC, 2005; LPC, 2014). This could indicate that these groups of workers face greater risk of negative employment effects from minimum wage upratings or, conversely, more likely to benefit in the form of higher wages. It is also possible that some workers gain while others lose out. There are a number of reasons why these groups are more likely to be in minimum wage jobs. Discrimination might be a factor for both groups, but other factors and labour market barriers are not shared. First generation migrants (born outside the UK) can face language barriers, non-recognition of qualifications gained abroad or a mismatch in occupation or industry specific skills. People with disabilities, can face labour supply constraints which limit job opportunities, certain impairments may also limit opportunities or be associated with lower levels of productivity.

Minimum wages can have a direct impact on ethnic/racial wage gaps through disproportionately increasing wage rates or indirectly through the amelioration of other factors that generate racial wage inequality, such as discrimination, job search frictions and interactions with other markets such as housing (Wursten and Reich, 2021). Derenoncourt and Montialoux (2021) find that the extension of minimum wages to new sectors of the US economy in the 1960s (through the 1967 amendments to the Fair Labor Standards Act) played a critical role in reducing the racial earnings gap in the late 1960s and early 1970s. Black workers were over-represented in these new sectors and disproportionately benefited from the extension of minimum wage policy. In addition, they find no statistically significant effects on working hours or on the probability of being in employment. In the context of widening US racial wage and employment gaps since the late 1990s, Wursten and Reich (2021) consider the effects of minimum wage policy on racial wage gaps in the between 1990 and 2019 using federal and state minimum wage changes. They estimate that minimum wage increases since 1995 reduced the black-white wage gap by 12% overall and by 60% among low educated workers. Wursten and Reich (2021) find that minimum wage policy reduced the racial wage gap through disproportionately increasing wages for black workers and reducing search frictions; increased earnings expanded job opportunities for black workers by allowing them to reach higher paid jobs outside their initial search radius (greater car ownership). They find no evidence of minimum wages having negative effects on employment and, moreover, find greater stability in black workers' employment and a reduction in racial differences in separation rates. However, black workers are less likely to live in states with higher minimum wage rates and are more likely to be covered by the federal minimum wage which has not increased in nominal terms since 2009. This means that despite the positive role of minimum wages in narrowing racial wage gaps, national racial wage gaps have increased. One of the few

studies that use difference-in-differences models to estimate heterogeneous effects by ethnicity found no negative minimum wage employment effects for black or Hispanic workers in the US (Godøy, and Reich, 2019). Earlier US research using state-level data, covering the period 1994-2005, estimated no negative effects of minimum wages on average employment rates or average hours worked among low-skilled, first generation migrants (Orrenius and Zavodny, 2008). In contrast, Bailey, DiNardo and Stuart (2020) estimate that the expansion of minimum wage coverage resulting from the 1967 amendments to the Fair Labor Standards Act, had a negative impact on employment for African-American men, particularly those with a less secure attachment to the labour market.

Decomposition of ethnic pay gaps for male workers in the UK, finds that the NMW and the NLW helped to narrow male ethnic pay gaps at the lower end of the wage distribution (Clark and Nolan, 2021). Surprisingly, the results are not statistically significant for Pakistani or Bangladeshi employees despite the greater incidence of minimum wage employment among these ethnic groups. Clark and Nolan (2021) put this down to minimum wage non-compliance disproportionately affecting these groups as they estimate higher proportions with wage rates under minimum wage levels. However, their analysis is based on a wage measure derived from gross weekly earnings divided by a measure of usual weekly hours of work which is known to suffer from measurement error (more on this below).

In the UK, one-fifth of the working-age population are classified as disabled (people reporting a limiting long-term health condition or disability) (DWP, 2021). The number of disabled people in the working-age population has increased since at least 2013[2] and this increase is largely driven by increases in mental health conditions (particularly among young women) (DWP, 2021). It is well established that, on average, people with disabilities have poorer labour market outcomes, with lower rates of employment, lower average wage rates and lower earnings growth (see, for example, Jones, 2021; Berthoud, 2008; Rigg, 2005). Disabled people also experience poorer outcomes in terms of transitions into work and job retention (Burchardt, 2000). There is considerable heterogeneity among people with disabilities both in terms of types of impairments and health conditions, experience of multiple health problems, whether conditions are likely to improve or worsen over time, age of onset and severity. Labour market outcomes also vary considerably. For example, pay gaps have been found to be particularly large for people with neurological disorders, mental illness, learning difficulties or disabilities (ONS, 2019; Longhi, 2017; Metcalf, 2009). Employment outcomes vary by types of impairment and, on average, disabled people with severe or specific learning difficulties have been shown to be the most

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[2] Changes to variable definitions have led to breaks in statistical series but a consistent measure is available from 2013.

disadvantage in the labour market (ONS, 2022). Poor working conditions, which are often associated with low pay, can lead to disability through work-related stress or even workplace injuries.

Prior to the introduction of the UK National Minimum Wage concern was raised by mental health and learning disability charities, that the risk that jobs of disabled employees with low levels of productivity might be jeopardised by the introduction of the minimum wage (LPC, 2001; Burchardt and McKnight, 2003). Research conducted shortly after the introduction of the NMW found some evidence that the impact of the introduction of the National Minimum Wage varied by age, gender, impairment and type of employment setting (Schneider, Simons and Everatt, 2001). How the minimum wage interacted with entitlements to social security was identified as an important determinant of whether disabled people gained from the NMW. However, this research did not provide a quantitative assessment of the impact of the NMW on employment. Burchardt and McKnight (2003) found that both disabled and non-disabled men and women actually increased their chances of remaining in work over the period that the NMW was introduced. This was most likely due to the buoyant labour market at that time. Using longitudinal data from the Labour Force Survey and difference-in-differences models, they found no evidence that the NMW had a statistically significant impact on employment retention among disabled employees but small sample sizes meant that they could not rule out a small negative effect on employment retention.

Recent US research estimates the impact of minimum wage increases on applications for disability related benefits (SSDI and SSI)[3] using county level data and state level differences in minimum wage rates and upratings (Duggan and Goda, 2020). If higher minimum wage rates lead to reductions in employment for workers with 'relatively low marginal product of labor', the demand for disability benefits could increase (Duggan and Goda, 2020). Conversely, higher minimum wage rates can lower the effective replacement rate (the ratio of disability benefits to potential earnings) and lead to a fall in the demand for such benefits. This research finds a statistically significant, although 'economically small', positive impact on applications for disability related benefits; a $1 increase in the minimum wage increases the total application rate by 0.04 percentage points. The authors conclude that their findings are consistent with the minimum wage slightly reducing employment and the loss of employment leading to a small fraction of those affected applying for disability benefits. Engelhardt (2020) uses state level data and finds a statistically insignificant relationship between SSDI applications and the minimum

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[3] Social Security Disability Insurance (SSDI) benefits provides out of work income insurance for people with a medically diagnosed disability that prevents them from working. The value of benefits are earnings related based on previous contribution records. The Supplemental Security Insurance (SSI) program is a means-tested benefit available to people with medically diagnosed disabilities.

wage. Duggan and Goda (2020) argue that their inclusion of county-level co-variates explain a large share of the variation in applications rates across counties which is why their finding of a small statistically significant differs from Engelhardt's estimated statistically insignificant relationship between minimum wage increases and applications for disability benefits.

Some have argued that specific impairments can limit productivity with minimum wages at risk of pricing some disabled people out of jobs. Productivity concerns have been raised about younger workers and used to justify why younger workers are exempt from statutory minimum wages or are covered by a lower minimum rate (OECD, 2015). On a similar basis, some countries also have exemptions for older workers (for example, Chile) or the long term unemployed (for example, Germany) (OECD, 2015; Umkehrer and Vom Berge, 2020).

While no explicit minimum wage exemptions exist for ethnic minorities or women[4], some countries have exemptions for workers with disabilities and as a result employers can pay such workers less than statutory minimum rates. For example, in the US, New Zealand, France, Czech Republic, Slovak Republic and Portugal there are some minimum wage exemptions for workers with disabilities (ILO, 2014). In New Zealand, the Minimum Wage Act 1983 allows Labour Inspectors[5] to issue minimum wage exemptions for people with disabilities if the worker and employer both agree that there is a good reason, and the Labour Inspectors think it is reasonable and appropriate to do so. In Australia, the Supported Wage System allows employers to pay employees with disabilities, and who have a reduced work capacity, a proportion of the minimum wage. In the US, it is possible for employers to pay workers with disabilities subminimum wage rates. Since 1938, employers in the US have been able to apply for certificates under Section 14(c) of the Fair Labor Standards Act which authorise them to pay subminimum wages to "workers with disabilities that impair their productivity for the work they perform". Employers calculate commensurate wage rates based on their assessment of the workers' individual productivity, no matter how limited. It was recently estimated that the average subminimum wage rate is $3.34 an hour which is less than half the $7.25 federal minimum wage (Forbes, 2021). The issue of subminimum wages for workers with disabilities has risen up the policy agenda in the US and a number of states have abolished these rates or have legislated to eliminate them (including Vermont, Maine, Maryland, Alaska, Nevada and New Hampshire). A recent review into subminimum wages by the US Commission on Civil Rights concluded that such rates limit people with disabilities from realizing their full potential and that Section 14(c) should end as it is

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[4] Exemptions for workers in certain sectors and occupations can have differential impacts by gender. For example, exempting domestic workers and au pairs who live-in has a much greater impact on women as they are much more likely to work in these occupations.
[5] In New Zealand, the Labour Inspectorate is responsible for ensuring compliance with minimum employment standards.

"inconsistent with the civil rights protections to which people with disabilities are entitled" (CCR, 2021). In his presidential election campaign, Joe Biden pledged to increase the federal minimum wage to $15 for *all* workers and expressed an ambition to index minimum wages to median hourly pay (the federal minimum wage of $7.25 is unchanged since 2009[6]). In April 2021 Biden signed an Executive Order raising the minimum wage for federal contractors to $15 from January 2022 (thereafter rising in line with CPI inflation); this order applies to all federal contract workers including those with disabilities. He has also repeated his pledge to completely phase-out the subminimum wage provision in section 14(c) of the Fair Labor Standards Act (White House, July 2021).

The LPC's position has always been that all employees should be entitled to statutory minimum wage rates whether they have disabilities or not. Prior to the introduction of the NMW in 1999, the LPC came under pressure from a number of disability charities who were concerned about a potential negative impact. This issue continues to be raised periodically. Famously, Lord Freud, at the time the welfare reform minister, speaking at the 2014 Conservative Party conference, was quoted as saying that some disabled people with intellectual disabilities were not worth the minimum wage (The Guardian, 15 October 2014). He later offered a full apology. Rosa Monkton, whose daughter has Down's Syndrome, recently wrote in the *Spectator* ('let my daughter work', 4th March 2017)[7] about how higher minimum wages threatened the possibility of therapeutic work for many people with severe learning disabilities. The challenge being that businesses employing people with such disabilities required to pay statutory minimum wage rates would run at a loss but the gains to the individual cannot be measured in pure monetary terms. The issue of therapeutic work has been revisited on a number of occasions by the LPC and the Government has issued guidance on what constitutes work and non-work activities. A wage subsidy has been suggested as a potential alternative to a minimum wage exemption for some severely disabled people, or people with particular types of disabilities or impairments (Dearing, 2020).

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[6] The federal minimum wage rate applies in 20 US states while the remainder have higher legal minimum wage rates https://www.dol.gov/agencies/whd/mw-consolidated
[7] https://www.spectator.co.uk/article/let-my-daughter-work

3. Data sources and variable definitions

Data from two key national household surveys are used in this research: The Annual Population Survey and Understanding Society (also known as the UK Household Longitudinal Survey). The Annual Population Survey is chosen for its large sample size which allows for more precise population sub-group analysis. Understanding Society is chosen for its longitudinal design which allows us to measure changes in labour market outcomes: employment retention and wage progression.

Annual Population Survey

The Annual Population Survey (APS) combines data from four successive quarters of the Labour Force Survey (LFS). Because the LFS is made up of a rotating panel of respondent households who remain in the survey for five quarters, the APS extracts data only from waves 1 and 5 in each of the four quarters. This means that each household only appears once in each APS. The achieved APS sample size is approximately 122,000 households (320,000 respondents). This large sample size makes the APS a valuable source of information on smaller population sub-groups. Annual datasets are available starting in January, April, July and October. This is helpful from a minimum wage analysis perspective as upratings have occurred in April or October.

In this analysis we use ten APS datasets which span the period October 2009 and March 2020, each dataset covering a unique minimum wage rate (see the Appendix for the full list of APS datasets used in this research). In the earlier part of the decade, minimum wages were uprated in October and our APS datasets for this period begin in October and end in September. The NLW was introduced in April 2016 and since then uprating has taken place in April. We, therefore, switch to APS datasets starting in April and ending in March from April 2016.

Understanding Society

Understanding Society (USoc), also known as the UK Household Longitudinal Study, was established in 2009 and replaced the British Household Panel Study. It is the largest UK longitudinal household survey, currently following around 26,000 households. Interviews are used to collect information from household members in annual waves. Although fieldwork periods for each wave can last up to two years, every sample member is interviewed at approximately 12 month intervals.

The main survey sample consists of a large general population sample and an Ethnic Minority Boost Sample. The objective of the wave 1 Ethnic Minority Boost Sample was to add at least 1,000 adults from each of five communities: Indians, Pakistanis, Bangladeshis, Caribbeans and Africans (Berthoud et al., 2009). As time passes the original sample becomes less representative of the UK

population as new immigrants are excluded. To address this selection issue an Immigrant and Ethnic Minority Boost Sample and a New Immigrant Boost Sample were added in 2015. The addition of these ethnic minority booster samples allows for detailed longitudinal research on ethnicity in the UK, although sample size constraints need to be considered when looking at finer breakdowns. In this analysis we use ten waves of USoc, covering the period 2009-2019.

For our analysis it is important to know when interviews took place so that we can compare respondents' wage rates with contemporaneous minimum wage rates, which vary across calendar years and USoc waves. To do this we created 'annualised' USoc data which refer to the year in which interviews took place (rather than the wave) and use the exact interview date to compare wages with minimum wage rates. This means that when we calculate, for example, minimum wage coverage rates in a given year it takes into account intra-year minimum wage upratings.

Ethnicity

Information on ethnicity in both the APS and USoc is based on survey respondents' self-reporting. For the APS, the Labour Force Survey asks a series of questions on what best describes survey respondents' ethnicity or background. Respondents are able to select from a number of predefined groups which can lead to follow-up questions to identify sub-groups. In Understanding Society, respondents are asked what their ethnic group is and can selected from a list of groups on a showcard. The Government Statistical Service (GSS) has recommended a detailed classification scheme for ethnicity and harmonization across national surveys. However, differences exist in classification schemes used across UK nations (between England and Wales, Scotland and Northern Ireland), in part reflecting differences in population size both overall and by ethnic minority groups. England and Wales has the most detailed classification but a less detailed version is required for analysis covering the whole of the UK. In addition, classification schemes used in official data sources have changed over time and some aggregation of groups can be required to produce consistent time series.

For the Annual Population Survey, we use the UK-level variable *ethukeul* which provides a consistent measure of ethnicity since 2010[8]. More detailed breakdowns are available for England (for example, distinguishing between Black African and Black Caribbean) but not for all UK nations and therefore to analyse a consistent measure of ethnicity across the UK, we follow the GSS ethnicity harmonization standard and use consistent aggregated categories. For Understanding Society, we use the derived variable *racel_dv* which has the potential to identify

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[8] This variable is not available in the first of our APS datasets (October 2009-September 2010).

18 separate groups. However, the sample sizes for many groups are too small and our analysis mainly focuses on comparing seven ethnic groups (see Table 1).

Table 1 Ethnic groups identified in APS and USoc

Annual Population Survey	Understanding Society
White	White
Indian	Indian
Pakistani	Pakistani
Bangladeshi	Bangladeshi
Chinese	Chinese
Other Asian	
Black/African/Caribbean	Black African
	Black Caribbean

In addition to the more detailed ethnic breakdowns, we use the binary classification of BAME (black, Asian and minority ethnic) and Non-BAME in both data sources, where Non-BAME refers to White and BAME to all ethnic minorities. We recognise that aggregating all ethnic minorities into a single category can mask disparities between ethnic minority groups and use the more detailed breakdowns where possible. The aggregate level variable can be used to test if there are common barriers and outcomes.

Disability

Disability status can be based on a medical definition, an administrative definition (for example, based on eligibility for social security benefits), a legal definition or self-definition (self-assessed and self-reported), or combine more than one of these definitions. Definitions can make reference to the extent to which disabilities are limiting and how long they have lasted or are expected to last. Legal definitions in the Equality Act 2010 (Great Britain) and Disability Discrimination Act 1995 (Northern Ireland) are used in official statistics (disability is one of nine protected characteristics in the Equality Act). The Acts define an individual as disabled if they have a physical or mental impairment that has a substantial and long-term negative effect on their ability to do normal day-to-day activities. Both aspects are important as many people experience physical or mental impairments that only last a short time (e.g. a broken leg, an illness or a short period of poor mental health) and long-term impairments do not necessarily limit normal day-to-day activities. However, some people can be missed such as those who do not expect a limiting impairment to have a long-term effect. The Government Statistical Service (GSS) has produced guidance on how to collect and combine the GSS long-lasting health conditions and illness (LLHCI)

standard[9] and the GSS activity restriction standard[10] to determine if classification of disability is consistent with the Acts[11]. Discontinuity exists as GSS harmonisation is recent and legal definitions have changed over time. In addition, questions used to collect information on disability in household surveys have changed over time, as have the methods used to derive variables, and this also create discontinuities.

In the APS, we use a derived variable (*disea*) which identifies disability status consistent with the legal definition of disability in the Equality Act (GSS harmonized). It is based on respondents' self-reporting on whether or not they have a disability or health condition lasting 12 months or longer which reduces their ability to carry out day-to-day activities. This variable is only available from April 2013 and discontinuities with information collected on disability (derived variables and the underlying information collected on disability) prior to this date, means that our APS analysis of disability and the NMW/NLW focuses on the period from April 2013. Although information on impairments is collected in the LFS, this information is not available in the safeguarded versions of APS available from the UK Data Service which were used in this study. This means that for the APS data, our analysis mainly focuses on the binary disability status variable.

For USoc, the disability variable is based on the USoc *health* variable for which respondents are asked: "*Do you have any long-standing physical or mental impairment, illness or disability? By 'long-standing' I mean anything that has troubled you over a period of at least 12 months or that is likely to trouble you over a period of at least 12 months.*" This variable doesn't make reference to legal definitions of disability in the Equality Act or the Disability Discrimination Act as it does not ask whether any impairments, illness or disability substantially limit day-to-day activities. However, respondents are also asked if they have substantial difficulties in relation to 11 different types of functional impairment and an 'other health problem or disability' category. These are not mutually exclusive and respondents can report multiple functional impairments. The functional impairments are:

1. Mobility (moving around at home and walking)
2. Lifting, carrying or moving objects
3. Manual dexterity (using your hands to carry out everyday tasks)
4. Continence (bladder and bowel control)
5. Hearing (apart from using a standard hearing aid)
6. Sight (apart from wearing standard glasses)
7. Communication or speech

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[9] https://gss.civilservice.gov.uk/policy-store/long-lasting-health-conditions-and-illness/
[10] https://gss.civilservice.gov.uk/policy-store/activity-restriction/
[11] https://gss.civilservice.gov.uk/policy-store/measuring-disability-for-the-equality-act-2010/

8. Memory or ability to concentrate, learn or understand
9. Recognising when in physical danger
10. Physical co-ordination (e.g. balance)
11. Difficulties with own personal care

These functional impairments are different from the harmonised list of impairments recommended by the GSS[12] and do not allow us to explicitly identify mental health impairments or social or behavioural impairments[13]. In line with other research on disability using USoc we combine the information on long-standing illness or disability with reported functional impairments to identify a group of disabled people who have a 'limiting' disability (Salis et al., 2021). We refer to this group as 'impaired disabled'. One advantage of the USoc data is that the questions used to collect information on disability have not changed over time.

Our samples are restricted to an age group which is in scope for the NLW and below the State Pension Age. The age group for men is 25-64 years and for women 25-59 years. At the start of the decade women's State Pension Age was age 60 but over the course of the decade it increased to 65. For consistency over the period, we use the 25-59 age group for women.

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[12] https://gss.civilservice.gov.uk/policy-store/impairment/
[13] Information on mental health is collected in USoc but they are not directly linked to the disability variables and are therefore not used in this research.

4. Wage measures

In household survey data, wage rates are typically derived by dividing reported earnings (usual or actual) by the number of hours worked over a pay period. However, it is well-documented that wage rates derived using this method are subject to considerable measurement error, leading to upward bias in both low pay estimates and in the share of employees earning at or below minimum wage rates (Skinner et al., 2002; Beissel-Durrant and Skinner, 2003). Beissel-Durrant and Skinner (2003) suggest that the proportion of jobs paid at or below the minimum wage rate may be overestimated by four or five times if this measurement error is ignored.

In both household surveys used here, respondents who are paid an hourly rate are asked to report this hourly rate of pay. In Understanding Society, employees reporting that they are paid by the hour, at a set amount for basic hours are asked: "W*hat is your hourly rate of pay for your basic hours of work?*" In the Annual Population Survey, respondents who are in paid work, who report being paid a fixed hourly rate are asked: "*What is your (basic) hourly rate?"* This applies to only a fraction of employees who tend to be lower paid. Although the directly reported wage measure has good coverage of minimum wage employees, it cannot be used to provide accurate estimates of minimum wage coverage as the distribution is skewed towards lower earners (see Figures 1 and 2). Note that directly reported wage rates are collected in addition to information on usual earnings and hours of work which is typically used to derive wage rates.

To overcome deficiencies with the derived and directly reported wage variables, we build on the work of Avram and Harkness (2020) who used the multiple imputation method developed by Skinner et al (2002). Wage rates are imputed for employees who do not directly report a wage rate using predictive mean matching. Multiple imputation by predictive mean matching is a semi-parametric method that uses linear predictions from a normal linear regression model to identify a set of 'nearest neighbour' donor wage rates for each missing value, from the complete set of non-missing values based on predictive means. An imputed value is randomly drawn from this set. Explanatory variables in the regression model include gender, age, qualifications, marital status, dependent children, region of residence, full- or part-time working, public or private sector employment, occupation and industry. Ten 'nearest neighbour' donor wage rates are identified for each employee who has a missing directly reported wage rate and the mean of the ten donor wage rates provides the final imputed wage value. In line with Skinner et al (2002) and Avram and Harkness (2020) our wage variable, which we label the imputed wage, takes the value of the directly reported wage where available and the imputed value where missing.

On behalf of the LPC, Ritchie, Whittard and Dawson (2014) conducted a review of original multiple imputation methodology developed by Skinner et al. (2002) and Beissel-Durrant and

Skinner (2003). They identified a number of potential problems with the methodology including issues related to cases where there were a small number of observations[14] and the methodology not recognising the asymmetry caused by the existence of the NMW (the imputation process assumes a smooth distribution). However, they concluded that the alternatives (no imputation or using an alternative wage measure) seemed less justified statistically.

In recognition of potential issues with the wage variables available, we report findings using three wage variables: (1) directly reported hourly wage; (2) derived hourly wage; (3) imputed hourly wage. This allows us to assess the sensitivity of findings to the wage variable and for findings to be compared with existing published research based on the derived hourly wage variable.

In Understanding Society, there are around four times as many cases for the derived wage measure compared to the direct wage measure (Table 2). Sample sizes in 2009 and 2019 are considerably smaller than in other years in the annualized dataset (the year refers to the interview date) and sample sizes fall over time. This fall is due to sample attrition (employment rates increased over this decade). Analysis of the impact of attrition in the Understanding Society General Population Sample (GPS), on representativeness of the remaining GPS sample found that it led to modest under-representation of some groups, including the youngest age groups, men, non-whites, residents of Greater London and those on the lowest incomes (Lynn and Borkowska, 2018). As we include ethnic minority boost samples, attrition is less likely to be an issue for non-whites compared to the GPS sample. The use of sample weights is important to help correct for attrition but we need to be aware that attrition can have an impact on sample composition.

Table 2 Unweighted sample sizes for the three wage measures - USoc

|	Direct wage	Derived wage	Imputed wage
2009	2313	9670	9373
2010	5068	20627	20008
2011	4968	19670	19094
2012	4349	17497	16909
2013	4155	16563	16248
2014	3806	15389	15005
2015	3797	15878	14886
2016	3662	15734	14690
2017	3405	14249	13163
2018	3085	13435	12218
2019	1324	5875	5230

Source: Understanding Society.

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[14] Morris, White and Royston (2014) also identify a specific concern with predictive mean matching where potential donors are sparse. Here this could be an issue for higher wage rates.

Figure 1 shows Kernel density wage distributions for the three wage variables for Understanding Society for a year prior to the introduction of the NLW (a) October 2014-September 2015) and a year post the introduction of the NLW (b) April 2016-March 2017). Figure 2 contains the same information for the Annual Population Survey. Wage rates are right-censored at £30 per hour. Comparing the three wage measures, there is a much higher concentration of wage rates at around the minimum wage (shown by the vertical line) for the directly reported wage variable. This reflects differences in sample composition between the three wage measures, with low paid employees much more likely to directly report wage rates. Measurement error in the derived wage leads to a greater share of employees with wage rates beneath the minimum wage and a much lower concentration around the minimum wage rate. The distribution of the imputed wage variable lies between the distributions of the derived wage and the directly reported wage. There is a greater concentration of the imputed wage variable around the minimum wage rate in APS compared with USoc. Although the imputation methodology used is the same, differences in variables and samples could be a factor. The concentration of wage rates slightly above the minimum wage rate reflects the fact that these distributions are based on annual data and wage rates increase throughout the year and particularly prior to uprating (increases in minimum wage rates are published in advance). Comparing the pre NLW with the post NLW periods, shows that the higher minimum wage rate led to an increase in concentration around the minimum wage.

Figure 1 Kernel density distributions for the three wage measures- USoc

a) October 2014-September 2015   b) April 2016-March 2017
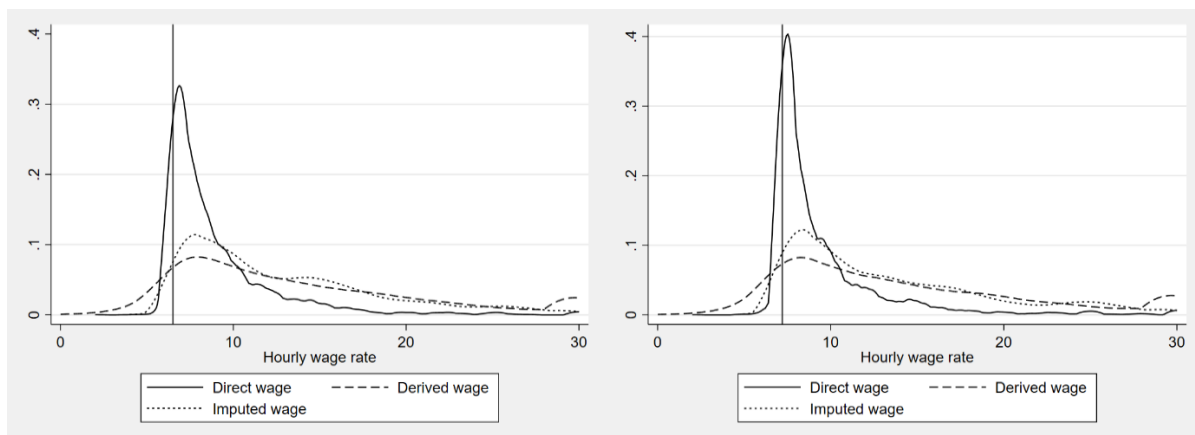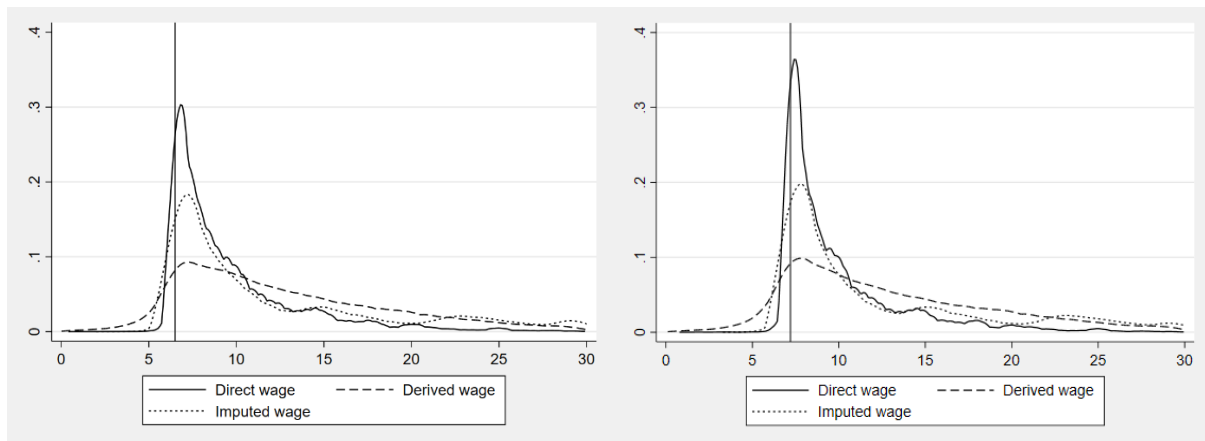

Data source: Understanding Society.
Notes: men aged 25-64, women aged 25-59. The vertical line denotes the NMW/NLW level.

Figure 2 Kernel density distributions for the three wage measures – APS

a) October 2014-September 2015   b) April 2016-March 2017

Data source: Annual Population Survey.
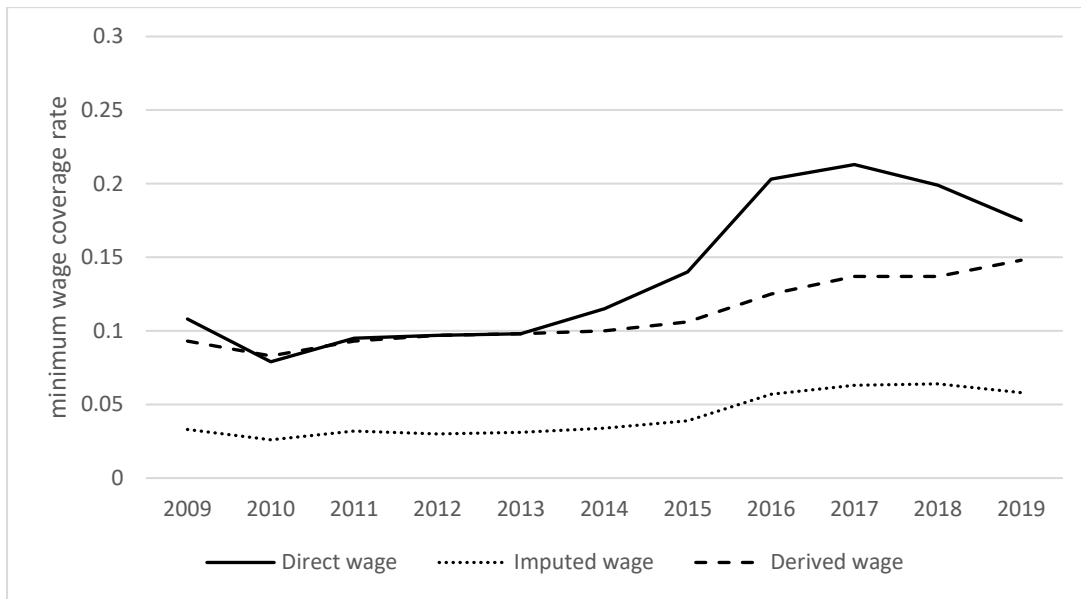Notes: men aged 25-64, women aged 25-59. The vertical line denotes the NMW/NLW level.

5. Minimum wage coverage

Minimum wage coverage rates measure the proportion of employees whose hourly rate of pay is at or below the minimum wage rate. Our wage measures are restricted to positive wage values but include values less than statutory minimum wage rates. Wage rates less than the minimum wage estimated using data from household surveys can be due to measurement error or non-compliance. We are not able to distinguish between the two but recent official estimates based on ASHE data for 2018 suggest that around 1.5% of all jobs held by employees paid below the applicable minimum wage (BEIS, 2020). The LPC estimated that in April 2019, just over 440,000 workers were paid less than the NMW (LPC, 2021a).

Trends in minimum wage coverage rates are shown in Figure 3 (USoc) and Figure 4 (APS). For the reasons noted earlier, measurement error affecting the derived wage measure and selection affecting the directly reported wage measure, lead to higher estimates of minimum wage coverage for these wage measures. USoc and APS estimates of coverage rates based on the imputed wage measure are much lower and more in line with estimates based on ASHE data which are regarded to be of higher quality.

Minimum wage coverage rates were fairly stable over the first half of the decade but increased after the introduction of the NLW. The direct wage and the imputed wage measures in both datasets show a decline in minimum wage coverage after 2017 but there is no decline in estimates based on the derived wage measure. Coverage rates based on the directly reported wage measure using USoc data increased to a greater extent after the introduction of the NLW than estimates based on APS data. It is not clear why this difference emerges but, as noted earlier, the directly reported wage is only available for a select group of employees who are paid a fixed hourly rate and these tend to be lower paid. Among this select group of lower paid employees, it would appear that in the smaller USoc sample, more are covered by the higher NLW (the APS sample size is larger). Measurement error in the derived wage variable and selection bias in the direct wage variable lead to over-estimates of minimum wage coverage. However, similar coverage rates are estimated in USoc and APS for the imputed wage variable and these rates are close to those estimated using ASHE data which is considered the most reliable source (LPC, 2021b).
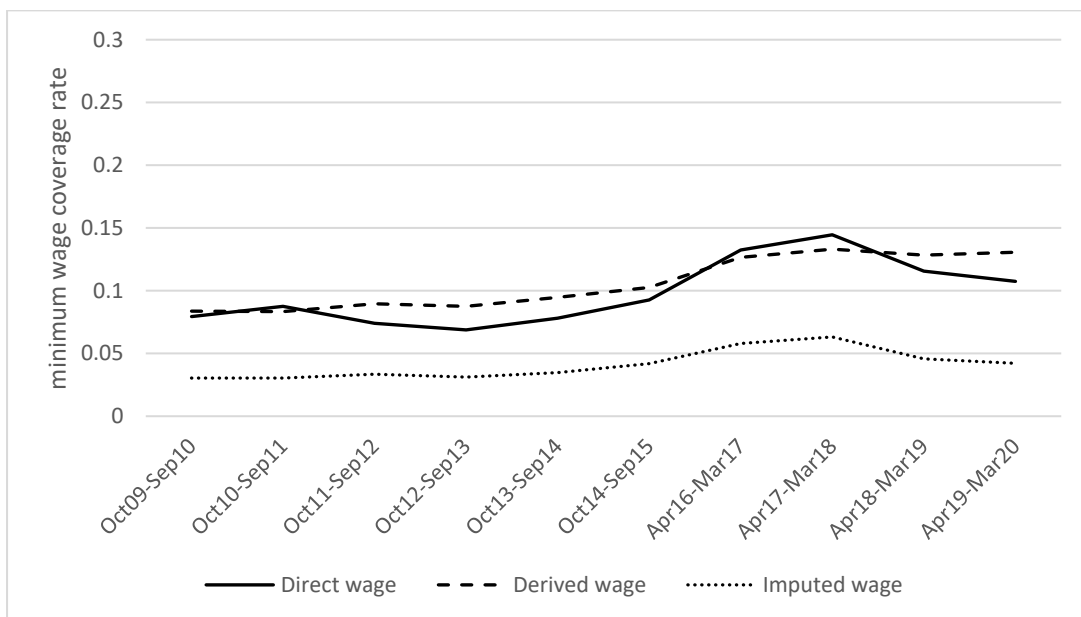
Figure 3 Trends in minimum wage coverage rates by wage measure– USoc

Data source: Understanding Society.
Notes: men aged 25-64, women aged 25-59.

Figure 4 Trends in minimum wage coverage rates by wage measure – APS

Data source: Annual Population Survey.
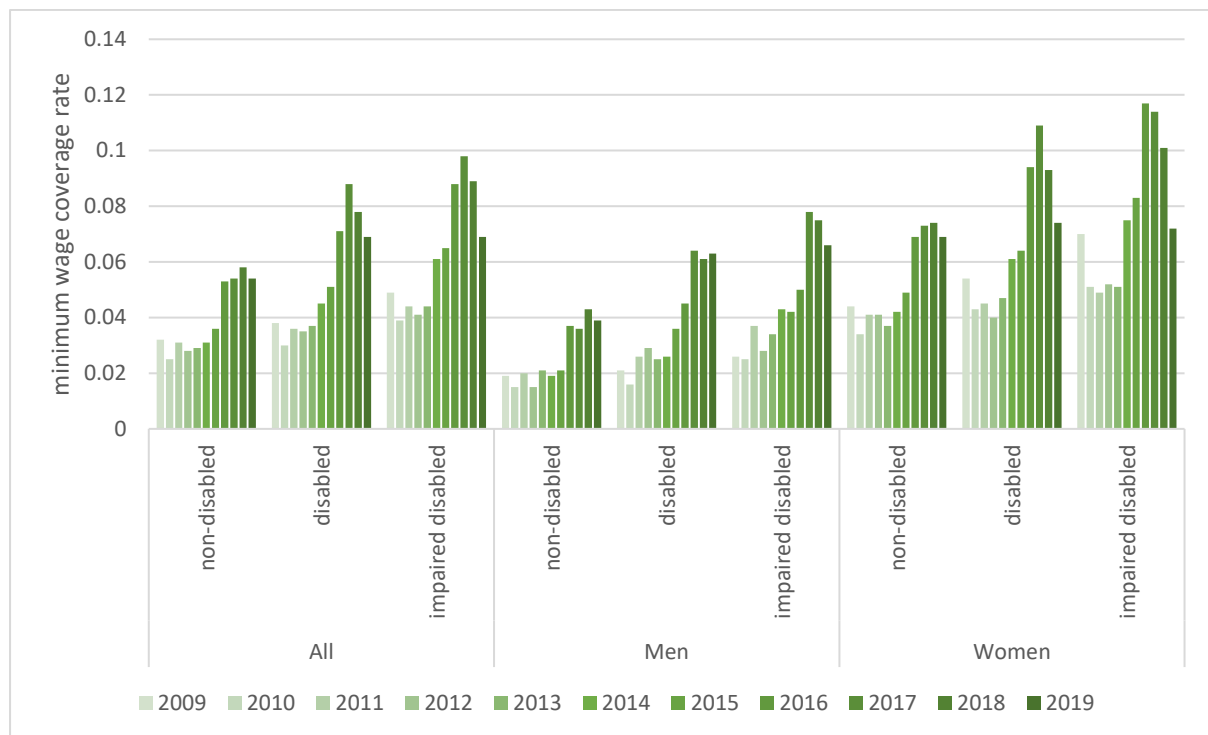Notes: men aged 25-64, women aged 25-59.

Next we examine trends in minimum wage coverage rates by disability, ethnicity and gender focusing on new estimates based on the imputed wage measure.

Minimum wage coverage rates by disability status and gender

Minimum wage coverage rates are higher among employees with disabilities and particularly high among female employees with disabilities (Figure 5 (USoc); Figure 6 (APS)). For USoc we report minimum wage coverage rates for non-disabled employees, disabled employees (based on

the USoc health variable) and impaired disabled employees (disabled people who report at least one functional impairment). Minimum wage coverage rates are highest for disabled employees who report at least one functional impairment. Coverage rates increased over the decade among disabled employees, particularly following the introduction of the NLW. Increases in minimum wage coverage rates were greater among disabled employees relative to non-disabled in both absolute and percentage terms. There is evidence that coverage rates declined after 2017 among employees with disabilities (rates are flatter for non-disabled employees in USoc but declines are shown for APS). Minimum wage coverage rates in USoc for disabled employees reporting at least one functional impairment are fairly similar to rates in APS where disability status is consistent with the Equality Act definition.
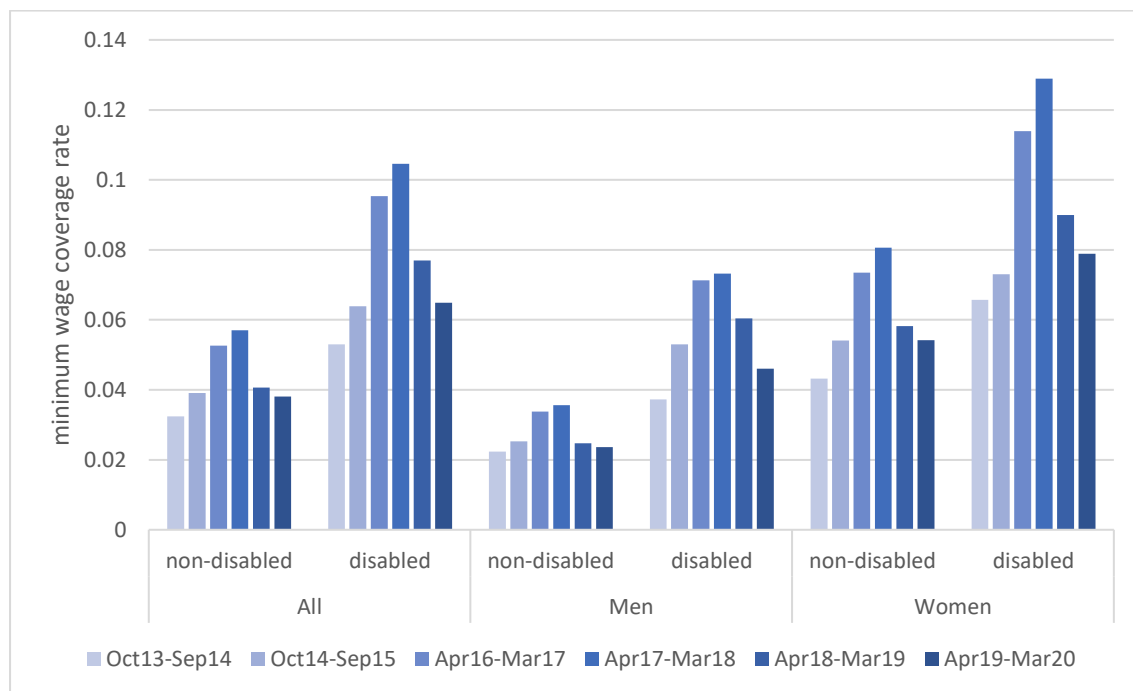
Figure 5 Trends in minimum wage coverage rates based on the imputed wage measure by disability status and gender – USoc

Data source: Understanding Society.
Notes: men aged 25-64, women aged 25-59.

Figure 6 Trends in minimum wage coverage rates based on the imputed wage measure by disability status and gender – APS


Data source: Annual Population Survey.
Notes: men aged 25-64, women aged 25-59.

Among employees with disabilities, coverage rates vary by type of functioning impairment (Figure 7)[15]. Minimum wage coverage rates are highest for people who report that they are impaired in terms of recognising when in physical danger, followed by speech and communication impairments (for both men and women). Disabled female employees have higher coverage rates than their male counterparts across all impairment types, the widest gender gap in coverage is for personal care which has the lowest minimum wage coverage rate for men. For disabled female employees, hearing impairments are associated with the lowest minimum wage coverage rates. Possible explanations for gender gaps in coverage include differences in the severity of impairments, occupational differences (for example, gender segregation) and heterogeneity within functional impairment types.

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[15] Note that survey respondents can report more than one type of functional impairment.

Figure 7 Trends in minimum wage coverage rates based on the imputed wage measure for disabled employees by type of functional impairment – USoc
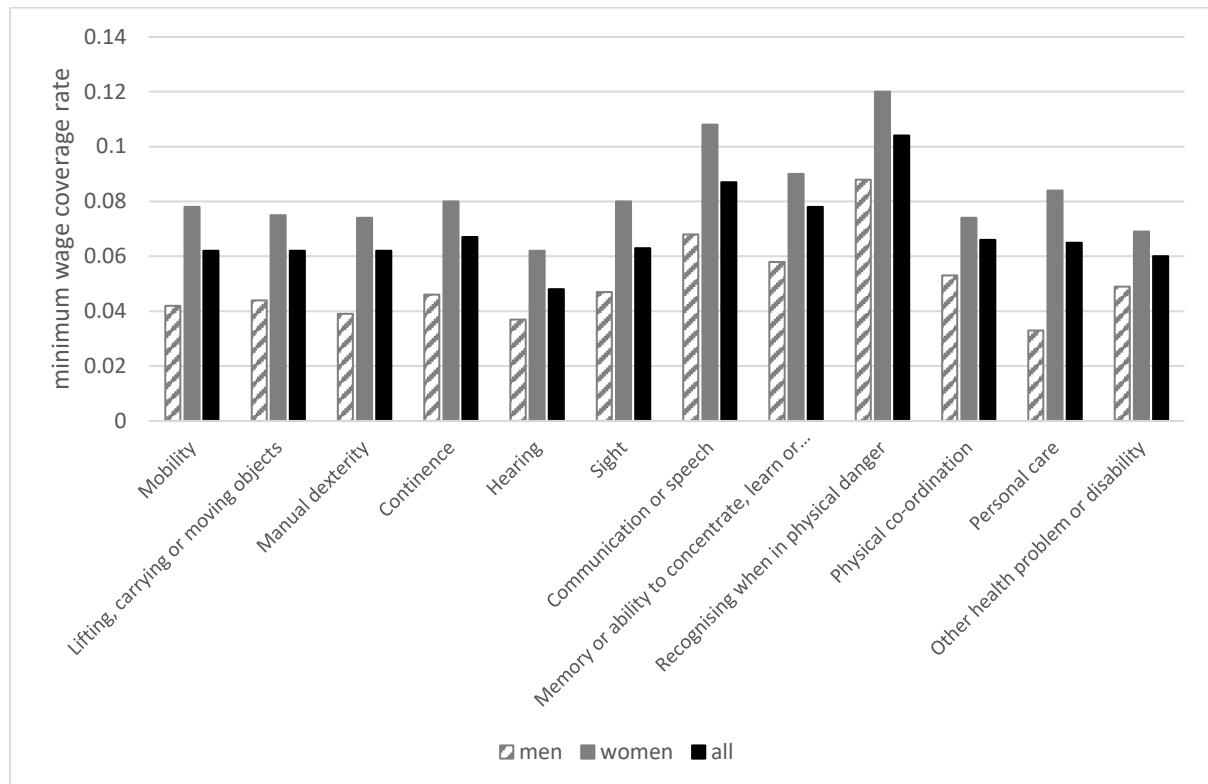
Minimum wage coverage rates by ethnicity and gender

BAME employees are more likely than non-BAME to be employed in minimum wage jobs (Figure 8 (USoc) and Figure 9 (APS)). BAME minimum wage coverage gaps vary over time and are lower in USoc than in APS. Large increases in coverage rates followed the introduction of the NLW among BAME and Non-BAME employees. After 2017 coverage rates fell (the fall is more marked in the APS) but rates are still higher than in most of the pre-NLW years (particularly in USoc). Minimum wage coverage rates can fall if minimum wage upratings do not keep up with general wage growth or due to other changes such as higher shares of low wage workers being covered by wage agreements which lead to increases in their pay above the NLW (for example, employers agreeing to pay the higher Living Wage set by the Living Wage Foundation). Coverage rates can also fall due to compositional change. For example, if higher minimum wage rates lead to job losses then the proportion of employees in minimum wage jobs can fall. This means that if job losses are greater among BAME employees who have higher rates of coverage, then the BAME coverage gap could fall.
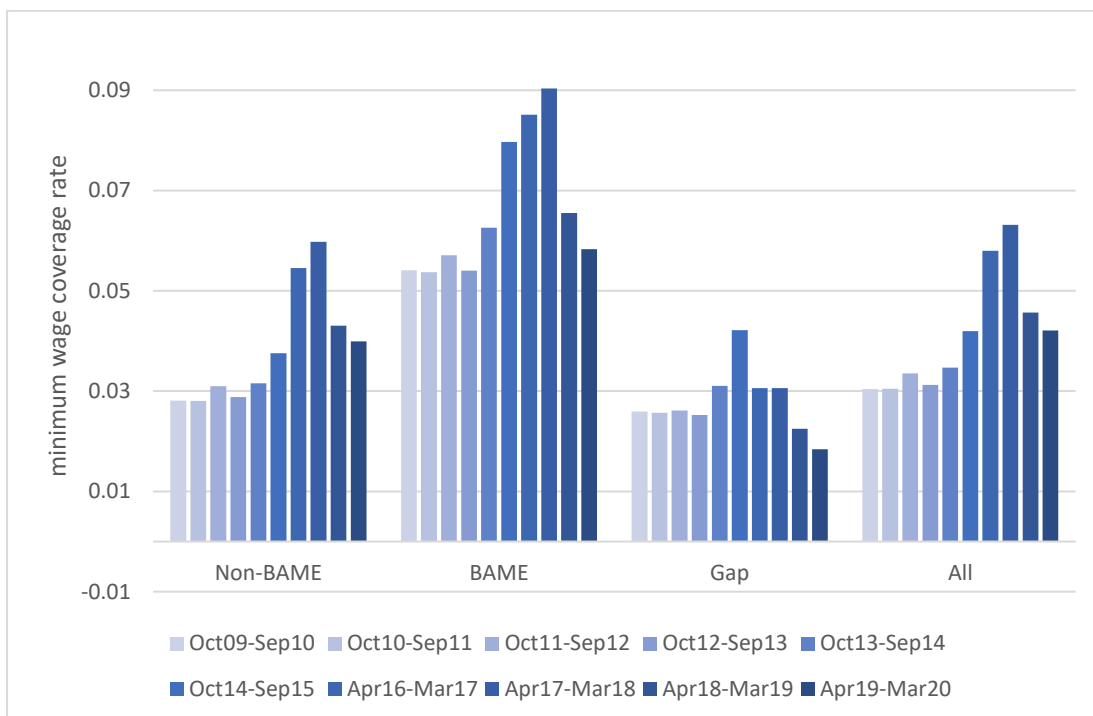
Figure 8 Trends in minimum wage coverage rates based on the imputed wage measure by BAME status – USoc
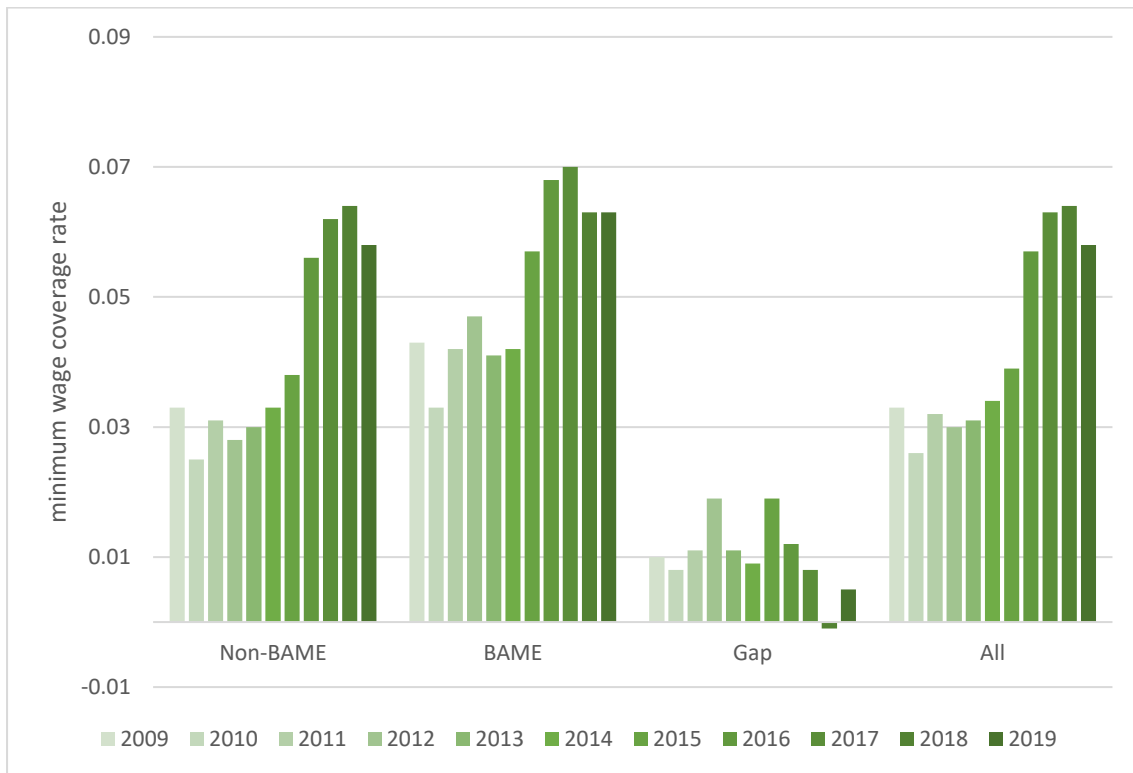
Data source: Understanding Society.
Notes: men aged 25-64, women aged 25-59.

Figure 9 Trends in minimum wage coverage rates based on the imputed wage measure by BAME status - APS

Data source: Annual Population Survey.
Notes: men aged 25-64, women aged 25-59.

The BAME minimum wage coverage gap is much higher for men than for women (Figure 11 for USoc; Figure 11 for APS). The low BAME coverage gaps for women reflect the fact that although coverage rates are higher, in general, for women than for men, the difference in coverage rates between BAME women and Non-BAME women is quite small. In contrast, coverage rates are lower among men but BAME men and BAME women have quite similar coverage rates. This means that the BAME gap for men is much larger.

Figure 10 Trends in minimum wage coverage rates based on the imputed wage measure by BAME status and gender - USoc

Data source: Understanding Society.
Notes: men aged 25-64, women aged 25-59.

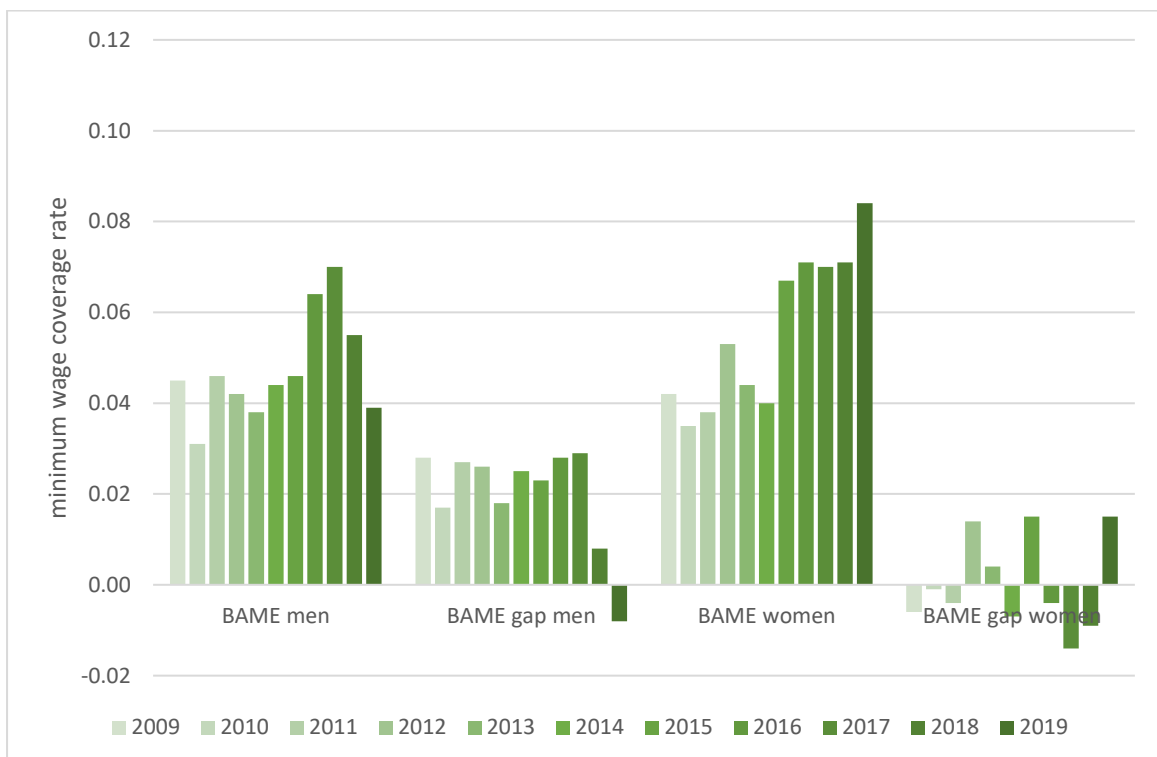**Figure 11 Trends in minimum wage coverage rates based on the imputed wage measure by BAME status and gender - APS**

Data source: Annual Population Survey.
Notes: men aged 25-64, women aged 25-59.

The binary BAME classification of ethnicity conceals important differences between ethnic minority groups. For example, Bangladeshi and Pakistani employees have relatively higher minimum wage coverage rates in contrast to Indian employees who have similar rates of minimum wage coverage to white employees (Figure 13 for USoc; Figure 13 for APS). The smaller sample size for the finer ethnic breakdown does result in some year-to-year fluctuation in estimates, particularly for the analysis using USoc.
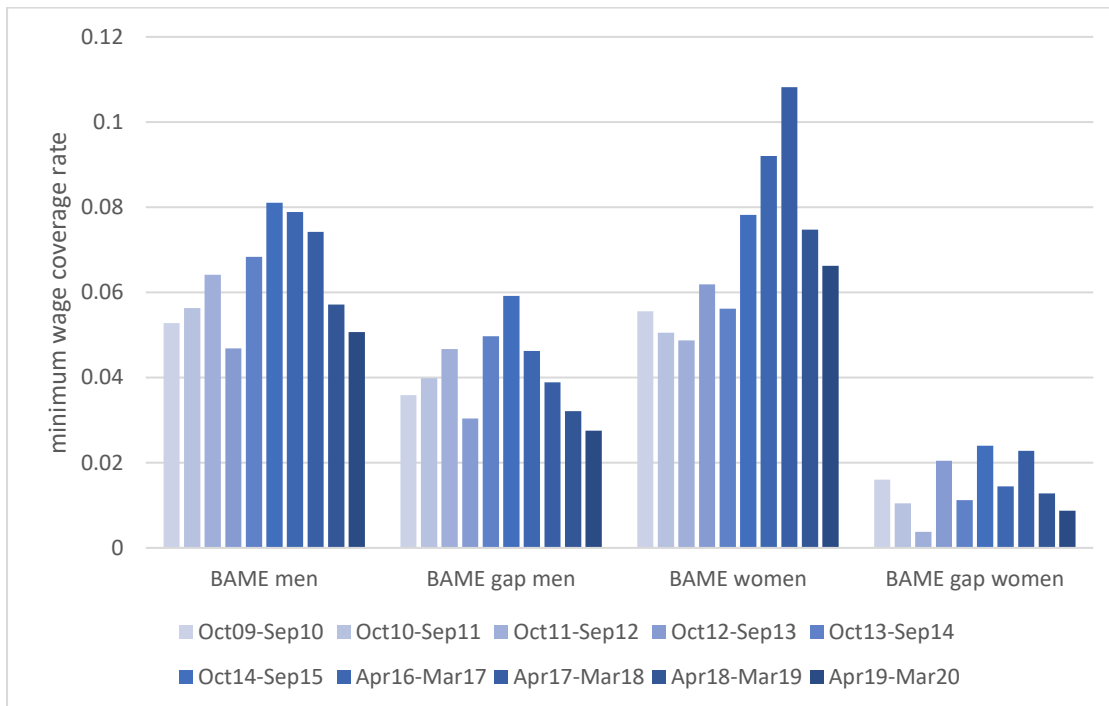
Figure 12 Trends in minimum wage coverage rates based on the imputed wage measure by ethnicity -USoc

Data source: Understanding Society.

Notes: men aged 25-64, women aged 25-59.

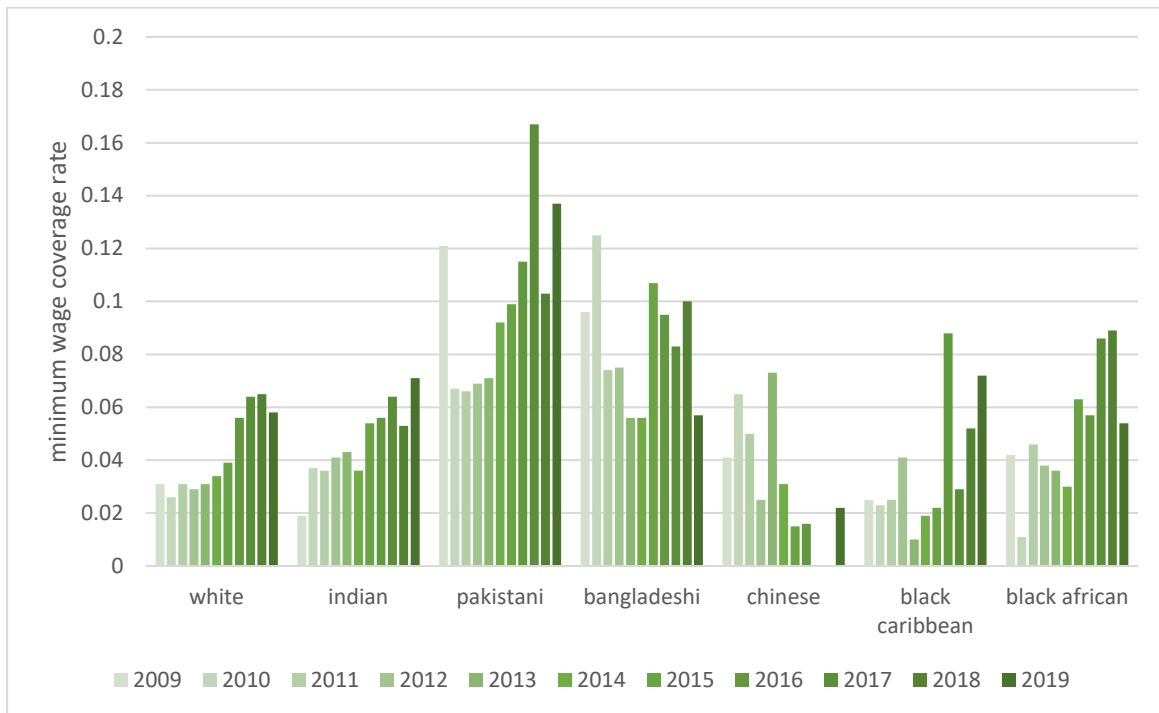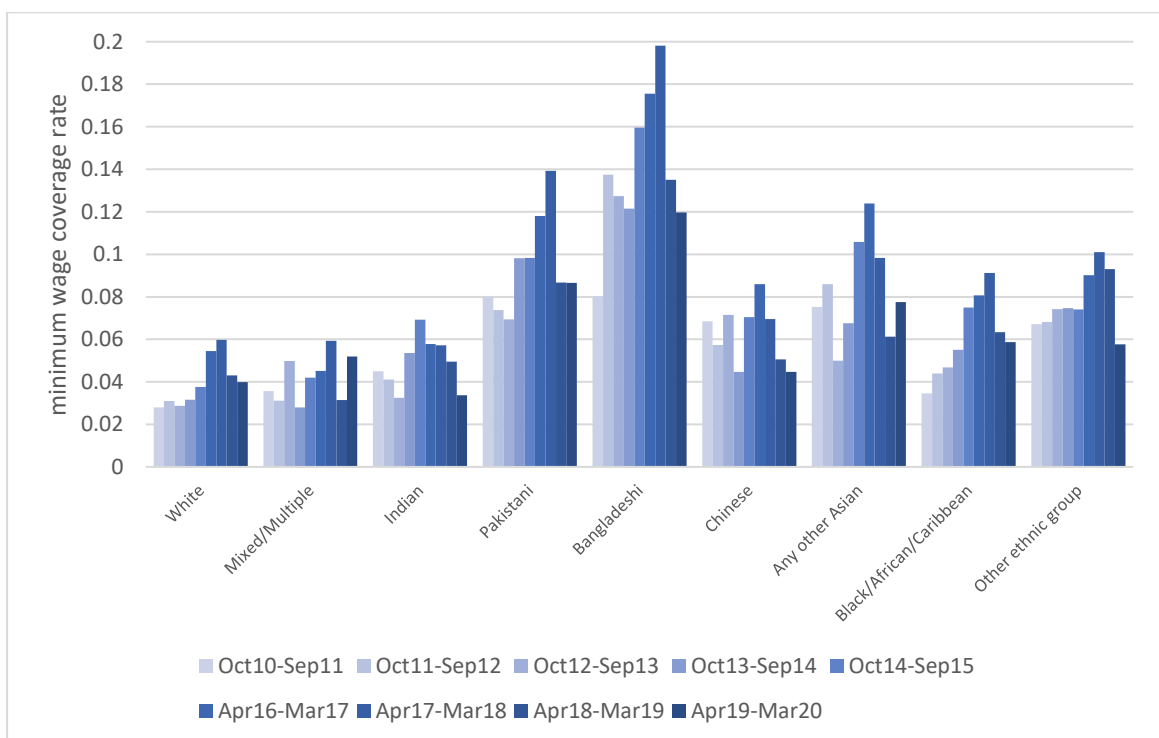**Figure 13 Trends in minimum wage coverage rates based on the imputed wage measure by ethnicity - APS**

Data source: Annual Population Survey.

Notes: men aged 25-64, women aged 25-59.

6. Employment

In this section we document trends in employment by disability status, ethnicity and gender. Employment rates are defined as the share of the relevant working age population in paid employment. Employment rates would be higher if self-employment was taken into account but self-employment is not covered by the minimum wage[16].
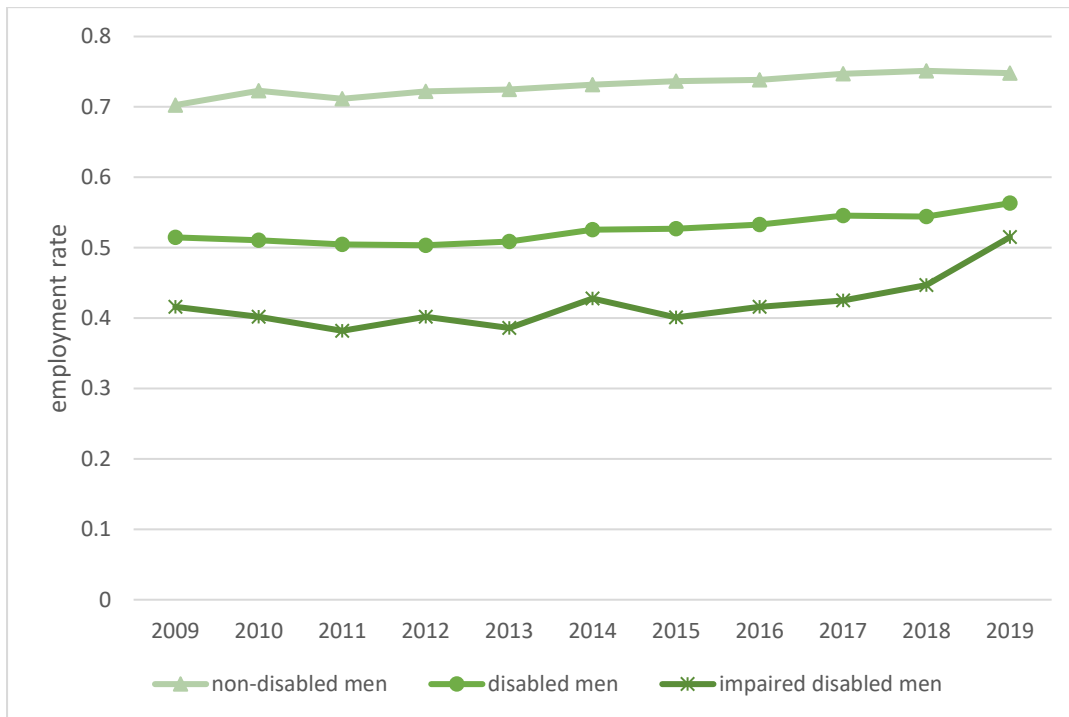
Disability

Using Understanding Society data we estimate paid employment rates for people with disabilities and for disabled people who report a functional impairment (Figure 14 for men; Figure 15 for women). Employment rates are lower among people with disabilities and lowest for disabled people who report at least one functional impairments but employment rates have trended upwards over the last decade. Employment rates continued to increase after the introduction of the NLW in 2016 and at an aggregate level the NLW does not appear to have hampered employment growth for disabled people (of course, there are limits to what aggregate level statistics can tell us as the counterfactual is unknown). The increase in the employment rate between 2018 and 2019 among impaired disabled men is likely to be due to the smaller sample size in 2019 in the annualized USoc dataset (see table A1 in the Appendix).

The upward trend in employment for disabled people is also evident in the shorter time series available for APS data (Figure 16). The APS data also show a narrowing in the disability employment gap. Differences in the definition of disability in USoc and APS are likely to contribute to differences in disability employment rates in the two surveys, with estimated paid employment rates lower in APS than in USoc (even for the definition of disability that includes at least one functional impairment which is thought to be closer to the Equality Act definition used in the APS). However, this is less likely to affect trends in employment rates over time. In both data sources, employment rates are higher for women with disabilities than for men with disabilities (in USoc this applies to disabled women overall and disabled women who report at least one functional impairment).

Employment among less advantage groups tends to be more cyclical. For example, recessions are more likely to have a negative impact on disabled people's labour market experience (Jones et al., 2020). As the labour market tightens, less advantaged groups are increasingly drawn into employment. The decade covered by our analysis is one in which labour market outcomes gradually improved after the 2007/08 financial crisis.

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[16] In the UK, people over school leaving age who are classed as 'workers' qualify for minimum wages with a few exceptions https://www.gov.uk/national-minimum-wage/who-gets-the-minimum-wage
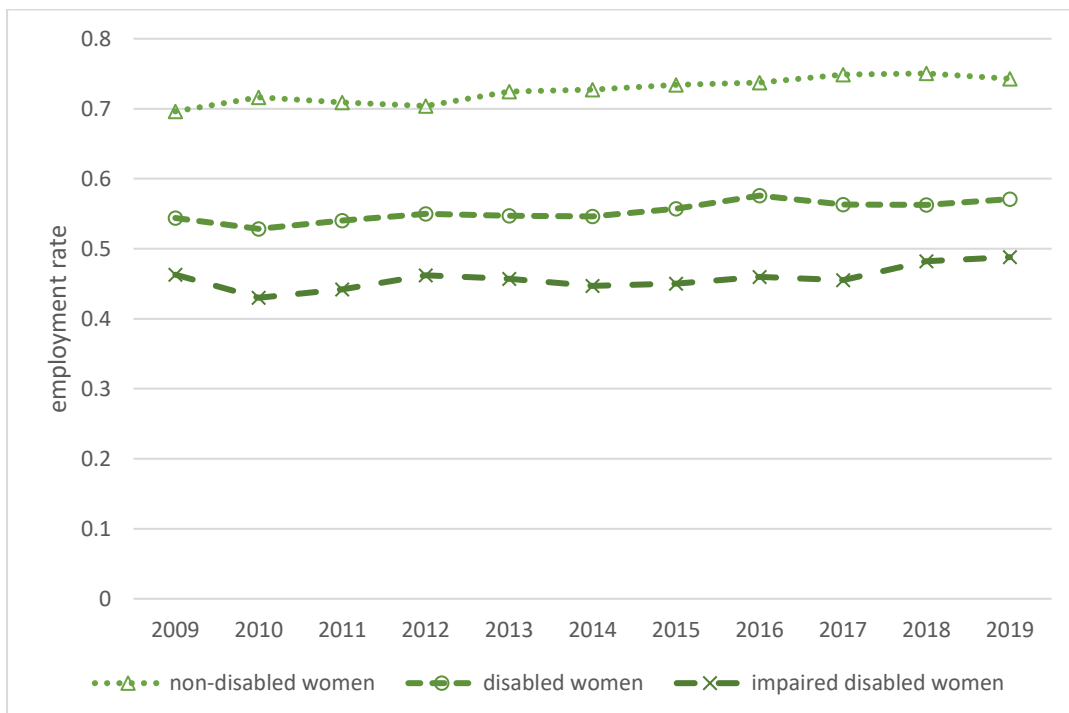
Figure 14 Trends in employment rates by disability status for men – USoc

Data source: Understanding Society.
Notes: men aged 25-64.

Figure 15 Trends in employment rates by disability status for women – USoc

Data source: Understanding Society.
Notes: women aged 25-59.

Figure 16 Trends in employment rates by disability status and gender - APS
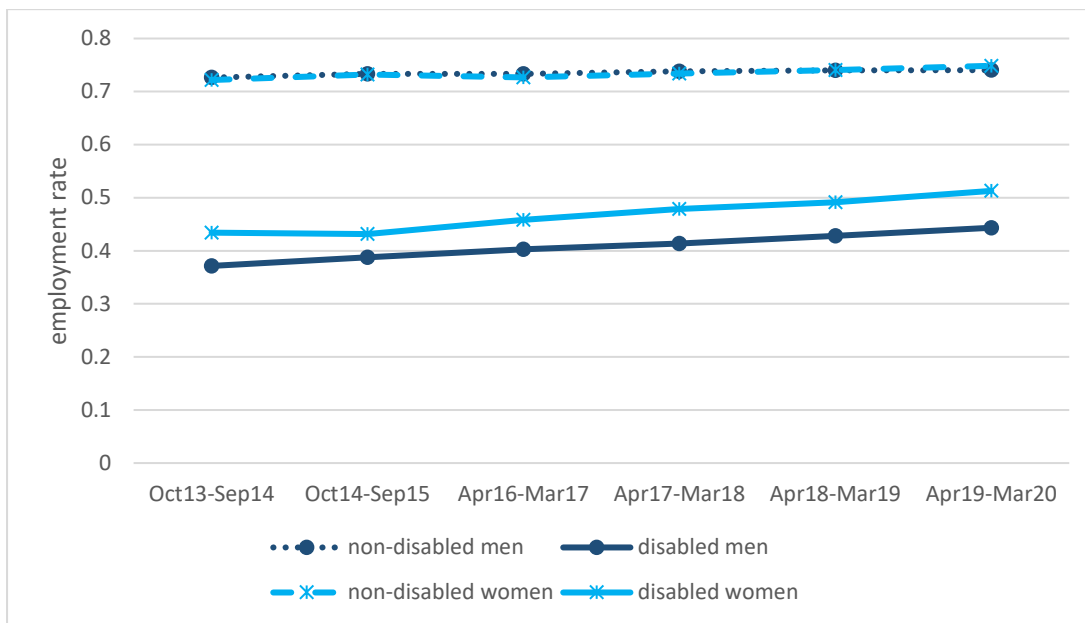
Data source: Annual Population Survey.
Notes: men aged 25-64, women aged 25-59.

Published employment rates for people with disabilities (aged 16-64) by type of impairment based on APS data, highlight considerable heterogeneity with very low rates of employment associated with some impairment types (DWP, 2021). The lowest employment rates (around 20%) are for disabled people with severe or specific learning difficulties or autism (autism is a new response category added in 2020). As mentioned earlier, these are groups for whom concern has been raised in relation to minimum wages. Employment rates have increased since 2013/14 across impairment types but, on average, increases have been greater for disabled people with mental health conditions relative to musculoskeletal conditions (DWP, 2021).

Using USoc data we are able to examine differences in employment rates between different functional impairments among men (Figure 17) and women (Figure 18) with disabilities. As raw sample sizes are relatively small for USoc respondents interviewed in 2019 for some functional impairment types (see Table A2 in the Appendix), we restrict the analysis to 2009-2018. There are relatively high employment rates among disabled people with hearing impairments; lifting, carrying or moving objects impairments; mobility impairments and sight impairments. In contrast, very low rates of employment are found among disabled people with: communication or speech impairments or who have difficulty recognising when in physical danger. Women with disabilities have higher employment rates than their male peers across impairment types, although patterns of employment by impairment types are similar between men and women.

Figure 17 Disability employment rates by type of functional impairment – USoc (men)
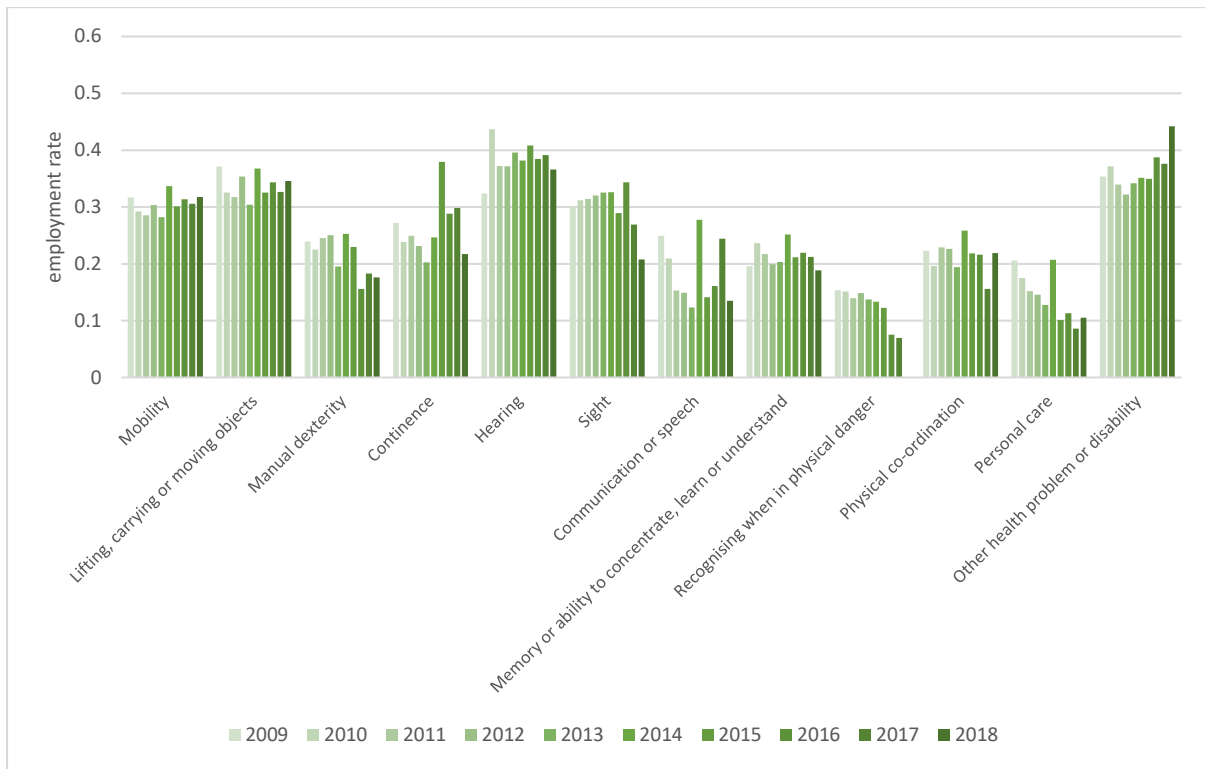
Data source: Understanding Society.
Notes: men aged 25-64.

Figure 18 Disability employment rates by type of functional impairment – USoc (women)
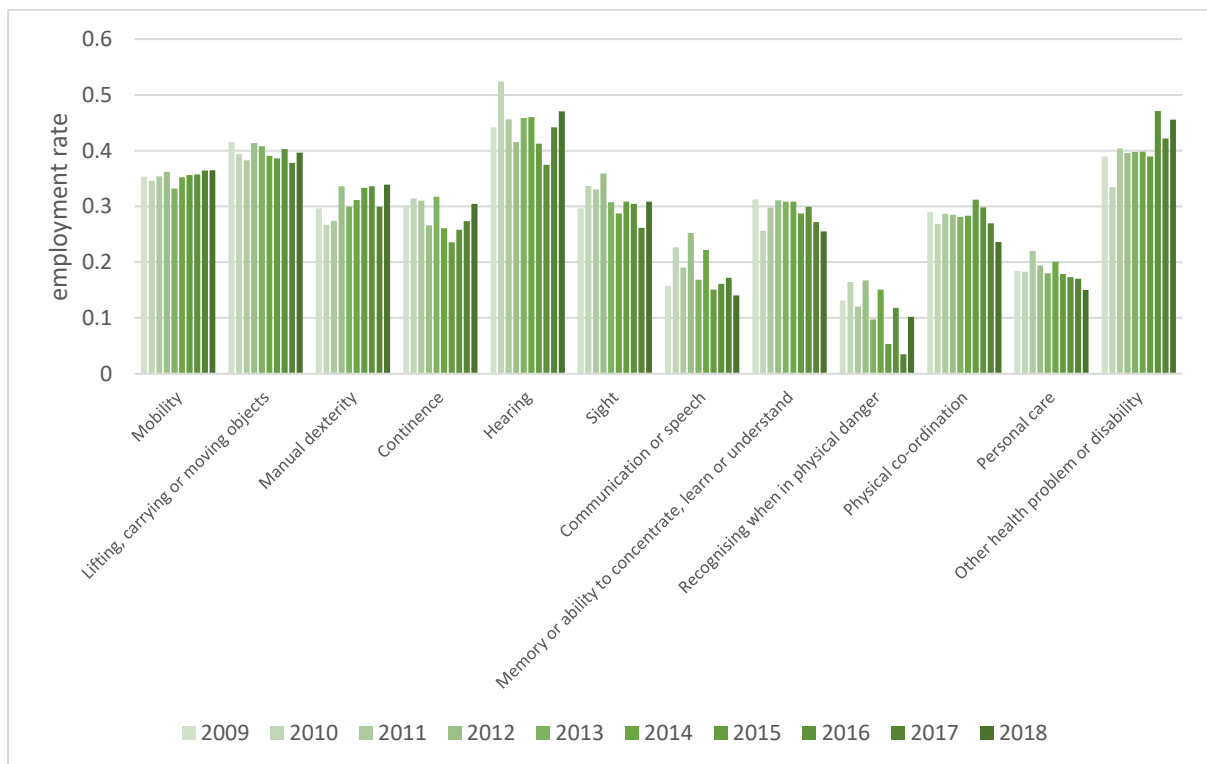
Data source: Understanding Society.
Notes: women aged 25-59.

As shown earlier, people with disabilities have lower employment rates and higher minimum wage coverage rates. When we look at the relationship between employment and minimum wage coverage across functional impairments we find that functional impairments with higher employment rates tend to be associated with lower minimum wage coverage rates. For example, hearing impairment has the highest employment rate and lowest minimum wage coverage rate and recognising when in physical danger impairment is associated with the lowest employment rate and one of the highest minimum wage coverage rates (Figure 19). However, the relationship is not strong, with a range of employment rates for different types of functional impairments each with similar minimum wage coverage rates. For example, the coverage rate for personal care impairments is 0.06 and the employment rate is 0.17, while lifting, carrying or moving objects impairment has a similar coverage rate but a much higher employment rate (0.37).

Figure 19 Relationship between minimum wage coverage (based on imputed wage measure) and employment rates by impairment types
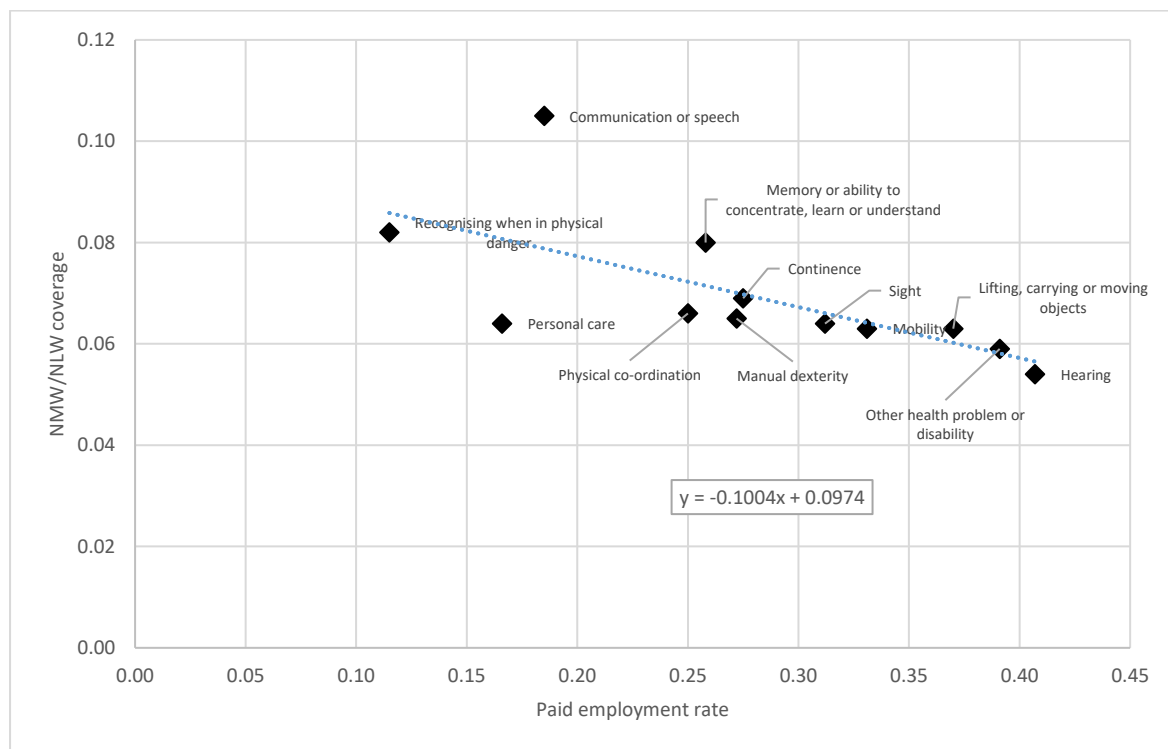
Data source: Understanding Society. Pooled data 2009-2019.
Notes: men aged 25-64, women aged 25-59.

Ethnicity

Consistent with existing research on ethnic inequalities, USoc and APS data show lower rates of employment among BAME individuals and particularly BAME women, relative to non-BAME (Figure 20 and Figure 21). Employment rates increased over this decade for BAME and Non-BAME men and women but a greater increase for BAME men and women meant that the BAME gap in employment narrowed. The growth in employment over this decade was particularly

strong among BAME women. Some of this growth in BAME employment is likely to be due to cyclical factors. Over this period the economy was recovering from the economic recession associated with the 2007/08 financial crisis. Employment among less advantaged groups tends to be more affected by cyclical factors and information on longer term trends is required to know if the increase in BAME employment is part of a longer term change.

Figure 20 Trends in employment rates by BAME status and gender - USoc

a) Men   **b) Women**
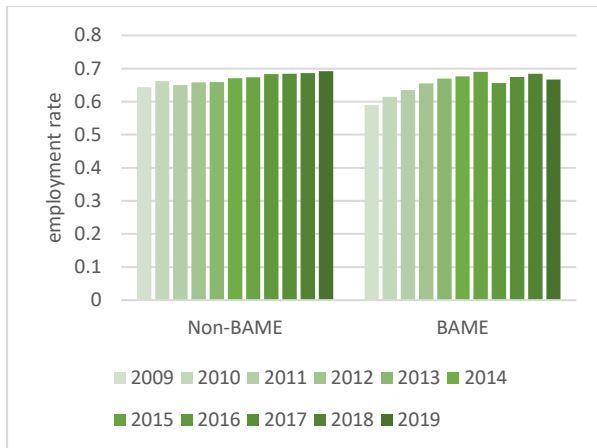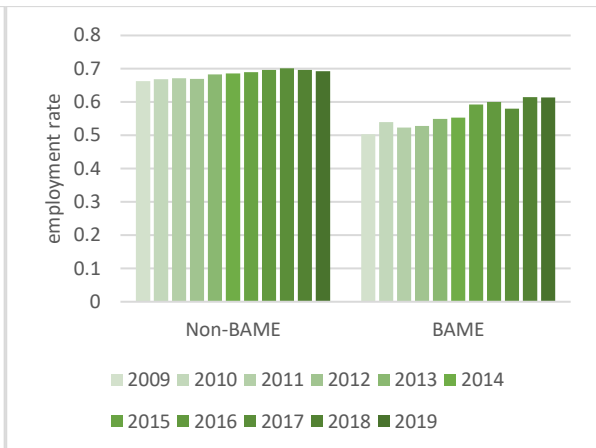
Data source: Understanding Society.
Notes: men aged 25-64, women aged 25-59.

Figure 21 Trends in employment rates by BAME status and gender - APS
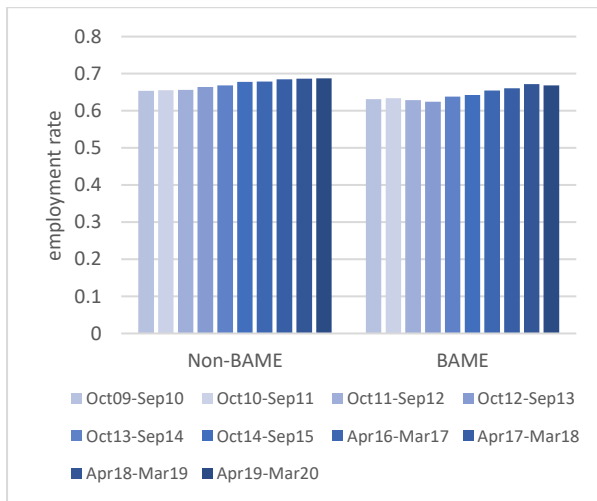
a) Men   **b) Women**
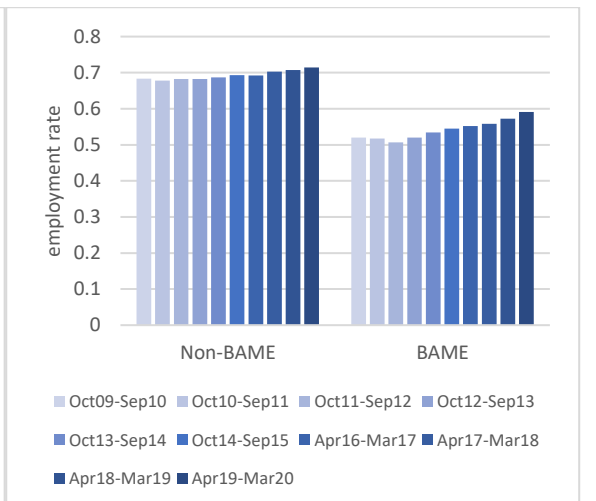
Data source: Annual Population Survey.
Notes: men aged 25-64, women aged 25-59.

The agregate BAME variable conceals large differences between ethnic minority groups. Employment rates are higher among Indian men (USoc and APS) relative to White men and lower

among Pakistani and Bangladeshi men (Figure 22 and Figure 24). The high rates of employment for Chinese men estimated in USoc are not found in the APS which has a larger sample size.

In general, there was an upward trend in employment rates within ethnic minority groups across the decade. For women, it is clear that lower BAME employment rates are largely driven by low rates of paid employment among Pakistani and Bangladeshi women (Figure 23 and Figure 25). However, these women experienced sizeable increases in employment over the decade. APS data, which has larger sample sizes, show this upward trend continuing after the introduction of the NLW in 2016. In contrast to Indian men, Indian women have lower employment rates relative to their White peers. In USoc data it is possible to examine differences between Black Caribbeans and Black Africans. This shows that Black Caribbean women have higher employment rates than Black African women and Black Caribbean men.

Figure 22 Trends in employment rates by ethnicity (men) – USoc
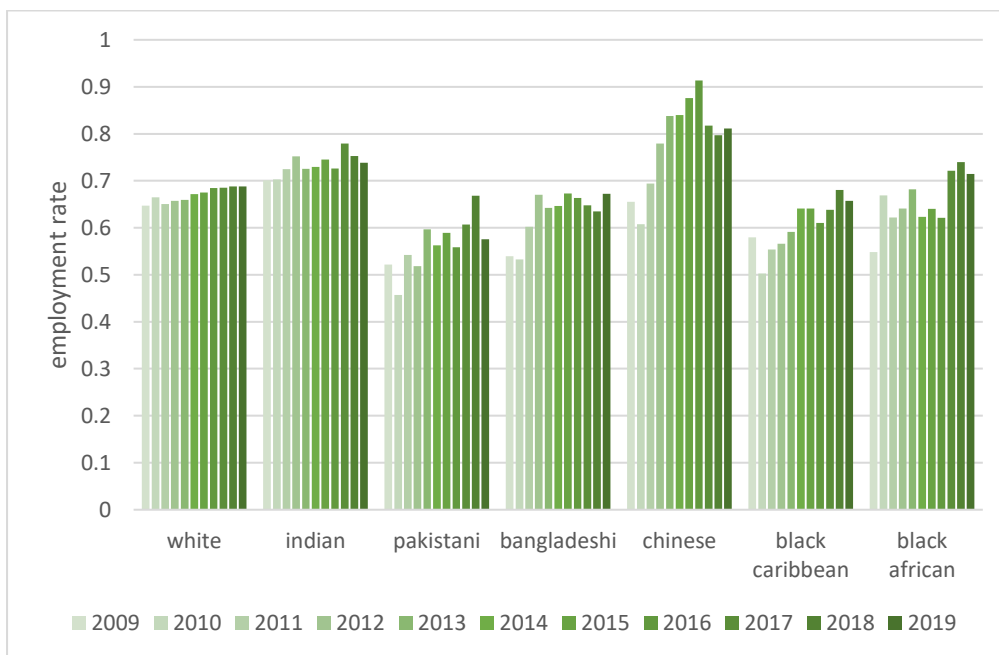
Data source: Understanding Society.
Notes: men aged 25-64, women aged 25-59.

Figure 23 Trends in employment rates by ethnicity (women) – Usoc
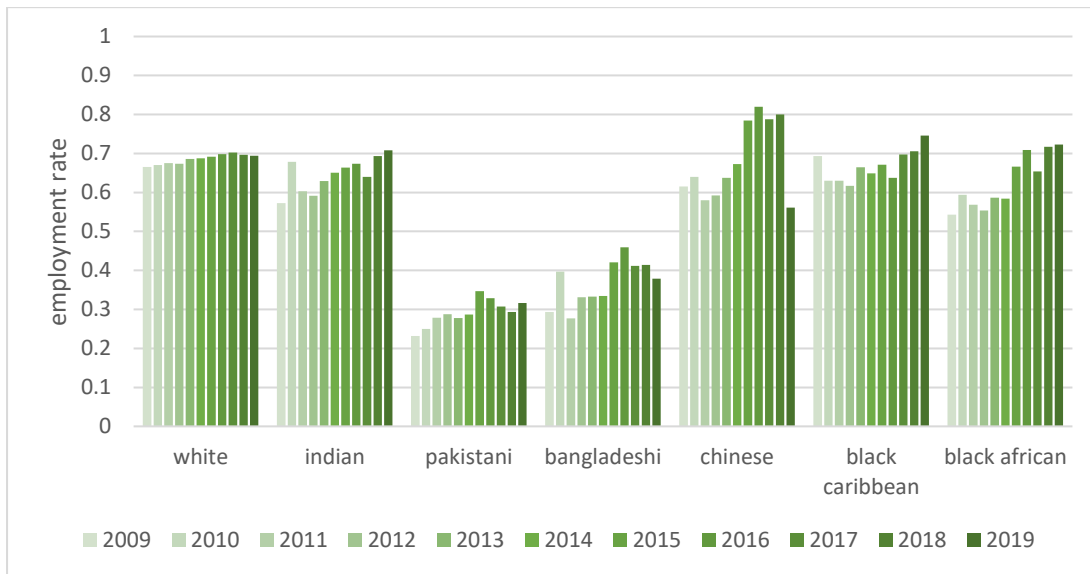
Data source: Understanding Society.
Notes: men aged 25-64, women aged 25-59.

Figure 24 Trends in employment rates by ethnicity (men) – APS
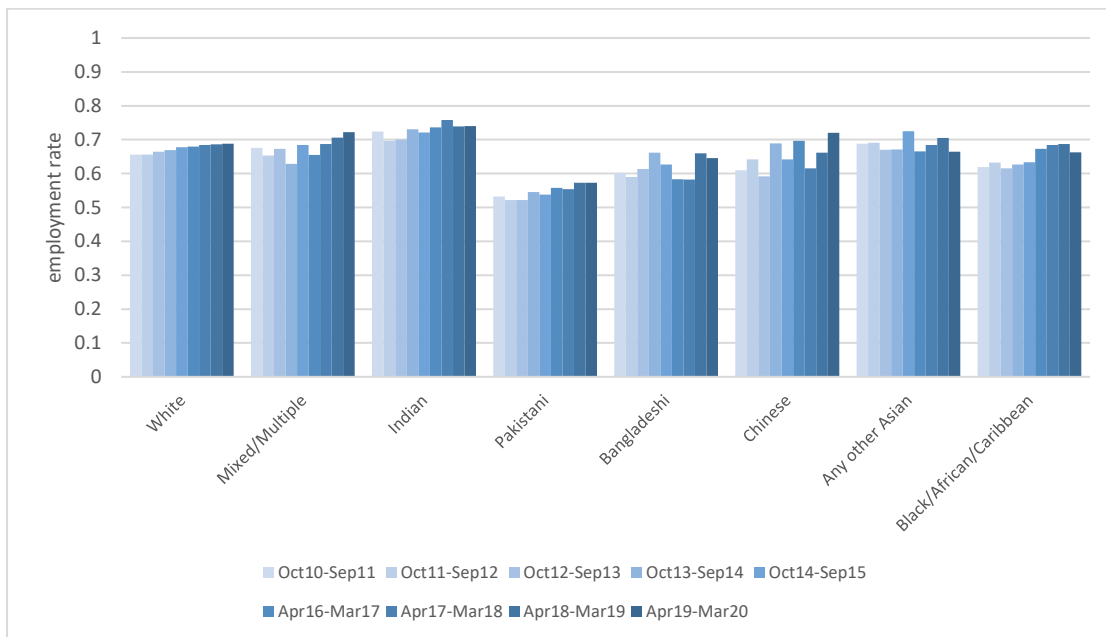
Data source: Annual Population Survey.
Notes: men aged 25-64, women aged 25-59.

Figure 25 Trends in employment rates by ethnicity (women) – APS
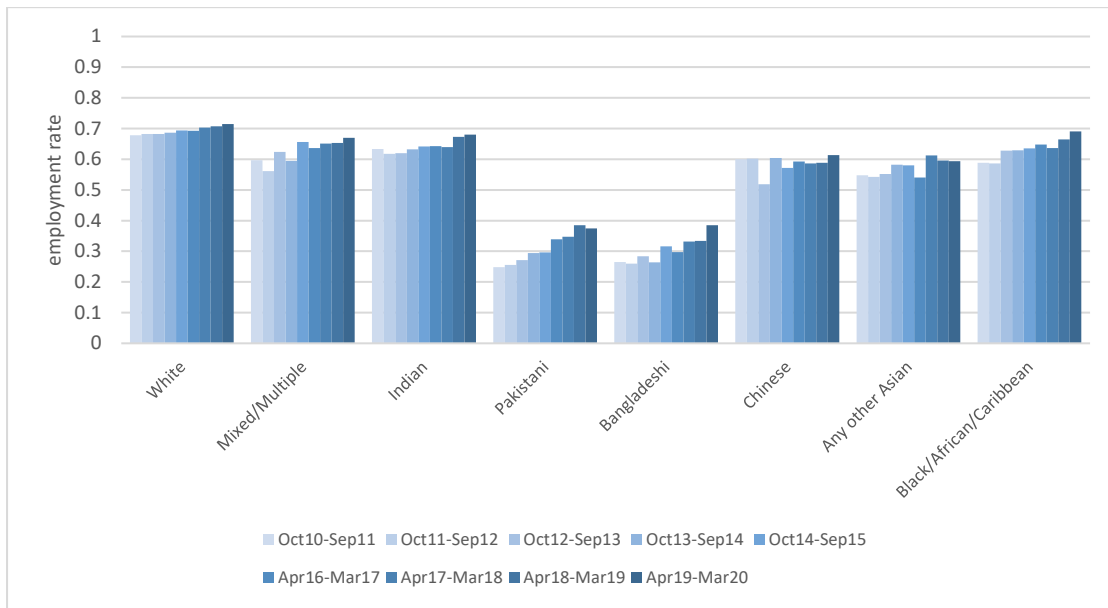
Data source: Annual Population Survey.

Notes: men aged 25-64, women aged 25-59.

7. The impact of the National Living Wage on employment retention

In this section we present estimates of the impact of the NLW introduction on employment retention and estimate heterogeneous effects by disability status, ethnicity and gender. We analyse changes in employment retention because if increases in the minimum wage rates price some workers out of employment we would expect to find a fall in employment retention (an increase in job loss). The reason for focusing on the introduction of the NLW is that it represents the largest annual increase in UK minimum wage rates over the decade covered by this research (see Table 3).

Table 3 UK statutory minimum wage rates applicable for employees aged 25 and over

Date of uprating	Minimum wage rate (£)	Absolute increase (£)	Percentage increase
April 2019	8.21	0.38	5%
April 2018	7.83	0.33	4%
April 2017	7.50	0.30	4%
April 2016	**7.20**	**0.50**	**7%**
October 2015	6.70	0.20	3%
October 2014	6.50	0.19	3%
October 2013	6.31	0.12	2%
October 2012	6.19	0.11	2%
October 2011	6.08	0.15	3%
October 2010	5.93	0.13	2%
October 2009	5.80	0.07	1%

Notes: In October 2009 the NMW rate applied to employees aged 22 and over. Between October 2010 and March 2016 the NMW rate applied to employees aged 21 and over. From April 2016 the NLW applied to employees aged 25 and over.

Employment retention is measured using the longitudinal information in Understanding Society. USoc interviews which are spaced at around one year apart. We use the precise interview dates to measure employment retention. The sample comprises all individuals in paid employment at time t whose employment status is known at time t+1 (one year later). A binary variable is set equal one for individuals who are in paid employment at time t and time t+1 (which might or might not be with the same employer) and set equal to zero for individuals who are in paid employment in time t but not in paid employment at time t+1[17]. In the base year (period t), one of the wage measures is used to determine treatment and control group status. Employees with a wage rate between the prevailing NMW rate and up to and including the incoming NLW rate are assigned to the treatment group. This is the group most likely to be affected by the introduction

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[17] Individuals might move into self-employment but here we focus on paid employment which is subject to the NMW/NLW.

of the NLW as assuming no other change in their employment takes place, their wage rates will increase to the NLW. Consistent with other studies, the control group are in a pay band just above this group in period t and have a wage rate greater than the incoming NLW rate and up to 10% higher than this rate. The date of USoc interviews is used to define a group of employees whose measure of annual employment retention spans the introduction of the NLW (span-treatment group: interview at time t is prior to the introduction of the NLW and interview at time t+1 is after the introduction of the NLW) and a second reference group for whom employment retention is measured prior to the introduction of the NLW (pre-treatment group: interview at time t and interview at t+1 both take place prior to the introduction of the NLW). Note that there can be some contamination due to earlier increases in the NMW. Another factor is that non-compliance will limit the impact of minimum wage upratings on employment retention if these workers' wage rates do not increase in line with upratings. The LPC estimated that 21.5 per cent of workers 'covered' by statutory minimum wage rates in 2019 were paid less than these rates (LPC, 2021a).

To estimate the overall impact of the NLW on employment retention we estimate Difference-in-difference models (DID models). These are the standard models estimated across the whole sample which provide an estimate of the overall impact of the NLW on employment retention. To estimate heterogeneous effects (by disability and ethnicity) of the NLW on employment retention, we estimate difference-in-difference-in-differences models (DDD models). For the DDD models, the first difference is between the treatment and control groups, the second between the span-treatment time period and the pre-treatment time period and the third difference between our groups of interest (for example, between disabled and non-disabled and between BAME and non-BAME).

Equation (1) shows the difference-in-difference-in differences model used for estimating heterogeneous effects by BAME status (for disability, the BAME indicator variable is replaced with a disability indicator variable). $Treat_i$ is the treatment status variable, where $Treat_i=1$ (Treat) if individual i is in the treatment group (their wage is between the NMW and the NLW prior to the NLW being introduced) and $Treat_i=0$ (Control) if individual i is in the control group (their wage is above the NLW and up to 10% higher than the NLW prior to its introduction in time period 2). The variable d_t indicates treatment time and equals one for observations in the span-treatment time period (time period 2) and zero for observations in the pre-treatment time period (time period 1). Additional control variables are added to this basic model, including variables denoting high earners (wage higher than 10% of the NLW) and very low earnings (wage less than the NMW).

$$y_{it} = \alpha + \beta_1 d_t + \beta_2 Treat_i + \beta_3 d_t \times Treat_i + \beta_4 BAME_i + \beta_5 BAME_i \times Treat_i$$
$$+ \beta_6 BAME_i \times d_t + \delta_0 d_t \times Treat_i \times BAME_i + \varepsilon_{it} \qquad (1)$$

δ_0 is the parameter of interest (DDD average treatment effect on the treated).

$$\delta_0 = [(\bar{y}_{Treat,2} - \bar{y}_{Treat,1}) - (\bar{y}_{Control,2} - \bar{y}_{Control,1})]BAME$$
$$- [(\bar{y}_{Treat,2} - \bar{y}_{Treat,1}) - (\bar{y}_{Control,2} - \bar{y}_{Control,1})]Non - BAME$$

Table 4 contains treatment effect estimates from 30 separate models of employment retention; the parameter of interest δ_0. The reported results are from linear probability models. Probit models were also estimated and the key results in terms of sign and statistical significance were replicated in these models. Each cell in Table 4 contains a model estimate of δ_0 and its standard error. Treatment effect estimates are shown for the standard difference-in-differences models (DID) (column (1)), and treatment effect estimates for heterogeneous effects from DDD models (columns (2) to (6)). The top panel provides estimates from models without additional demographic control variables and the bottom panel from models which include controls for gender and age. The reason for adding additional controls for age and gender is that these variables are known to be correlated with employment retention and the composition of the treatment and control groups can change over time. Time invariant compositional differences between the treatment and control groups are netted out through benchmarking the difference in employment retention between these two groups in a pre-treatment period (prior to the introduction of the NLW in this case) and between sub-groups of interest in a similar way. However, if important compositional change occurs between the pre-treatment time period and span-treatment time period (for example, employment retention is known to increase with age and if the sample of disabled people is older in the treatment period than in the pre-treatment period) we could reach the wrong implications. Including age and gender in the models, allows us to control for changes in sample composition for these variables.

Separate models are estimated based on the three wage measures (directly reported, derived and imputed), where the wage variables are used to determine who is in the treatment and control groups. This allows us to gauge how sensitive the findings are to the different wage measures and for the results to be compared with previously published impact estimates based on the derived wage measure. Note that sample sizes vary between the models due mainly to differences in the number of individuals with valid wage information for the three wage measures and the wage distribution of the different measures (sample sizes for the different models can be found in Table 1A in the Appendix). As fewer respondents directly report a wage rate, the sample sizes for models based on this wage measure are the smallest with over four times as many cases in the models based on the derived and imputed wage measures. In addition, not only are differences in samples likely to affect the precision of estimated model coefficients but differences in sample composition based on the wage variables can potentially lead to biased estimates. For example, if

some individuals have incorrectly been assigned to the treatment group due to measurement error in the wage variable, higher wage individuals unaffected by minimum wage upratings could lead to under-estimates of the impact of the NLW on employment retention. This problem is most likely to affect models based on the derived wage measure.

We estimate that the introduction of the NLW had no overall negative impact on employment retention: none of the DID treatment effect estimates in column (1) are negative and statistically significant. The only statistically significant effect we estimate (at the 10% level) is for the model based on the direct wage measure but the treatment effect is estimated to be positive. This would suggest that the introduction of the NLW was associated with an improvement in employment retention but the effect is not statistically significant when we control for age and gender which suggests that the higher employment retention is due to changes in composition in the treatment group relative to the control group. Turning next to the DDD model estimates shown in columns (2) to (6). The second column of Table 4 contains estimates of heterogeneous effects by BAME status. The results show no statistically significant effects on employment retention for BAME employees in models with and without control variables. Given their relatively high rates of minimum wage coverage and relatively low rates of employment, Pakistani and Bangladeshi ethnic groups would appear to be particularly at risk of experiencing negative employment effects from the introduction of the NLW. To increase sample size and precision of the treatment effect estimates, we aggregate the two ethnic groups and create a single binary variable. The results in column (3) show no statistically significant effects on employment retention among Pakistani-Bangladeshi relative to other ethnic groups with the exception of the models based on the direct wage (with and without control variables) where we estimate a positive and statistically significant effect on employment retention associated with the introduction of the NLW.

The Indian ethnic group have relatively high rates of employment and relatively low minimum wage coverage rates and, a priori, might be considered to be at low risk of negative employment effects from the introduction of the NLW. However, we find statistically significant negative treatment effects for models based on the direct and imputed wage measures, with and without controls for age and gender. This suggests that the introduction of the NLW led to falls in employment retention among Indian employees whose wage rates would have increased to the NLW had they stayed in employment (column (4)). Among this group of generally advantaged employees, those in minimum wage employment appear to have been at greater risk of job loss.

In relation to disability, the results show that in the models based on the imputed wage the introduction of the NLW led to an increase in employment retention but once we control for age and gender this result becomes statistically insignificant (column (5)). This means that the increase in employment retention is likely due to changes in the composition of the treatment

and control group in terms of age and gender. For a sub-group of disabled employees who report at least one functional impairment, no statistically significant effects are estimated (column (6)). Sample sizes are too small to estimate heterogeneous effects by type of impairment.

Table 4 Impact of the NLW introduction on employment retention. Treatment effect estimates from DID (1) and DDD (2-6) models

Wage variable	All	BAME	Pakistani-Bangladeshi	Indian	Disabled	Impaired disabled
	(1)	(2)	(3)	(4)	(5)	(6)
No controls						
Direct wage	**0.045***	0.024	**0.180** *	**-0.145** **	0.037	0.029
	(0.025)	(0.051)	(0.096)	(0.066)	(0.042)	(0.053)
Derived wage	0.029	0.053	-0.044	-0.079	-0.016	-0.009
	(0.023)	(0.055)	(0.095)	(0.108)	(0.038)	(0.044)
Imputed wage	0.003	-0.029	0.058	**-0.161** **	**0.059** *	0.048
	(0.019)	(0.041)	(0.073)	(0.069)	(0.033)	(0.042)
Age & gender controls						
Direct wage	0.042	0.026	**0.184** **	**-0.146** **	0.035	0.027
	(0.025)	(0.051)	(0.094)	(0.066)	(0.042)	(0.053)
Derived wage	0.031	0.058	-0.041	-0.069	-0.021	-0.013
	(0.022)	(0.055)	(0.096)	(0.108)	(0.038)	(0.044)
Imputed wage	0.002	-0.023	0.059	**-0.150** **	0.050	0.043
	(0.019)	(0.041)	(0.073)	(0.069)	(0.033)	(0.043)

Data source: Understanding Society.
Notes: Estimates from linear probability models. Men aged 25-64 and Women aged 25-59. Robust standard errors in parentheses. *, **, *** denote significance at the 10%, 5%, 1%, respectively.

Next we assess whether the impact of the NLW introduction varies by gender and estimate models separately for men and women (we do not control for age in these models). The top panel of Table 5 present the treatment effects estimates for men. There are no estimated statistically significant effects on employment retention associated with the introduction of the NLW among all men (DID model estimates shown in column (1)). In addition, there are no heterogeneous effects, estimated in DDD models, by BAME status (column (2)) or for Pakistani-Bangladeshi men (column (3)). Consistent with the pooled sample, negative employment retention effects are estimated for Indian men, in models based on the direct and imputed wage measures (column (4)). No statistically significant effects of the NLW on employment retention are estimated for male employees with disabilities (column (5)) or for disabled men reporting at least one functional impairment (column (6)).

The lower panel of Table 5 contains the treatment effects estimates for women. There are no statistically significant effects among all women (DID model estimates shown in column (1)). Heterogeneous effects estimated in DDD models show no statistically significant effects for BAME women (column (2)) or Indian women (column (3)). However, for the models based on the derived wage measure, there is an estimated negative effect on employment retention for Pakistani-Bangladeshi women (significant at the 10% level). No statistically significant effects are found for women with disabilities (column (5)) or for disabled women who report at least one functional impairment (column (6)).

Table 5 Impact of NLW introduction on annual employment retention by gender: Treatment effect estimates from DID (1) and DDD (2-6) models

Wage variable	All	BAME	Pakistani-Bangladeshi	Indian		Disabled	Impaired disabled
	(1)	(2)	(3)	(4)		(5)	(6)
Men							
Direct wage	0.060	-0.096	0.119	**-0.315**	***	0.032	0.079
	(0.043)	(0.079)	(0.098)	(0.120)		(0.068)	(0.094)
Derived wage	0.046	0.065	0.024	-0.103		-0.088	-0.042
	(0.041)	(0.091)	(0.130)	(0.181)		(0.074)	(0.083)
Imputed wage	-0.003	-0.067	-0.018	**-0.247**	***	0.046	0.084
	(0.033)	(0.062)	(0.100)	(0.092)		(0.058)	(0.078)
Women							
Direct wage	0.037	0.107	0.240	-0.006		0.037	0.008
	(0.032)	(0.069)	(0.167)	(0.070)		(0.054)	(0.067)
Derived wage	0.020	0.022	**-0.209**	-0.061	**	-0.013	0.005
	(0.023)	(0.068)	(0.102)	(0.133)		(0.043)	(0.049)
Imputed wage	0.006	0.0003	0.155	-0.101		0.066	0.034
	(0.023)	(0.056)	(0.116)	(0.097)		(0.041)	(0.051)

Data source: Understanding Society.
Notes: Estimates from linear probability models. Men aged 25-64 and Women aged 25-59. Robust standard errors in parentheses. *, **, *** denote significance at the 10%, 5%, 1%, respectively.

8. The impact of minimum wages on wage progression

The majority of studies evaluating the impact of minimum wages and upratings focus on changes in employment at the extensive (retention and recruitment) and intensive (hours worked) margins. Higher minimum wages can also have an impact on wage progression. For example, progression out of minimum wage jobs can fall if minimum wage rates become "going rates" in a significant number of occupations or if wage differentials become more compressed above a higher minimum wage. In this section we use the longitudinal information available in Understanding Society to analyse wage progression from minimum wage jobs over the last decade and assess whether minimum wage upratings, including the introduction of the NLW, have had a negative impact on progression. We estimate heterogeneous effects by ethnicity, disability and gender and consider four main outcomes: minimum wage employment (wage at or below the minimum wage rate), low wage employment (wage above the minimum wage rate and up to 1.5 times the value of the minimum wage[18]), high wage employment (wage greater than 1.5 times the value of the minimum wage), and non-employment (not in paid employment)[19]. Table 6 shows the minimum wage rates and the corresponding low wage threshold for each period.

Table 6 UK statutory minimum wage rates for employees aged 25+ and low wage threshold

Date of uprating	Minimum wage rate (£)	Low wage threshold (£)
April 2019	8.21	13.08
April 2018	7.83	12.32
April 2017	7.50	11.75
April 2016	**7.20**	**11.25**
October 2015	6.70	10.80
October 2014	6.50	10.05
October 2013	6.31	9.75
October 2012	6.19	9.47
October 2011	6.08	9.29
October 2010	5.93	9.12
October 2009	5.80	8.90

Notes: Minimum wage rates apply to employees not qualifying for an apprentice rate. In October 2009 the NMW rate applied to employees aged 22 and over. Between October 2010 and March 2016 the NMW rate applied to employees aged 21 and over. From April 2016 the NLW applied to employees aged 25 and over.

Figure 26 shows trends in minimum wage and low wage employment, overall and by BAME and disability status for the three wage measures: a) directly reported wage; b) derived wage and c) imputed wage. The left-hand column shows the minimum wage coverage rates, highlighting the

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[18] Low pay thresholds are somewhat arbitrary. Other options include using two-thirds of the median wage but the disadvantage with this threshold is that the risks of being low paid (between the minimum wage and the low pay threshold) fall as the bite of the minimum wage increases.

[19] Individuals could be in self-employment but here we focus on paid employment.

higher coverage rates for the directly reported wage and the derived wage measures relative to the imputed wage measure. Higher proportions of BAME employees and disabled employees are in low wage employment relative to the overall rate for the derived wage measure and the imputed wage measure. Clear differences over time are not apparent for the directly reported wage measure. This is likely to be because there is already selection into this wage measure which is only available for employees who know their hourly rate of pay and tend to be lower paid. Comparing the three wage measures, higher proportions of employees directly reporting wage rates are classified as low wage employees relative to the derived and imputed wage measures. This is consistent with lower paid employees more likely to be paid an hourly rate and reporting this rate in the survey. The lowest rates of low wage employment are observed for the derived wage measure, reflecting the flatter wage distributions for this measure shown in Section 5.

Figure 26 Trends in minimum wage and low wage employment (imputed wage)

Proportion minimum wage　　　　　　**Proportion low pay threshold**

a) Direct wage measure
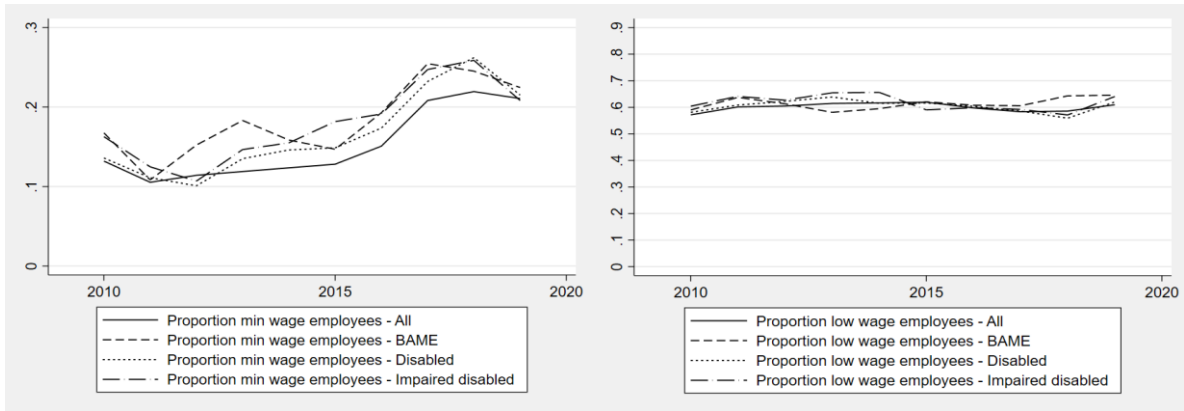
b) Derived wage measure
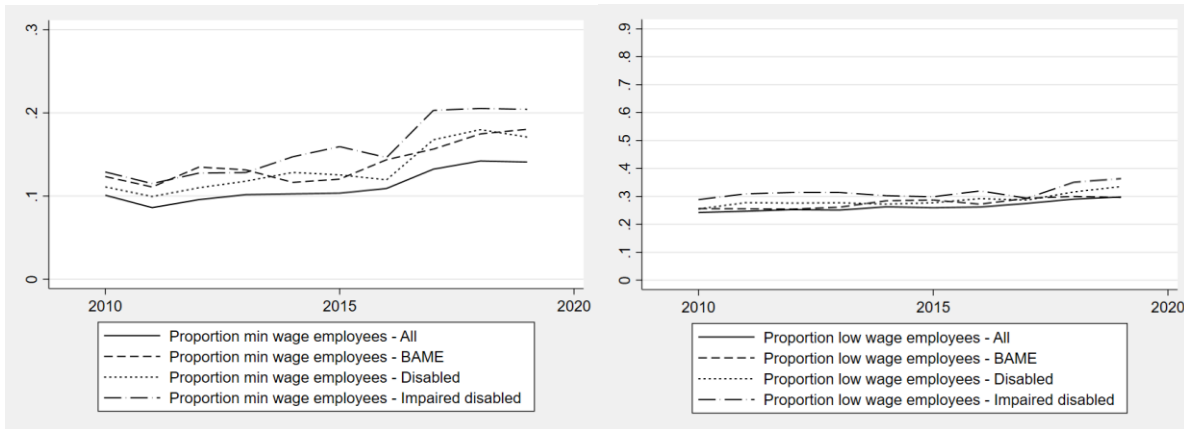
c) Imputed wage measure
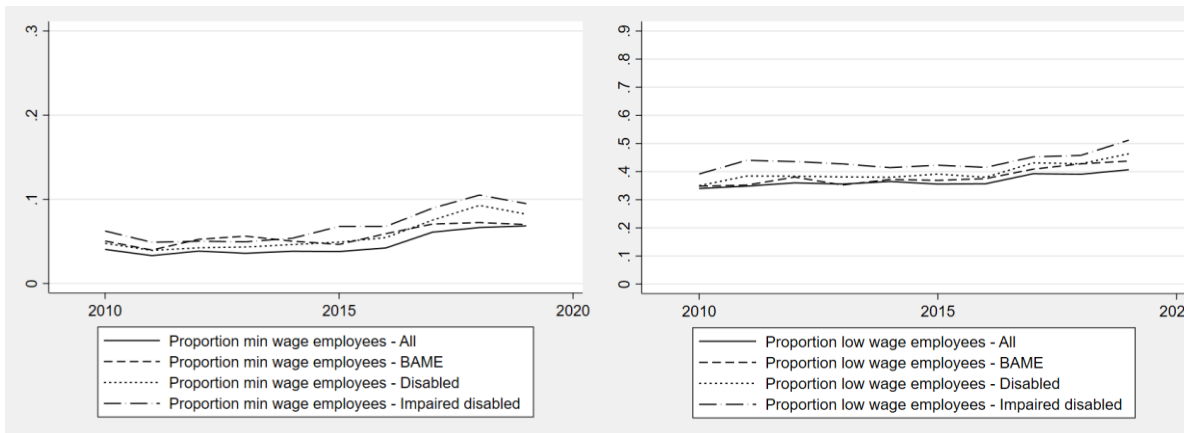
Data source: Understanding Society.
Notes: men aged 25-64, women aged 25-59.

The longitudinal information available in Understanding Society is also used to compute annual transition rates between minimum wage employment and the four possible outcomes. The results can be found in Figure 27 for the direct wage measure, Figure 28 for the derived wage measure and Figure 29 for the imputed wage measure. The vast majority of minimum wage employees either remain in a minimum wage job or progress to a low paid job one year later. For the imputed wage measure the split between these two destinations is fairly even. For the derived and direct wage measures a much larger share remain in minimum wage employment rather than progress to low wage employment. Small proportions of employees in minimum wage jobs transition to non-employment or high paid jobs one year later. Comparing the three wage measures, higher proportions of minimum wage employees defined in terms of the derived wage measure progress to high pay relative to the directly reported or imputed wage measures. For the imputed wage measure, equal shares of minimum wage employees remain in minimum wage jobs or progress to low pay.

BAME minimum wage employees are relatively more likely to progress to low wage employment and less likely to remain in a minimum wage job. Minimum wage employees with disabilities are relatively more likely to move into non-employment and less likely to progress to low wage employment the following year. Here we are looking at short-term wage progression and progression out of minimum wage employment is likely to be higher over longer time horizons but annual wage transitions are likely to be sensitive to minimum wage upratings. Trends suggest that there appears to be some evidence that after the introduction of the NLW in 2016 a higher proportion of employees remained in minimum wage jobs. This is consistent with a study by Brochu and Green (2013) who find that higher minimum wages are associated with lower job separate rates among unskilled workers in Canada (1979-2008).

Figure 27 Annual transition rates: remaining on minimum wage, minimum wage to low pay, minimum wage to high pay and minimum wage to non-employment (direct wage)
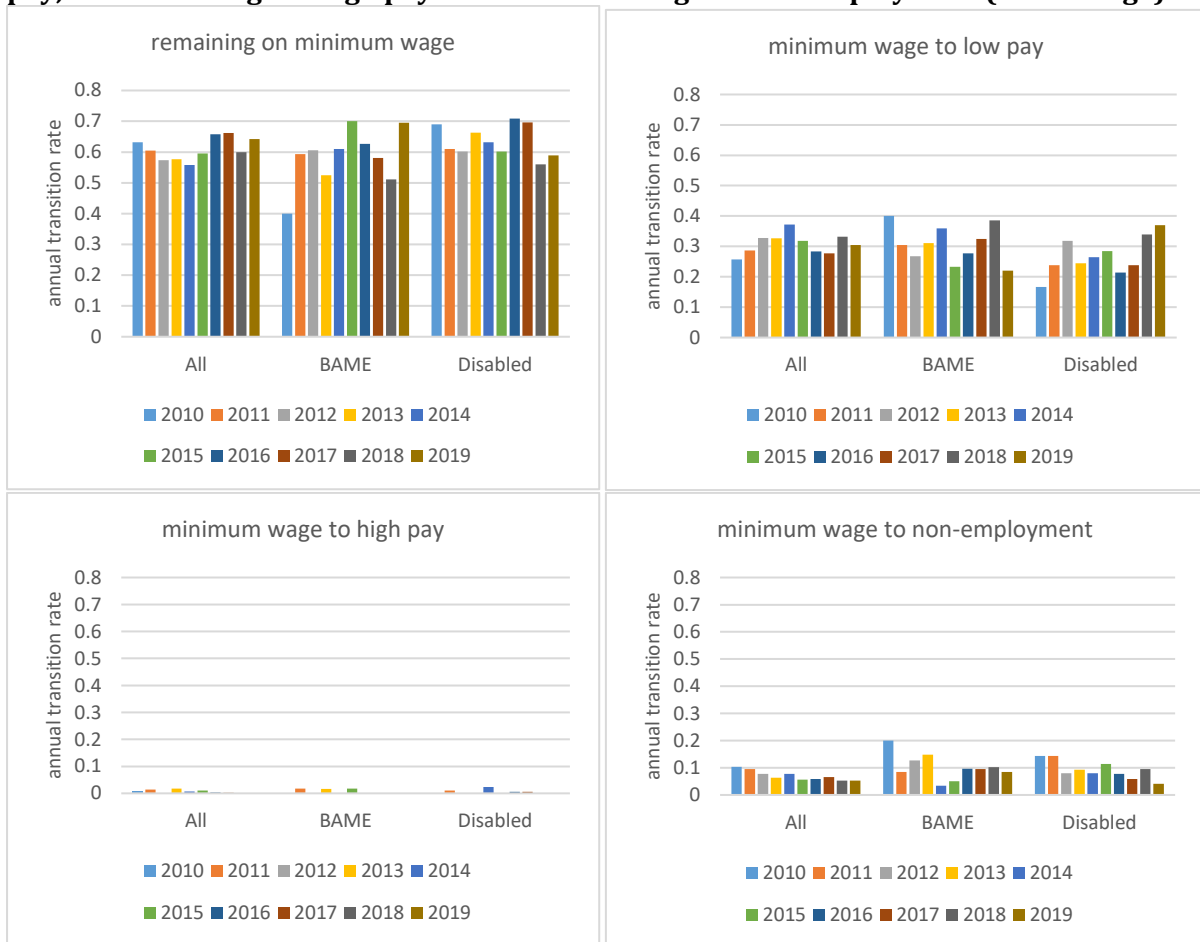
Data source: Understanding Society.

Notes: Low pay is above minimum wage (mw) and up to 1.5*mw. High pay is greater than 1.5*mw.

Figure 28 Annual transition rates: remaining on minimum wage, minimum wage to low pay, minimum wage to high pay and minimum wage to non-employment (derived wage)
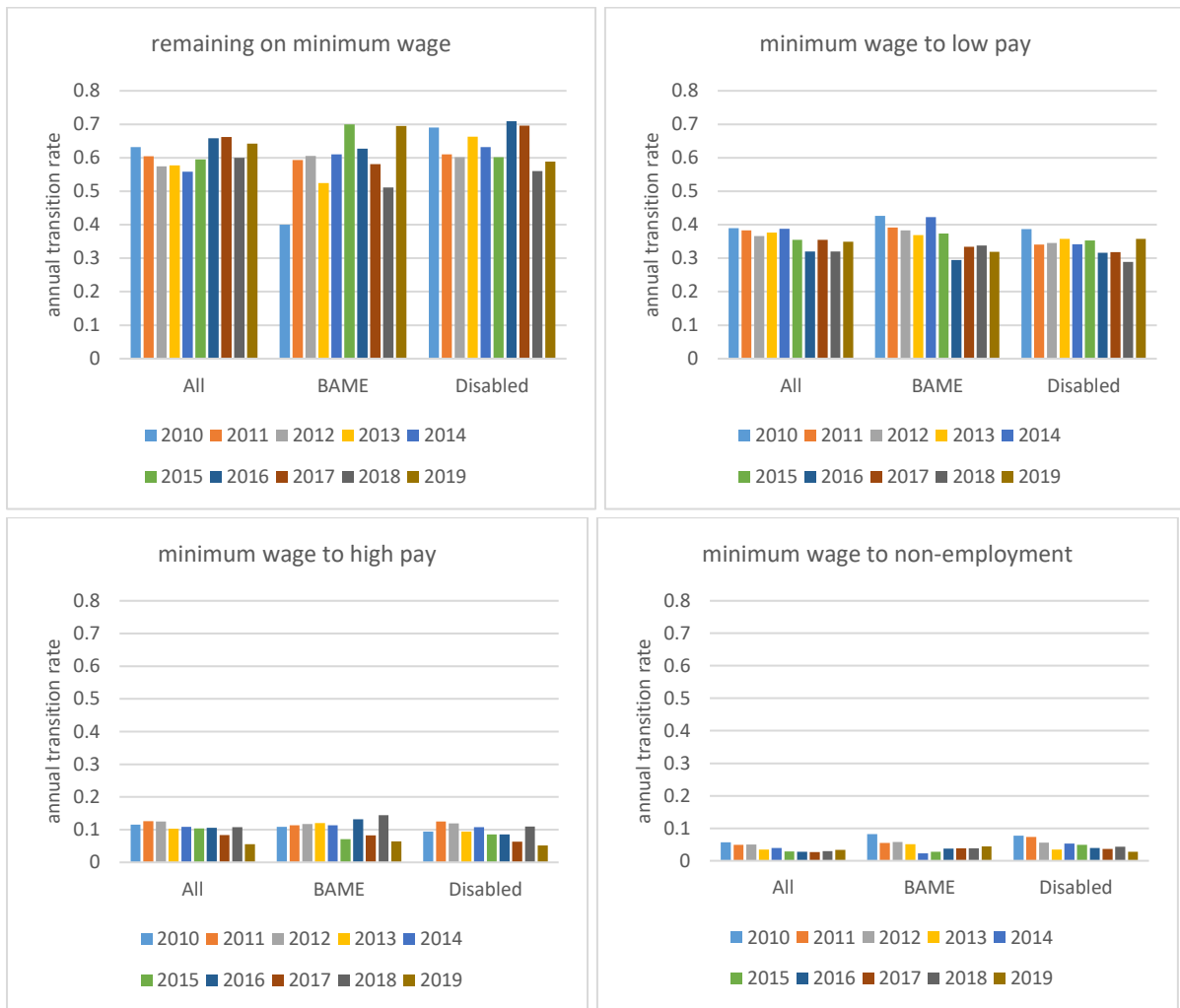
Data source: Understanding Society.

Notes: Low pay is above minimum wage (mw) and up to 1.5*mw. High pay is greater than 1.5*mw.

Figure 29 Annual transition rates: remaining on minimum wage, minimum wage to low pay, minimum wage to high pay and minimum wage to non-employment (imputed wage)
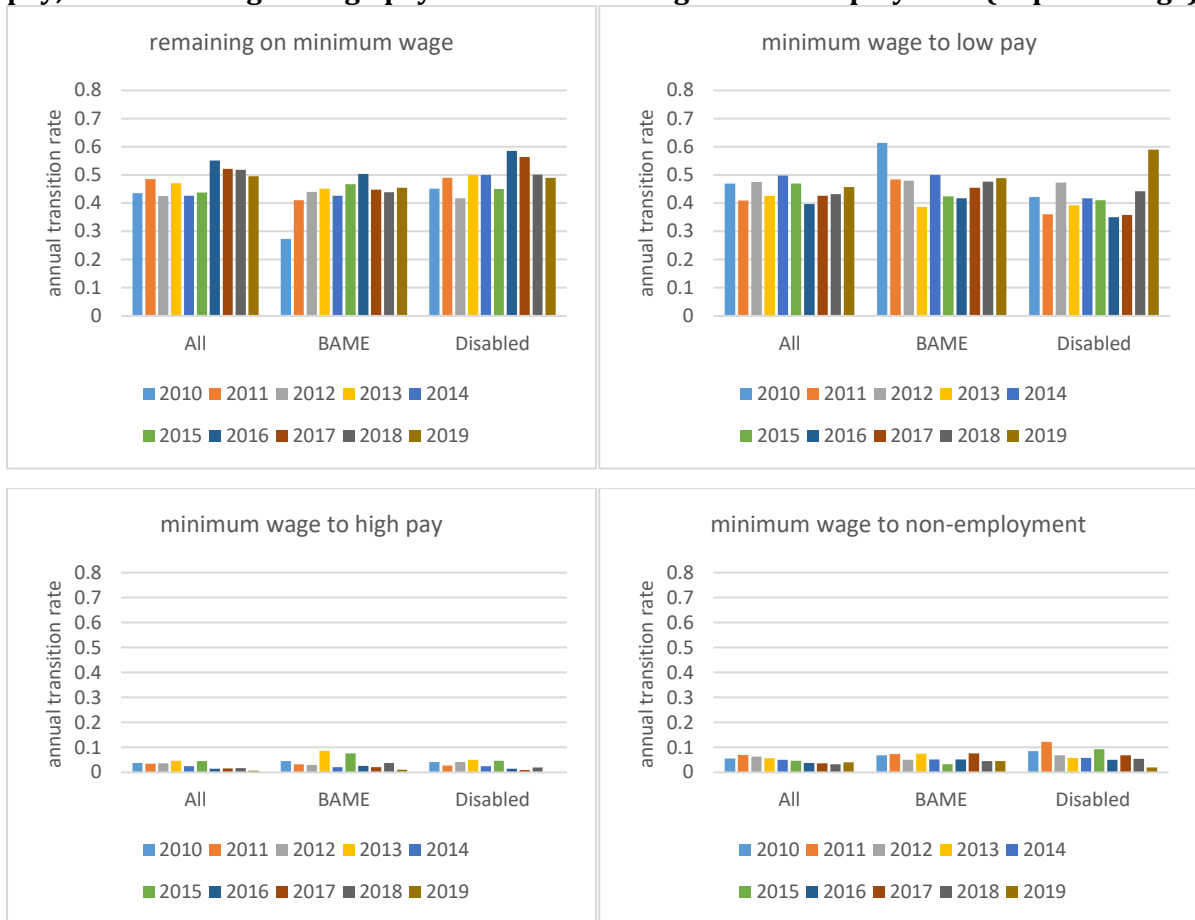
Data source: Understanding Society.

Notes: Low pay is above minimum wage (mw) and up to 1.5*mw. High pay is greater than 1.5*mw.

We test for statistically significant changes in annual transitions from minimum wage employment by modelling the probability of moving to higher wage employment one year later (upwardly mobile) and the probability of remaining in a minimum wage job one year later (stuck). Higher wage employment includes any wage above the minimum wage rate (i.e. it includes both low pay and high pay from the previous charts). These are simple linear probability models with a binary dependent variable for the two outcomes and years included as independent variables. These models cannot identify causal effects of minimum wage upratings on wage progression but they allow us to assess whether or not changes in predicted transition probabilities occurred over the decade were statistically significant and if changes occurred following the introduction of the NLW. We find statistically significant falls in upward mobility for all three wage measures (Table 7) and, conversely, statistically significant increases in minimum wage employees becoming stuck in minimum wage jobs, from one year to the next, after the introduction of the NLW (Table 8).

Estimating transition probability models for different groups reveals that the fall in upward mobility and the increase in becoming stuck in minimum wage employment are found for male minimum wage employees (all wage measures). For the models based on the derived wage measure, BAME employees also experience similar statistically significant changes and for disabled employees there is a statistically significant increase in the probability of becoming stuck in minimum wage employment. For the directly reported wage measure and the imputed wage measure, there are no statistically significant changes in upward mobility or becoming stuck for employees with disabilities or BAME employees. We also estimate models for minimum wage employees with impaired disabilities and find no statistically significant changes for the derived wage measure (see Tables A8 and A9 in the Appendix). For the direct wage measure, relative to 2014, we find an increase in upward mobility in 2018 and 2019 and fall in no progression from minimum wage employment and an increase in 2019 for the imputed wage measure. These improvements for disabled employees who report at least one functional impairment occur sometime after the introduction of the NLW. Due to sample size limitations it was not possible to estimate models for different ethnic minority groups or by impairment type.

Table 7 Progression from minimum wage to a higher wage employment (upward mobility)

a) direct wage measure

Year	All Coeff.	P>|t|	BAME Coeff.	P>|t|	Disabled Coeff.	P>|t|	Men Coeff.	P>|t|
2011	**-0.078**	0.037	-0.034	0.699	-0.040	0.538	-0.091	0.186
2012	-0.050	0.185	-0.088	0.282	0.031	0.659	-0.056	0.413
2013	-0.033	0.383	-0.028	0.748	-0.043	0.522	**-0.135**	0.043
2014								
2015	-0.051	0.189	-0.106	0.209	-0.003	0.962	**-0.152**	0.022
2016	**-0.093**	0.012	-0.079	0.324	-0.074	0.245	**-0.134**	0.037
2017	**-0.099**	0.005	-0.032	0.680	-0.043	0.463	**-0.192**	0.001
2018	-0.045	0.203	0.030	0.710	0.058	0.344	**-0.110**	0.070
2019	**-0.073**	0.092	-0.136	0.103	0.083	0.270	**-0.239**	0.001

b) derived wage measure

Year	All Coeff.	P>|t|	BAME Coeff.	P>|t|	Disabled Coeff.	P>|t|	Men Coeff.	P>|t|
2011	0.011	0.560	-0.031	0.487	0.016	0.656	0.032	0.343
2012	-0.007	0.730	-0.036	0.439	0.015	0.687	0.013	0.705
2013	-0.018	0.358	-0.048	0.319	0.003	0.939	-0.024	0.488
2014								
2015	**-0.038**	0.055	**-0.091**	0.059	-0.012	0.746	-0.015	0.669
2016	**-0.071**	0.000	**-0.108**	0.013	-0.048	0.181	**-0.068**	0.047
2017	**-0.059**	0.002	**-0.119**	0.006	**-0.069**	0.049	-0.045	0.175
2018	**-0.069**	0.000	-0.054	0.214	-0.051	0.147	**-0.064**	0.053
2019	**-0.092**	0.000	**-0.154**	0.001	-0.040	0.355	**-0.126**	0.002

c) imputed wage measure

Year	All Coeff.	P>|t|	BAME Coeff.	P>|t|	Disabled Coeff.	P>|t|	Men Coeff.	P>|t|
2011	**-0.079**	0.012	-0.005	0.945	-0.054	0.375	-0.038	0.505
2012	-0.012	0.713	-0.011	0.880	0.072	0.242	0.041	0.462
2013	-0.052	0.111	-0.048	0.514	-0.000	1.000	-0.049	0.398
2014								
2015	-0.009	0.793	-0.021	0.776	0.016	0.804	-0.008	0.882
2016	**-0.112**	0.000	-0.077	0.264	-0.077	0.206	**-0.125**	0.027
2017	**-0.081**	0.007	-0.045	0.496	-0.074	0.192	**-0.101**	0.054
2018	**-0.074**	0.014	-0.006	0.933	0.002	0.977	-0.084	0.110
2019	-0.059	0.117	-0.021	0.779	0.048	0.480	**-0.126**	0.064

Data source: Understanding Society.

Notes: Estimates from linear probability models. 2014 is the reference year. 2010 has been dropped from this analysis as far fewer interviews took place in 2009 compared with other years – USoc data have been annualised using the actual date of the interview. Bold denotes statistical significance >10%.

Table 8 No progression from minimum wage employment (stuck)

a) direct wage measure

Year	All Coeff.	P>|t|	BAME Coeff.	P>|t|	Disabled Coeff.	P>|t|	Men Coeff.	P>|t|
2011	0.046	0.232	-0.017	0.852	-0.023	0.748	0.039	0.584
2012	0.016	0.687	-0.005	0.958	-0.030	0.685	-0.005	0.947
2013	0.018	0.640	-0.086	0.346	0.031	0.675	0.061	0.385
2014								
2015	0.037	0.359	0.090	0.304	-0.030	0.685	0.087	0.214
2016	**0.100**	0.009	0.016	0.845	0.077	0.265	**0.140**	0.034
2017	**0.103**	0.004	-0.029	0.716	0.064	0.308	**0.174**	0.006
2018	0.041	0.251	-0.099	0.237	-0.073	0.261	**0.120**	0.052

b) derived wage measure

Year	All Coeff.	P>|t|	BAME Coeff.	P>|t|	Disabled Coeff.	P>|t|	Men Coeff.	P>|t|
2011	-0.021	0.258	-0.001	0.979	-0.036	0.321	-0.053	0.113
2012	-0.004	0.825	0.000	0.996	-0.017	0.633	-0.030	0.392
2013	0.022	0.251	0.019	0.684	0.015	0.687	0.013	0.703
2014								
2015	**0.048**	0.016	**0.085**	0.078	0.016	0.666	0.026	0.466
2016	**0.082**	0.000	**0.094**	0.031	**0.062**	0.088	**0.087**	0.011
2017	**0.071**	0.000	**0.103**	0.017	**0.086**	0.015	**0.060**	0.070
2018	**0.078**	0.000	0.038	0.378	**0.061**	0.084	**0.078**	0.018
2019	**0.097**	0.000	**0.132**	0.006	0.064	0.137	**0.127**	0.002

c) imputed wage measure

Year	All Coeff.	P>|t|	BAME Coeff.	P>|t|	Disabled Coeff.	P>|t|	Men Coeff.	P>|t|
2011	**0.060**	0.057	-0.017	0.817	-0.010	0.809	0.014	0.795
2012	-0.001	0.971	0.013	0.856	-0.082	0.181	-0.048	0.379
2013	0.045	0.163	0.025	0.785	0.000	1.000	0.034	0.555
2014								
2015	0.012	0.706	0.040	0.580	-0.050	0.427	0.012	0.833
2016	**0.124**	0.000	0.077	0.318	0.086	0.167	**0.147**	0.009
2017	**0.096**	0.001	0.021	0.853	0.064	0.268	**0.117**	0.025
2018	**0.091**	0.002	0.012	0.892	0.002	0.966	**0.134**	0.010
2019	**0.070**	0.062	0.027	0.761	-0.010	0.881	**0.132**	0.055

Data source: Understanding Society.

Notes: Estimates from linear probability models. 2014 is the reference year. 2010 has been dropped from this analysis as far fewer interviews took place in 2009 compared with other years – USoc data have been annualised using the actual date of the interview. Bold denotes statistical significance >10%.

9. Conclusion

Lower rates of employment and higher rates of low pay might suggest that ethnic minorities and people with disabilities are at greater risk of experiencing negative employment effects from minimum wage increases. The Low Pay Commission has regularly monitored employment rates for these groups for any signs that minimum wage increases have had a negative effect. While this monitoring exercise is useful, heterogeneous impacts can be missed and monitoring aggregate trends in employment rates is not sufficient to detect whether minimum wage increases have led to higher job losses for some groups or if there are offsetting effects. The main aims of this research were to provide a more detailed statistical picture of disability and ethnicity in relation to minimum wage rates and new estimates of the impact of minimum wage increases on employment retention and wage progression by ethnicity, disability and gender. We do this using data from two national household surveys covering the decade 2009-2019 and three wage measures.

It is well-documented that wage rates derived from self-reported earnings and hours of work in household survey data contain measurement error and lead to upward bias in estimates of the proportion of employees earning at or below minimum wage rates relative to estimates using ASHE data (Skinner et al., 2002; Beissel-Durrant and Skinner, 2003). While ASHE wage data, which are based on employer reports from administrative records, are considered to be of higher quality, ethnicity and disability variables are not available in this dataset. This means that to conduct research on disability, ethnicity and minimum wages, analysis of household survey data is required. For some household survey respondents, higher quality wage information is available in the form of directly reported wage rates but this information is only available for a proportion of employees who are paid at an hourly rate rather than a salary. This is a select group of employees who tend to be lower paid. These two wage measures are available in the Annual Population Survey and Understanding Society, the two data sources used in this research. As an alternative, we use a method developed by Skinner et al. (2002) and Beissel-Durrant and Skinner (2003), and recently used in LPC research by Avram and Harkness (2020), to impute wage values for survey respondents with missing directly reported wage rates. Estimated minimum wage coverage rates using the imputed wage measure are similar to those estimated using the higher quality ASHE data. We use this imputed wage measure to provide new estimates of minimum wage coverage by ethnicity and disability status and estimate heterogeneous impacts of minimum wage upratings on employment retention and wage progression, alongside estimates based on the derived and directly reported wage measures.

Minimum wage coverage rates increased over the last decade, particular after the introduction of the higher NLW. However, estimated coverage rates declined after 2017. Coverage rates can decline if minimum wage upratings do not keep up with general wage growth (note that NLW upratings have exceeded wage growth), if some employees paid at the minimum wage lose their jobs or if fewer minimum wage jobs are created.

Disability

Minimum wage coverage rates are higher among male and female disabled employees relative to their non-disabled peers. The introduction of the NLW led to large increases in coverage rates and increases in the difference between disabled and non-disabled employees in absolute and percentage terms. Declines in minimum wage coverage occurred after 2017 for employees with and without disabilities. Estimated minimum wage coverage rates vary considerably among disabled employees by types of functional impairment. The highest rates of coverage are found for disabled employees reporting impairments in communication or speech, or recognising when in physical danger. Employment rates rose over the decade among men and women with disabilities with the main increase occurring after the introduction of the NLW, and there is evidence of a fall in the disability employment gap (APS). Increasing employment among people with disabilities is consistent with a tightening of the labour market which helps to draw in more disadvantaged workers.

We estimate the impact of the introduction of the NLW on employment retention for employees with disabilities using difference-in-difference-in-differences (DDD) models. For models using the derived wage measure and the directly reported wage measure to define treatment and control groups, we find no statistically significant negative effects on employment retention for disabled employees. For models based on the imputed wage measure, we estimate statistically significant positive effects on employment retention for disabled employees but when we control for age and gender the effect is statistically insignificant.

Disabled employees in minimum wage employment are relatively more likely to transition out of paid employment one year later and relatively less likely to move to higher wage employment. For minimum wage employees with disabilities, there are no statistically significant changes in predicted probabilities of progression to higher wage employment or becoming stuck in minimum wage employment estimated in transition models using the directly reported wage measure or the imputed wage measure. For models based on the derived wage measure, there is a statistically significant increase in the predicted probability of remaining in minimum wage employment after the introduction of the NLW and a fall in progressing to higher paid employment in 2017. However, this wage measure is known to suffer from measurement error.

For disabled employees reporting at least one functional impairment, none of the changes in wage progression over the decade appear to be related to the introduction of the NLW.

Overall, the findings suggest that higher minimum wage rates have been beneficial to people with disabilities, leading to higher earnings without significant detrimental impacts on employment retention and wage progression. However, it is important to acknowledge that we have not been able to estimate the impact of minimum wage upratings on small, specific groups of disabled people such as individuals with severe learning disabilities for whom particular concerns have previously been raised.

Ethnicity

New estimates of minimum wage coverage by ethnicity show higher rates among Black, Asian and Minority Ethnic (BAME) employees relative to non-BAME employees (on all three wage measures). Minimum wage coverage rates for BAME and non-BAME employees increased over the last decade, particularly after the introduction of the NLW. Minimum wage coverage rates are higher among BAME women than BAME men but the BAME coverage gap is higher for men than it is for women. This is the result of much lower minimum wage coverage rates among non-BAME men. Beneath this simple binary classification there are considerable differences in coverage rates between ethnic minority groups. Higher rates are found among Bangladeshi and Pakistani employees and low rates of minimum wage coverage among Indian employees.

BAME employment rates are lower than non-BAME rates and the BAME employment gap is much larger for women than it is for men. BAME employment rates have increased over the last decade with particularly strong growth for BAME women, which led to a narrowing in the BAME employment gap. This growth in employment continued after the introduction of the NLW. More detailed analysis across ethnic minority groups shows that the lower employment rate among BAME women is largely due to particularly low employment rates among Bangladeshi and Pakistani women but both experienced large increases in employment over the decade.

A number of interesting results emerge from the statistical modelling of employment retention and wage progression. There are no negative effects on employment retention associated with the introduction of the NLW by BAME status; models based on all three wage measures, with and without control variables and separate models for men and women. Pakistani and Bangladeshi employees might have been expected to be most at risk from minimum wage upratings (lower employment rates and higher minimum wage coverage rates) but no negative impacts on employment retention are estimated overall (in models with and without controls for age and gender), or for Pakistani and Bangladeshi men and women (the exception is for women when the derived wage measure is used to identify the treatment and control groups). In contrast, we

estimate negative effects on employment retention for Indian employees (models based on the direct and imputed wage measures) and separate models by gender show that this finding is driven by negative effects experienced by Indian men; a group which, a priori, might be considered to be less likely to be at risk on the basis of high rates of employment and low minimum wage coverage rates. This suggests that while in general Indian men enjoy an advantaged position in the labour market, Indian men who are in minimum wage employment appear to be particularly disadvantaged and at risk from minimum wage upratings.

For the direct and imputed wage measures, we estimate no statistically significant change in annual transitions for minimum wage BAME employees either in terms of remaining stuck in minimum wage employment or progressing to higher paid employment over the last decade (including following the introduction of the NLW). For the derived wage measure, we estimate a statistically significant fall in predicted probability of upward mobility and an increase in remaining stuck in minimum wage employment for minimum wage BAME employees.

Sample size constraints do not allow us to estimate transition probability models for ethnic minority groups by gender but estimating wage progression models by gender revealed that following the introduction of the NLW the predicted probability of remaining in minimum wage employment increased for men, and, conversely, the predicted probability of moving to higher wage employment fell.

One of the main contributions of this research is the use of three wage measures: directly reported; derived and imputed. We have shown that some of the findings are sensitive to the wage measure used. For example, for disabled employees the findings of an increase in the predicted probability of remaining stuck in minimum wage employment after the introduction of the NLW is only statistically significant for the derived wage measure. Given the known measurement error in the derived wage variable we should be more skeptical of findings which are only statistically significant for this wage measure. This is because analysis which focuses on identifying a group of employees earning around the minimum wage to estimate the impact of minimum wage upratings on employment outcomes, can be affected by misclassification. For example, if employees whose true wage rate is above the minimum wage are incorrectly assigned to the treatment group as a result of measurement error, treatment effect estimates will be measured with error and can be biased downwards (if these employees have higher employment retention than the true treatment group and if the higher minimum wage led to a fall in employment retention among the true treatment group).

The direct wage measure is available for a select group of employees who are more likely to be lower paid (lower paid employees are more likely to be paid at an hourly rate and directly report

this wage rate in household surveys). While this wage measure will not provide reliable measures of minimum wage coverage, it is less likely to suffer from misclassification of minimum wage employees and impact estimates are more likely to be reliable. The imputed wage measure (taking the value of the directly reported wage where available, imputed wage values where missing) provides estimates of coverage which are close to estimates based on ASHE data. However, as with any imputation process we should not rule out the possibility of some measurement error.

Overall, the evidence suggests that ethnic minorities and people with disabilities have largely benefited from minimum wage upratings over the last decade, including after the introduction of the more generous National Living Wage. In general, higher minimum wages have increased earnings among these groups who are more likely to be paid at minimum wage rates. We found two exceptions to this generally positive picture. There is some evidence that the introduction of the NLW led to a fall in employment retention for Indian men in jobs that were in scope for the new higher NLW. There is also evidence that men in minimum wage jobs were less likely to progress to higher wage employment and more likely to be stuck in minimum wage employment after the introduction of the NLW, but it is important to recognise that they were more likely to become stuck at a higher wage rate.

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Appendix

The following ten Annual Population datasets are used in this study:

    October 2009-September 2010

    October 2010-September 2011

    October 2011-September 2012

    October 2012-September 2013

    October 2013-September 2014

    October 2014-September 2015

    April 2016-March 2017

    April 2017-March 2018

    April 2018-March 2019

    April 2019-March 2020

The NMW was uprated in October 2015 but the NLW was introduced six months later and therefore we do not include an APS dataset starting in October 2015.

Table A1: Understanding Society sample sizes for respondents with disabilities who report at least one functional impairment by gender and year

	All	Men	Women	Total
2009	3,266	1,509	1,757	16,205
2010	6,399	2,898	3,501	34,549
2011	5,663	2,580	3,083	32,993
2012	4,967	2,228	2,739	29,273
2013	4,538	1,985	2,553	27,312
2014	4,311	1,918	2,393	25,837
2015	4,165	1,860	2,305	26,118
2016	4,230	1,898	2,332	25,180
2017	4,002	1,805	2,197	22,293
2018	3,884	1,736	2,148	20,907
2019	1,855	800	1,055	9,551

Table A2 Understanding Society unweighted sample sizes for people with disabilities by type of functional impairment

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Mobility	1,571	3,080	2,797	2,446	2,221	2,125	2,016	1,995	1,838	1,688	789
Lifting, carrying or moving objects	1,973	3,744	3,174	2,806	2,466	2,214	2,050	2083	1,886	1,788	827
Manual dexterity	652	1,357	1,111	1,034	942	888	894	840	749	738	357
Continence	386	792	670	623	588	524	482	514	538	555	271
Hearing	310	605	490	430	374	359	343	338	317	263	110
Sight	324	668	554	445	409	405	386	394	350	299	145
Communication or speech	174	367	313	272	247	252	264	295	238	233	124
Memory or ability to concentrate, learn or understand	731	1,445	1,219	1,072	1,031	956	936	983	864	855	401
Recognising when in physical danger	120	257	202	179	178	167	169	171	143	149	73
Physical co-ordination	589	1,139	962	905	914	818	750	732	632	619	283
Personal care	462	952	762	697	618	583	581	627	532	541	268
Other	871	1,789	1578	1,375	1,345	1,391	1,352	1,448	1,496	1,521	735

Note: respondents can report more than one functional impairment.

Table A3 Sample sizes for models estimating treatment effect from DID and DDD models

Wage variable	All	BAME	Pakistani-Bangladeshi	Indian	Disabled	Impaired disabled
	(1)	(2)	(3)	(4)	(5)	(6)
Direct wage	6,860	6,829	6,829	6,829	6,856	6,856
Derived wage	28,713	28,570	28,570	28,570	28,691	28,691
Imputed wage	27,502	27,370	27,370	27,370	27,481	27,481

Data source: Understanding society.

Table A4 Sample sizes for models estimating treatment effect estimates from DID and DDD models

Wage variable	All	BAME	Pakistani-Bangladeshi	Indian	Disabled	Impaired disabled
	(1)	(2)	(3)	(4)	(5)	(6)
Men						
Direct wage	2,971	2,959	2,959	2,959	2,970	2,970
Derived wage	13,429	13,358	13,358	13,358	13,424	13424
Imputed wage	12,784	12,719	12,719	12,719	12,780	12,780
Women						
Direct wage	3,889	3,870	3,870	3,870	3,886	3,886
Derived wage	15,284	15,212	15,212	15,212	15,267	15,267
Imputed wage	14,718	14,651	14,651	14,651	14,701	14,701

Data source: Understanding society.

Table A5 Sample sizes for models estimating progression from minimum wage to higher wage employment and no progression (direct wage)

	All	BAME	Disabled	Impaired disabled	Men	Women
n	3,137	645	966	556	976	2,161

Data source: Understanding Society.

Table A6 Sample sizes for models estimating progression from minimum wage to higher wage employment and no progression (derived wage)

	All	BAME	Disabled	Impaired disabled	Men	Women
n	11,814	2,390	3,345	1,866	3,923	7,891

Data source: Understanding Society.

Table A7 Sample sizes for models estimating progression from minimum wage to higher wage employment and no progression (imputed wage)

	All	BAME	Disabled	Impaired disabled	Men	Women
n	4,497	956	1,307	768	1,411	3,089

Data source: Understanding Society.

Table A8 Progression from minimum wage to a higher wage employment

a) direct wage measure

Year	Impaired disabled Coeff.	P>|t|
2011	0.010	0.906
2012	0.072	0.419
2013	0.002	0.979
2014		
2015	0.039	0.641
2016	-0.026	0.734
2017	0.027	0.717
2018	**0.134**	0.082
2019	**0.206**	0.029

b) derived wage measure

Year	Impaired disabled Coeff.	P>|t|
2011	0.072	0.140
2012	0.066	0.170
2013	0.053	0.290
2014		
2015	0.027	0.597
2016	0.008	0.865
2017	-0.037	0.425
2018	0.037	0.420
2019	0.004	0.948

c) imputed wage measure

Year	Impaired disabled Coeff.	P>|t|
2011	-0.004	0.961
2012	**0.153**	0.051
2013	0.062	0.470
2014		
2015	-0.004	0.964
2016	-0.055	0.480
2017	-0.013	0.862
2018	0.091	0.215
2019	**0.151**	0.078

Data source: Understanding Society.

Notes: Estimates from linear probability models. 2014 is the reference year. 2010 has been dropped from this analysis as far fewer interviews took place in 2009 compared with other years – USoc data have been annualised using the actual date of the interview. Bold denotes statistical significance >10%.

Table A9 No progression from minimum wage employment (stuck)

a) direct wage measure

	Impaired disabled	
Year	Coeff.	P>|t|
2011	-0.077	0.395
2012	-0.117	0.230
2013	-0.056	0.568
2014		
2015	-0.097	0.294
2016	-0.006	0.942
2017	-0.037	0.654
2018	**-0.138**	0.098

b) derived wage measure

	Impaired disabled	
Year	Coeff.	P>|t|
2011	**-0.092**	0.061
2012	-0.075	0.122
2013	-0.038	0.452
2014		
2015	-0.038	0.465
2016	-0.005	0.922
2017	0.047	0.324
2018	-0.020	0.676
2019	0.013	0.811

c) imputed wage measure

	Impaired disabled	
Year	Coeff.	P>|t|
2011	-0.083	0.300
2012	**-0.200**	0.011
2013	-0.069	0.428
2014		
2015	-0.084	0.308
2016	0.023	0.780
2017	-0.048	0.527
2018	-0.082	0.273
2019	-0.140	0.103

Data source: Understanding Society.
Notes: Estimates from linear probability models. 2014 is the reference year. 2010 has been dropped from this analysis as far fewer interviews took place in 2009 compared with other years – USoc data have been annualised using the actual date of the interview. Bold denotes statistical significance >10%.